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http://online.agris.cz

ISSN 1804-1930
XVII, 2025, 2

International scientific journal
Prague

Agris on-line Papers in Economics and Informatics

The international reviewed scientific journal issued by the Faculty of Economics and Management of the Czech University of Life Sciences Prague.

The journal publishes original scientific contributions from the area of economics and informatics with focus on agriculture and rural development.

Editorial office

AGRIS on-line Papers in Economics and Informatics
Department of Economics of FEM CZU Prague
Kamýcká 129, 165 00 Praha-Suchdol
Czech Republic
Phone: +420 224 382 056
E-mail: agrisonline(at)pef.czu.cz

Publisher

Faculty of Economics and Management
Czech University of Life Sciences Prague
Kamýcká 129, 165 00 Praha-Suchdol
Czech Republic
Reg. number: 60460709

ISSN 1804-1930

XVII, 2025,
30th of June 2025
Prague

Agris on-line

Papers in Economics and Informatics

ISSN 1804-1930

XVII, 2025, 2

Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

Content:

Volume XVII Number , 2025

Analysis of Determinants of Maize Farmers Adaptation Strategies to Climate Change in South-South Nigeria

Adeyinka Richard Aroyehun[1], Anthony Ojonimi Onoja[1,2], Vivian Chinelo Ugwuja[1]

[1] Agricultural Economics and Agribusiness Management Department, University of Port Harcourt, Nigeria

[2] Department of Agriculture and Animal Health, College of Agriculture and Environmental Sciences, University of South Africa (UNISA), Jonaeburg, Republic of South Africa

Abstract

Adaptation to climate change is critical for sustainable livelihood in developing countries like Nigeria where agriculture production depends majorly on rainfall. This research examined the analysis of determinants of maize farmers' adaptation strategies to climate change in South-South Nigeria. Multistage sampling techniques were used for the selection of 260 maize farmers from 36 communities in the study area. Primary data were collected using a set of questionnaires and an interview schedule. The result of the Variance Inflating Factor (VIF) and Tolerance level revealed that multicollinearity does not exist. The majority (96.9%) of the maize farmers adopted the use of adaptation techniques. The majority (81.9%), (81.5%), and (78.5%) adopted the use of improved crop species, planting of drought tolerant crop species, and changing in planting dates respectively. The multivariate probit (MVP) model results show that among all determinants, access to information on climate change was the most important influencing factor that enabled farmers to adopt different adaptation strategies because it was statistically significant in all the dependent variables used in the analyses. The research, recommends collaboration among the tiers of institutions to improve access to credit/ finance facilities, avail affordable farm inputs, adequate extension service delivery, eliminate the risk of maize pests and disease, and provide necessary and timely information for the maize farmers.

Keywords

Adaptation, climate change, diversification, mixed farming, MVP.

Aroyehun, A. R., Onoja, A. O. and Ugwuja, V. C. (2025) "Analysis of Determinants of Maize Farmers Adaptation Strategies to Climate Change in South-South Nigeria", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 3-23. ISSN 1804-1930. DOI 10.7160/aol.2025.170201.

Introduction

The global average temperatures have significantly increased since the Industrial Revolution (Baumann, 2018). The Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change IPCC (2021) provides strong evidence for the increasing trend of global mean temperature in the 21st century. The rising trend in temperatures due to greenhouse gas emissions has contributed to global warming. Global warming increased by + 1.07°C (0.8–1.3°C; likely range) for 2010–2019 compared to the reference period 1850–1900 (IPCC, 2021). Gemeda, Korecha, and Garedew (2023) noted that there are more hot days and fewer cold temperature extremes projected in most places as global mean temperatures increase. Increase in population growth and stressors on agricultural productivity triggered by climate change, have a significant impact on food security (Dasgupta and Robinson, 2022; Kumar et al., 2022; Rahut et al., 2022). Hence, it could be widely recognized that climate change is having an adverse effect on food security.

Climate change has induced an adverse impact on all sectors of the economy with high severity on rain-fed agriculture due to its sensitivity. Climate change affects agricultural yields and thus may increase food insecurity in the absence of adaptation options (IPCC, 2019; Mequannt et al., 2020). Hence, irreversible climate change threatens food supplies, including Nigeria, especially South-South Nigeria. The decline in agricultural production is one of the key factors to poverty as climate change significantly affects food supplies (Abbass et al., 2022). To enhance public awareness of the interlinkages between climate change and food security, the 27th UN Climate Change Conference of the Parties in 2022 made food systems part of the agenda of COP27. It has been reported that climate change can reverse food security improvements in Africa (Dasgupta and Robinson, 2022). Various adaptation strategies and policies have been made so far to minimize the effects of climate change on agriculture. Like other countries, Nigeria is experiencing climate change.

Previous studies conducted on climate change adaptation include Kabira, Alauddinb, and Crimp (2017); Mercer (2020); Ogunnaike, Oyawole, Afolabi, and Olabode (2021); and Aroyehun (2023) among others, noted that climate change influences the seasonal variability's that severely affecting agricultural output and the livelihood of the farmer's. Changes in rainfall and temperature from normal conditions can significantly affect agricultural production. Hence, climate change is impacting Nigeria's agricultural production and economy. Agricultural yield reductions and food insecurity caused by climate change continue to be the major concerns affecting the nutritional needs and food preferences of agricultural communities. Increasing temperatures, changing precipitation patterns, and the occurrence of extreme events negatively affected food security (IPCC, 2019). As such, climate change adaptation strategies are designed to enhance agricultural productivity and build farmers' resilience (Bedeke et al., 2019). There is a great consensus that policymakers require climate information to advise the best adaptation strategies (Gebrechorkos et al., 2020). Therefore, maize farmers' understanding of climate change impact is the prerequisite information to design adaptation strategies. Yet, none of these studies examined the effects on maize farmers' adaptation to climate change: particularly, concerning Nigeria's maize production for society utilization. Some research like Adeagbo, Ojo, and Adetoro (2021); Aderinoye-Abdulwahab, and Abdulbaki (2021); Osuafor, Ude, and Ositanwosu (2021) has been done on maize and climate change adaptation but nor of this use multivariate probit (MVP) which this study want to fill, particularly to the effect of climate change adaptation strategies on maize farming in South-South Nigeria. Consequently, this current research attempts to close the aforementioned gap by exploring climate change adaptation strategies and maize production. This will provide evidence for policy on the efficient use of adaptation strategies in building maize farmers' productivity and resilience in a changing climate in Nigeria, especially in the South-South region of Nigeria. Given this, this research aimed to fill this knowledge gap by examining the effect of selected independent variables on climate change adaptation strategies adopted by the maize farmers; and analyze the determinants of adaptation strategies adopted by the maize farmers to cope with climate change impacts in South-South Nigeria in order to increase the speed of Nigerian's to achieve the Sustainable Development Goals (SDGs) of no poverty, zero hunger and climate action.

Literature review

Climate a phenomenon as well as a demonstration regarding weather and diverse atmosphere (baroscopic) conditions, has widely been recognized and accepted as one of the definite basic constituent indexes that determine crop farming and animal rearing. Climate is a long-term numerical mean of weather and other baroscopic conditions that directly and indirectly influence the function and performance of the farms (Aderinoye-Abdulwahab and Abdulbaki, 2021). Prevailing climatic conditions of any environment (biosphere) determine the selection of crops, mode of planting, and yields. According to Aderinoye-Abdulwahab and Abdulbaki (2021) biophysical component determinants for instance energy from the sunlight, temperature, moisture, wind, and humidity, including other climatic factors control and influence universal crop distribution, productivity and profitability. Conversely, climate change is the long-term variation in arithmetic medium point of temperature owing to the effect of the earth's warming that could ultimately transpose toward exhaustion or reduction of the ozonosphere stratification. Higher greenhouse gas (GHG) emission concentration into the troposphere results in earth warming (Mboera, Mayala, Kweka, and Mazigo, 2012). Human activities that advance contribution to GHG include the use of fossil fuel, changes in land utilization, and agricultural operations among others.

United Nations Framework Convention on Climate Change [UNFCCC] expresses climate change using any variation/ alteration in climatic factors covering an excessive length of duration (35 years), which could be either natural variation or due to human activity. In another way, the Intergovernmental Panel on Climate Change IPCC (2001 as cited in Onoja, Achike, and Enete, 2018), described climate alteration to be the deviation in a climate that is associated with direct and/ or indirect activity of human beings known to mutates constituent of the universal troposphere as well as substratosphere coupled with inherent fluctuations noticed over a comparable period. The World Bank (2016) reported the Paris Climate Conference informed that climate change, if abandoned or not attended to may be a "foundational hazard to the development of economy in our generation and capable of pushing over hundred (100) million people in abject poverty by 2030." This possibly will weaken all advancement achieved globally in combating poverty for about 18 years. Climate change is a great risk and uncertainty to the agricultural sector and socioeconomic development of the nation, agricultural production enterprises are more predominantly open to vulnerability attacks of climate change than any other sectors of the economy (Onoja et al, 2018). Hence, climate change poses a greater and increasing risk to food security globally.

Adaptation strategies to climate change are critical at the farm level, features such as increasing crop failures due to erratic rainfall, prolonged drought during growing, early termination of rainfall, crop loss as a result of storms and floods, increasing temperatures, and pest and diseases scourge compels for efficient adaptation. Adaptation to climate change involves taking appropriate and suitable actions to minimize the adverse effects of climate change by adopting relevant adaptation strategies. Climate change adaptation has three (3) potential objectives: to minimize exposure to the uncertainty of the hazard; to improve the ability and scope to tackle and manage the inevitable damages; and to annex the advantages of advanced new opportunities (Akinnagbe and Irohibe, 2014). Crop adaptation strategies to climate change impacts according to Akinnagbe and Irohibe (2014) are as follows: planting of drought-resistant species of crops; crop diversification; change in cropping and planting date pattern; mixed cropping; enhancement and optimization of irrigation infrastructure effectiveness; soil moisture conservation; afforestation (planting of trees) and agroforestry; labour migration; diversification of income; effective use of insurance; meteorological information; and farm-level financial management scheme. Table 1 below shows other (extracted) adaptation strategies adopted by crop farmers in sub-Saharan Africa as itemized by the World Bank (2008 as cited in Onoja, 2014).

Practice	Adaptation strategies
Crop and livestock improvement	
Crop rotations	Minimize weed completion with crops, and pest attacks; reduce depletion of particular soil nutrients.
Agroforestry practice combined with crops/ livestock	Increase soil nutrients via leaves, enhance water permeations, and reduce soil dryness.
Utilization of additional resources productive of crops, trees, and livestock	Enhances water and/ or nutrient utilization productivity both presently and in future climate change.
Enclosures	Facilitates metamorphosis of vegetation cover, valuable plants, and spring reclamation.
Enhanced grazing methods	Preservation and reformation of vegetation cover and minimize soil compression.
Safekeeping of vegetation from fire incidence	Conservation and protection of vegetation and essential varieties
Soil management improvement	
Cover cropping	Minimize soil erosion, and weed growth and support soil carbon accumulation.
Mulching and compost	Minimizes soil erosion, and increases soil moisture maintenance, soil nutrients, and organic matter.
Manure application	Improves soil organic matter
Crop residue inclusion	Addition of nutrients and organic matter to the soil
Intercropping with legumes	Enhances infiltrations, soil nutrients, and carbon improvement via nitrogen fixation
Terrace planting	Prevents soil erosion
Minimal tillage	Improves soil moisture and accelerates soil carbon
Windbreaks and protection supports	Minimizes winds and rain erosions
Water management improvement	
Contour farming/ planting	Equally proportioned water circulation and penetration in sloppy areas, and minimizes water runoff and overflow.
Harvesting of rainwater	Rainwater storage in tanks or ponds compensates for prolonged drought periods
Establishment of irrigation systems	Compensates impacts of drought periods. Restrain farmland accumulation of excess water.
Management of watershed	Adequate and efficient management of rainwater, surface, and underground waters should be adopted at the hierarchy beyond the household level.

Source: Authors

Table 1: Crop farmers' adaptation strategies.

Maize production

Maize is widely well-known to be the Queen of cereal crops because of its requirement and vast adaptability. It is the second most essential cereal crop globally to land expanse and yield. Maize production globally was about 1040 million metric tons (MT) in the years 2016-2017, where USA and China output contributions were 38% and 23% respectively (Jaidka, Bathla, and Kaur, 2019). Maize is the third major vital food crop subsequently to rice and wheat crops in India. Whereas, maize is the main cereal crop and one of the major vital and essential food crops in Nigeria (Kamara, Kamai, Omoigui, Togola, Ekeleme and Onyibe, 2020). Maize's genetic resilience has made it the largest broadly planted crop in Nigeria from the Coastal evergreen climate region of the forest zone to the dry Sudan savannah region. Maize is photoperiod indifferent; these make it grow at any time of the year, giving it better adaptability to fit into various cropping systems.

In Nigeria, maize has become a vital crop, taking over expansive land from common crops like millet and sorghum. Maize yield in Nigeria in the year 2018 was about 10.2 million tons from 4.8 million hectares of land (Fig 1), making Nigeria the largest maize producer in Africa (FAO, 2018 as cited by Kamara et al, 2020).

Scientific work and results by crop breeders and agronomists have resulted in the adaptability of maize to innovations such as drought-resistant species, high-producing species, and diseases-resistant, low nitrogen among others. However, despite various availabilities of maize species, outputs are yet low in Nigeria to meet up with the population increase.

Maize can be grown favourably and profitably on loamy sandy to massive clayey soils, well-aerated soil, and soils with neutral pH. Maize originated from Central America and Mexico, which in Mexico existed significantly for about 5000 years ago with different maize crop species. Maize is of tropical origin, is very susceptible to water stagnation, and poorly drained farmland (Jaidka et al, 2019). In addition, extensive low temperature of about less than 5oC exclusively affects the yields of maize. The optimum temperature range for maize optimal growth and yield is 21-35°C (Jaidka et al, 2019), with rainfall distribution of 480-880 mm for proper yield (Kamara et al, 2020). Maize is day day-neutral crop, it can be grown all year around which results in high output levels in a very short time. Maize cultivar selection depends on temperature and volumes of moisture content in the soil. Table 2 below shows maize cultivars according to Jaidka et al. (2019).

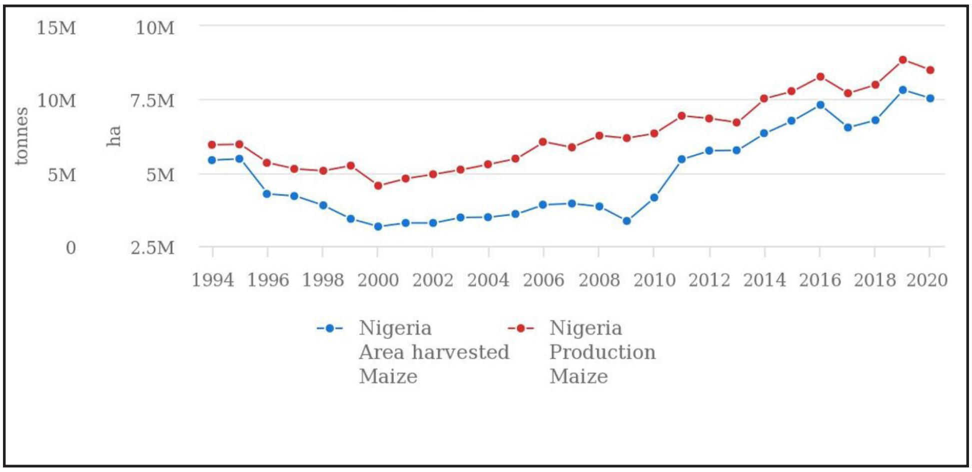
Kind of maize cultivar	Length of maize cropping period (in days)
Early maturity	80-90
Medium maturity	90-100
Late maturity	100 and above

Source: Authors

Table 2: Maize cultivars.

The effect of climate change on the agricultural system in the study area

South-South Nigeria, which includes the States of Rivers, Bayelsa, Delta, Cross River, Akwa Ibom, and Edo, is particularly sensitive to climate change due to its coastal position and reliance on agriculture. Frequent floods, increasing sea levels, coastal erosion, and shifting rainfall patterns



Source: Authors computation (2023)

Figure 1: Maize production trends in Nigeria (yields).

all have a significant impact on agricultural output and livelihoods (Nigerian Meteorological Agency NIMET, 2015). The primary consequences of climate change on agriculture in the region include:

Flooding and coastal erosion: Intense rains and inadequate drainage systems have resulted in regular floods, notably in the Niger Delta. As a result, farmlands get submerged, crops are lost, and soil nutrients are depleted (NDDC, 2019). Coastal erosion also lowers maize land, jeopardizing food security in coastal populations (Akpodiogagaa and Odjugo, 2010).

Irregular rainfall patterns: Unpredictable rainfall disrupts planting and harvesting schedules, resulting in crop failures and decreased yields. Traditional agricultural calendars are becoming less accurate, pushing farmers to try novel planting tactics that may not always work (Adejuwon, 2005).

Increased temperature and heat stress: Rising temperatures cause heat stress in crops and cattle. Crops such as cassava, maize, and rice exhibit reduced production under excessive heat, while animals suffer from decreased fertility and increased disease prevalence (Ozor and Nnaji, 2011).

Salinity intrusion and soil degradation: Sea-level rise causes saline intrusion into freshwater systems and farmlands, lowering soil fertility and damaging crops like yam, cassava, and vegetables that are susceptible to salinity (Eze and Efiong, 2017).

Pest and disease outbreaks: Pests and illnesses thrive in warm, humid areas. For example, the prevalence of the Fall Armyworm, which destroys maize harvests, has been connected to changing climatic circumstances (Ifeanyi-Obi, Etuk, and Jike-Wai, 2012).

The socioeconomic effects of climate change on farmers in the region include:

- Reduced income and livelihoods: Climate-induced crop failures have a direct impact on household income, contributing to greater poverty in agricultural areas (IFAD, 2020).
- Food insecurity: Declining agricultural production jeopardizes food security in both rural and urban regions (FAO 2016).
- Migration and displacement: Farmland loss due to floods and erosion drives rural-urban migration, increasing demand for urban resources (UNDP, 2020).

Agricultural climate adaptation policies/ programmes relevant to the study area

Agricultural climate adaptation strategies and initiatives are critical in South-South Nigeria because the region is vulnerable to climate change impacts such as floods, coastline erosion, saline intrusion, and erratic rainfall patterns. The region's economy is strongly reliant on agriculture, making it critical to develop methods that improve resilience and sustainability. Agricultural climate adaption strategies and programmes relevant to the research region include:

National Adaptation Strategy and Plan of Action on Climate Change for Nigeria (NASPA-CCN): NASPA-CCN offers an extensive framework for tackling climate change implications in several industries, including agriculture. The strategy encourages sustainable land management, climate-resilient crop varieties, and integrated water resource management, all of which are critical in flood-prone areas like the Niger Delta (Federal Ministry of Environment, 2011).

Climate-Smart Agriculture (CSA) initiatives: The Federal Ministry of Agriculture and Rural Development (FMARD) is implementing CSA projects with help from international organizations like as the FAO and the World Bank to promote sustainable practices such as drought-tolerant crops, effective irrigation, and agroforestry. These methods serve to reduce the dangers of unpredictable rainfall and floods in South-South Nigeria (FAO, 2013).

National Agricultural Resilience Framework (NARF): NARF strives to improve agricultural resilience by using climate-smart technology, systems for risk management, and early warning techniques. Its emphasis on developing adaptive capability is crucial for the South-South, where farmers experience recurring flooding and soil degradation (FMARD, 2014).

FADAMA III programme (additional financing): While FADAMA III was initially designed to promote dryland agriculture, it also includes components that aid in climate adaptation in wetter places. It encourages effective management of water resources, flood control measures, and livelihood diversification to strengthen the adaptability of small-holder farmers in South-South Nigeria (World Bank, 2020).

The Green Alternative (Nigeria's Agricultural Promotion Policy APP (2016-2020)): The APP, also referred to as the Green Alternative, emphasizes agricultural production, sustainability, and resilience. It fosters the use of climate-smart agricultural practices, better extension services, and the creation of flood-resistant crop varieties, which are especially pertinent to the climate conditions in South-South Nigeria (FMARD, 2016).

Niger Delta Development Commission (NDDC) climate adaptation initiatives: To address climate-related concerns such as coastal erosion and saline intrusion, the NDDC has implemented region-specific initiatives like as the restoration of mangrove forests, flood control systems, and environmentally friendly aquaculture programs (Ogbodo, 2022).

International climate adaptation programmes: International organizations, such as the International Fund for Agricultural Development (IFAD) and the United Nations Development Programme (UNDP), fund programmes that aim to improve smallholder farmers' climate resilience through capacity building, access to climate information, and sustainable agricultural practices (IFAD 2020; UNDP 2020).

Theoretical framework

The theory appropriate to this research is the theory of utility which is related to individual or corporate decisions. Utility simply means the satisfaction (adaptation) that each selection gives (benefit) to the actual decision-maker (farmer). Theoretically, utility comprises all the factors that affect the adaptation strategies' decision perspective of the maize crop farmers' psychology, culture and production. Hence, aforementioned utility theory appropriates that any decision (adaptation strategies adopted) follows the principle of utility maximization based on the best option chosen that gives the ultimate utility (that is satisfaction) to the farmer who makes the decision (Otitoju, 2013). In utility theory, $U(x)$ is a consumer's (like maize crop farmers) utility for definite sort of items X (like adaptation strategies), if the farmer assumes, that the utility derived from Y is not higher than the utility derived from Z, in this case, the expression will be $U(y) \leq U(z)$, or $y \leq z$. For the adaptation strategies question, if 'the adaptation strategy of u is not larger than the adaptation strategy v' then, we can express this type of ineffective selection using this symbol mark '$\precsim$' to evaluate orders and write it thus as $u \precsim v$ (Jian and Rehman, 2016). In all cases actual utility (satisfaction) well known to the decision-maker (maize crop farmer) derives by choosing a distinct climate change adaptation strategy is gauged and calculated through a utility function U, which is a measurable portray of actual decision-makers (that is maize crop farmer) strategy of alternative and preferences such that; $U(X_1)>U(X_2)$, where the preferred climate change adaptation strategy X_1 is adopted instead of X_2 or $Ux_1= Ux_2$, where adoption of X_1 is indifferent from the adoption of X_2, that's both adaptation strategies are preferred equally or give equal utility. Hence, the total utility from many available quantities of strategies for adaptation depends on the socio-economic typical feature of the individual maize crop farmers, and then total utility is; $U = f(X_1, X_2, X_3 \dots X_n)$. Utility can be stated thus;

$$U_t = U_1(X_1) + U_2(X_2) + U_3(X_3) + \dots + Un(Xn)$$

Therefore, the total utility of the climate change adaptation strategies of the maize crop farmers depends and the function of the available strategy. The climate change adaptation strategies were modeled into the production of the actual maize crop farmers' production activities in South-South Nigeria. Descriptive statistics were utilized to identify the climate change adaptation strategies utilized and adopted by the maize crop farmers in South-South Nigeria.

Another theory relevant is the theory of change. The theory of change is an approach that describes how a certain intervention or group of interventions, is anticipated to induce and give rise to definite development change, outlined on a causative analysis centered on obtainable substantiate evidence and sign (United Nations Development Group UNDG, 2017). Hence, a theory of change for the maize crop farmers should be driven by firm and reliable analyses, discussion with the major stakeholders, and ascertaining what strategies climate change adaptation adopted that are efficient and do not in different contexts described in the study. Theory of change aids in ascertaining solutions to efficiently tackle the causes of the problems that hamper strategies and adaptation as well as guide farmers' decisions on which climate change adaptation should be adopted, considering equivalent benefits, efficiency, and risks as well as uncertainties that are associated with any change processes (UNDG, 2017; Pringle and Thomas, 2019). Theory of change likewise aids in recognizing the fundamental assumptions and associated risks that are crucial to comprehend and reevaluate all through the adoption to guarantee the adaptation strategies that will enhance the anticipated change of the maize farmers which is high productivity and profit. Theory of change can be linked with adaptation strategies and improve relationships throughout climate change adaptation areas and measurements (Pringle and Thomas, 2019). The theory of change outlines the linkage between a long-term goal of adaptation adopted and the initial to average changes needed to bring the desired productivity (Bours, McGinn, and Pringle, 2014; Pringle and Thomas, 2019).

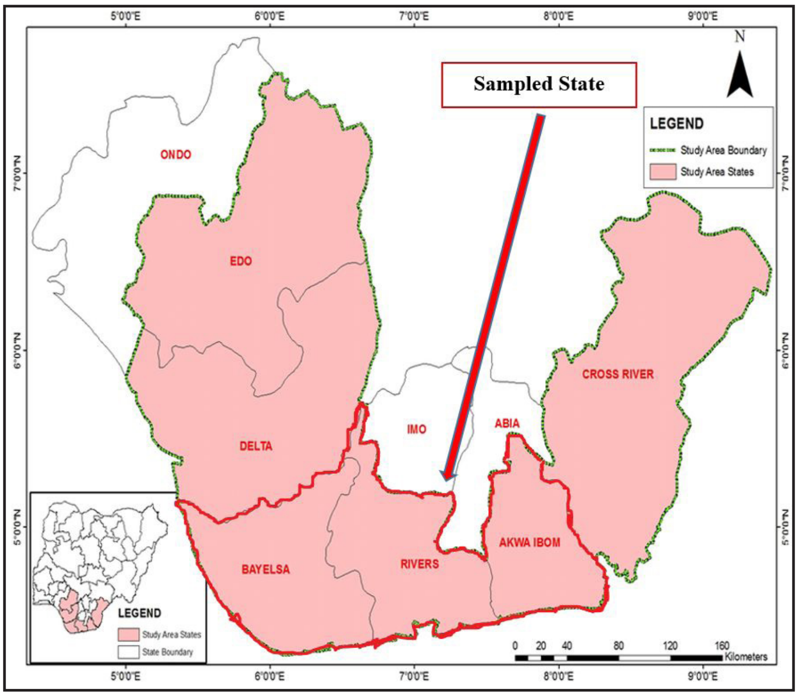
Additionally, the action theory of adaptation to climate change is appropriate for this study. The action entails actors and purpose, this purpose focuses directly on the repercussions of climate change, which involves the utilization of resources as a way to accomplish the desired ends of productivity (Eisenack and Stecker, 2011). The difference between prospective adaptation and definite adaptation adopted required showing momentary magnitude of climate change. Adaptation is governing decision-making procedures and actions that ensure improvement in the adaptive capacity of the farmers (Bours, McGinn and Pringle, 2014). Adaptation is also the rate of control variables that avert climate becoming susceptible. Essentially, the action theory of adaptation to climate change acknowledges farmers are prone and possibly face unanticipated challenges and require redirecting adaptation plans (Pringle and Thomas, 2019). This is coherent with adaptation planning which involves a continuous process of readjustment. The theory of change has been formulated and incorporated into climate change adaptation. Hence, the theory of change and the action theory of adaptation to climate change are inseparable. Climate change adaptation theory is actual actions that minimize the hazard consequence of climate change on maize crop production while taking benefit of the prospective new opportunities.

Materials and methods

Study area

The research was carried out in the South-South zone of Nigeria. The natural boundaries of the South-South zone can be distinct by its topography and hydrographic nature. South-South region's northern boundaries are close to the divergence of the Niger River at Aboh, and the western and eastern boundaries are near the Benin River and the Imo River, respectively. The South-South region consists of Cross River, Edo, Rivers, Delta, Akwa-Ibom, and Bayelsa States. The Region has a population of about 29,812,989 projected for 2022 (National Population Commission of Nigeria NPC, 2020). South-South region land area covers about 84,587 km^2 of Nigeria’s aggregate land area and the vegetation is characteristically tropical savanna, rainforest, mangrove, and monsoon (Ibrahim, 2020). Figure 2 shows the map of the study area.

The region consists of four distinctive ecological zones defined by both landscape and hydrological characteristics; they are coastal sandy barricade



Source: : Ukhurebor and Uzuazor (2020)

Figure 2: Map of the study area.

crest, mangrove swamp, freshwater swamp, and lowland rainforest zones (Arokoyu and Weje, 2015). The climate in the South-South zone favours the planting of cash crops like coconut, cocoa, cashew, oil palm, kolaunt, gum Arabic, sesame, and rubber among others. Arable crops cultivated in the zone include rice, cassava, maize, melon, yams, cocoyam, and sweet potatoes. Hence, this study focuses on maize as being a staple and most vulnerable crop to climate change effects.

Sampling procedure

Multistage sampling procedures were used in the selection of the maize farmers for the study. First, three (3) States were selected using a simple random technique from the six States. Secondly, all the agricultural zones were selected in each State, making twelve (12) agricultural zones selected. Thirdly, one (1) Local Government Area (LGA) was selected from each agricultural zone using simple random technique, making a total of twelve (12) LGAs in all. Fourthly, three (3) communities were selected from each LGAs using simple random technique making a total of nine (9) and eighteen (18) communities respectively from each State and thirty-six (36) communities in all. Lastly, from each community, ten (10) and five (5) maize farmers were selected respectively (based on the number of Agricultural Zones in the State) using a simple random technique. This makes a total sample size of two hundred and seventy (270) maize farmers selected for the study. A multivariate probit (MVP) model was used to analyze the data obtained using SPSS 25.0 and the multicollinearity of the variables was also tested.

A sample size estimator by Andrew Fisher and used by Kibuacha (2021) was adopted, with a confidence level of 90% (1.65) standard deviation of 0.5, and a margin error of 5%. The sample size estimator is stated as;

$$n = \frac{Z^2 * P(1-P)}{e^2} \tag{1}$$

Where: n = Sample size needed; Z = Confidence level (z-score); P = Standard deviation; and e = Margin error. The sample size estimator yielded 272.08. Thus, 270 sample sizes were used and 260 samples were retrieved for actual analysis.

Multicollinearity was tested using Variance Inflating Factor VIF (Geeks for Geeks, 2021). VIF is expressed in the regression model as;

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \tag{2}$$

$$VIF = \frac{1}{1-R^2} \tag{3}$$

$$R^2 = \frac{\Sigma(y_{cal} - \bar{y})^2}{\Sigma(y_{given} - \bar{y})^2} \tag{4}$$

Decision rules;

If the value of VIF = 1; it indicates not correlated. Multicollinearity does not exist.

If the value of VIF ranged between 1 and 5; indicates relatively correlated. A level of multicollinearity exists.

If the value of VIF > 5; indicates extremely correlated. High levels of multicollinearity exist.

The inverse of VIF is known as Tolerance and expressed as;

$$TOL = \frac{1}{VIF} = (1 - R^2) \tag{5}$$

Hence, when R^2 is equal to zero ($R^2 = 0$), it implies that no collinearity exists, then the Tolerance is high (that's equal to 1).

State	Agricultural zone	LGA	Community	Population of the maize farmers	Number of respondents (sample)	Number of samples retrieved
Rivers	Ahoada	Etche	Igbodo	195	10	10
			Okehi	192	10	10
			Okomoko	182	10	9
	Degema	Abua/Odual	Otabha	118	10	9
			Abual	113	10	9
			Okana	124	10	10
	Eleme	Tai	Kporghor	153	10	10
			Gio	141	10	10
			Borobara	124	10	10

Source: Author's survey, 2023.

Table 3: summary of the study area sampling procedure (To be continued).

State	Agricultural zone	LGA	Community	Population of the maize farmers	Number of respondents (sample)	Number of samples retrieved
Bayelsa	Brass	Nembe	Ogbolomabiri	112	10	10
			Agrisaba	98	10	10
			Egbokabiriyai	93	10	9
	Yenagoa	Southern Ijaw	Korokosei	113	10	10
			Okolobiri	116	10	10
			Amasoma	125	10	10
	Sagbama	Ekeremor	Aleibiri	114	10	10
			Tantua	116	10	9
			Bolou-Orua	106	10	10
Akwa-Ibom	Abak	Etim Ekpo	Ikot Igwe	104	5	5
			Ikot-Obioma	102	5	5
			Ikot-Udobong	119	5	4
	Eket	Eastern Obolo	Iko	102	5	4
			Utu ikot Ukpong	103	5	4
			Elekpon	117	5	4
	Etinan	Etinan	Ikot Abasi	105	5	5
			Edem Ekpat	113	5	4
			Afaha Akpan Ekpo	102	5	5
	IkotEkpene	Essien Udim	Ikiot Ebak	116	5	5
			Utu Ekpenyong	97	5	5
			Odoro Ikot	106	5	5
	Oron	Mbo	Udini	104	5	5
			Ibete	96	5	5
			Ekiebong	112	5	4
	Uyo	Uruan	Idu Uruan	114	5	5
			Anakpa	102	5	5
			Ikot Akan	98	5	5
∑ **3**	**12**	**12**	**36**	**4247**	**270**	**260**

Source: Author's survey, 2023.

Table 3: summary of the study area sampling procedure (Continuation).

Data collection

Data for this research were collected from primary and secondary sources. The primary data sources were collected by using questionnaires, interview schedules, and/ or group discussions as the case may demand. The primary data were obtained from the maize farmers that are still operating not from outdated or non-existing farms. Secondary sources include textbooks, journal publications, magazines, internet sources, and reports such as FAOSTAT.

Data analysis

Data for this research were analyzed by using descriptive and inferential statistics tools. The descriptive statistics instruments that were used for the study include frequency and percentages. The inferential statistics tools that were used are the correlation coefficient and multivariate probit (MVP) model.

Model specification

The Multivariate probit (MVP) model for climate change adaptation strategies as used by Ogunnaike et al (2021) and Purwanti et al (2022) expressed as;

$$Y(i=0,1,\ldots n) = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha X_3 + \\ + \alpha_4 X_4 + \alpha_5 X_5 + \alpha_6 X_6 + \alpha_7 X_7 + \alpha_8 X_8 + \\ + \alpha_9 X_9 + \alpha_{10} X_{10} + \alpha_{11} X_{11} + \alpha_{12} X_{12} + \\ + \alpha_{13} X_{13} + \alpha_{14} X_{14} \quad (6)$$

Where: Y_1 = Choice of using crop diversification ($Y=1$); Y_2 = Change planting dates ($Y=2$); Y_3 = Use of mixed farming – crop and rearing of livestock (Y = 3); Y_4 = Use of drought tolerant crop species ($Y=4$); Y_5 = Use of improved crop species ($Y=5$); and Y_6 = Off-farm job opportunities ($Y=6$).

The independent variables are: X_1 = Age of the farmer (in years); X_2 = Gender (Dummy: male = 1; female = 0); X_3 = Marital status (Level: single = 1; married = 2; widow/widower = 3; divorced = 4); X_4 = Farming experience (in years); X_5 = Educational level (years spent in school); X_6 = Household size (in number); X_7 = Farm size (in ha); X_8 = Off-farm income (in Naira ₦); X_9 = Farm income (in Naira ₦); X10 = Access to information on climate change (Dummy: yes = 1; no = 0); X_{11} = Access to extension service (Dummy: yes = 1; no = 0); X_{12} = Access to credit/ finance (Dummy: yes = 1; no = 0); X_{13} = Farm/ crop insurance (Dummy: yes = 1; no = 0); and X_{14} = Farm association membership (Dummy: yes = 1; no = 0); α_0 = Constant; and α_1 - α_{14} = Coefficients of parameter estimated.

Partial eta squared in the MVP model is expressed as;

$$\delta_p^2 = \frac{SS_{effect}}{SS_{effect}+SS_{error}} \quad (7)$$

Where: δ_p^2 = Partial eta squared; and SS = Sum of squares.

Partial eta squared was employed to examine the effect of independent variable(s) on the dependent variable(s). Rule of thumb: δ_p^2 = 0.01; indicates a small effect; δ_p^2 = 0.06; indicates a medium effect; and δ_p^2 = 0.14; indicates a large effect.

Model justification

The MVP model is intended to examine scenarios involving multiple binary (yes/no) dependent variables. Unlike typical probit models, the MVP considers the potential that these outcomes are not independent, which is common in real-world data. One of the MVP model's main features is its ability to model the relationship between the error terms of the various binary outcomes (Greene, 2012). This is especially important when dealing with associated decisions or occurrences since disregarding these connections might result in skewed estimations and inaccurate inferences. The MVP model is ideal for complicated decision-making processes in which individuals or organizations make many, possibly connected choices at the same time. This makes it suitable for research in fields such as health economics, marketing, agriculture, and behavioral sciences, which are appropriate for this study (Belderbos, Carree, and Lokshin, 2004). The MVP model delivers more efficient and accurate parameter estimations than computing separate univariate probit models since the equations are estimated simultaneously (Cappellari, and Jenkins, 2003). This efficiency is derived by utilizing the covariance structure of the many outcomes. When there is endogeneity between various outcomes, the MVP paradigm may be modified to address these difficulties more effectively than simpler models. This increases the reliability and validity of the research findings. The MVP model is consistent with the study's theoretical framework, particularly if the research aims to investigate the drivers of several connected decisions or actions. Its theoretical base, which includes utility maximization and latent variable modelling, is sound. The MVP model (Belderbos et al., 2004) can be used to analyze joint decision-making processes in which maize farmers use multiple climate adaptation strategies at the same time, such as crop diversification, shifting planting dates, mixed farming, and the use of drought-tolerant crop species. These decisions are not independent; the choice to adopt one strategy may influence the likelihood of adopting another.

Results and discussion

From Table 4 it could be concluded that multicollinearity does not exist; which indicates that the variables were not correlated. Since the VIF values were greater than one (1) as well within the acceptable region and the Tolerance level (approximately equal to one, T = 1). Therefore, the models were accurate and appropriate o measure the data gathered.

Table 5 shows the climate change adaptation strategies techniques adopted the maize farmers in the study area. Majority (96.9%) of the maize famers actually adopted the use adaptation techniques as regards their maize farming. Majority (81.9%), (81.5%), (78.5%), (78.1%), (77.7%) and (68.1%) adopted the use of improved crop species, planting of drought tolerant crop species and changing in planting dates, crop diversification, mixed farming and off-farm job opportunities respectively. This implies that most of the maize farmers aimed to achieve optimum production and adopted several adaptation techniques to cope with the effects of climate change.

Table 6 depicts the correlation matrix of the relationships between various agricultural climate adaptation strategies adopted by maize farmers (crop diversification, changes in planting dates, mixed farming, planting of drought-tolerant crops, use of improved crop species, and off-farm job opportunities). Off-farm work possibilities and adoption of improved crop species (0.423)

Variable	Collinearity Statistics	
	Tolerance	VIF
Age (in years)	0.422	2.370
Gender	0.769	1.301
Marital status	0.501	1.997
Farming experience (in year)	0.563	1.778
Educational level (in year)	0.719	1.390
Household size (in number)	0.792	1.263
Maize farm size (in ha)	0.778	1.286
Average on-farm income in a year (in naira)	0.622	1.608
Average off-farm income in a year (in naira)	0.510	1.960
Access to information on climate change	0.724	1.382
Extension contact within a year	0.730	1.370
Access to credit/ finance facilities	0.598	1.671
Insure arable crop farm	0.694	1.440
Farmers association	0.682	1.466

Note: VIF means Variance Inflating Factor
Source: Field Survey, 2023.

Table 4: Collinearity diagnostics of multivariate probit (MVP) model used for climate change adaptation strategies analysis.

Variable	Frequency	Percentage
Used climate change adaptation strategies techniques		
Yes	252	96.9
No	8	3.1
Crop diversification		
Yes	203	78.1
No	57	21.9
Changing planting dates		
Yes	204	78.5
No	56	21.5
Mixed farming – crop and rearing of livestock		
Yes	202	77.7
No	58	22.3
Planting of drought tolerant crop species		
Yes	212	81.5
No	48	18.5
Use of improved crop species		
Yes	213	81.9
No	47	18.1
Off-farm job opportunities		
Yes	177	68.1
No	83	31.9
Total	260	100.0

Source: Field Survey, 2023.

Table 5: Climate change adaptation strategies and techniques adopted by the maize farmers.

are substantially positively connected, implying that maize farmer families participating in off-farm activities are more likely to adopt improved crop species, presumably due to increased money to invest in such technologies. Off-farm work possibilities and drought-tolerant crop planting

Variables	Crop diversification	Change planting dates	Mixed farming	Planting of drought-tolerant crop species	Use of improved crop species	Off-farm job opportunities
Crop diversification	1					
Change planting dates	0.288**	1				
Mixed farming	0.140*	0.146*	1			
Planting of drought-tolerant crop species	0.230**	0.142*	0.155*	1		
Use of improved crop species	0.307**	0.360**	0.069	0.290**	1	
Off-farm job opportunities	0.334**	0.186**	0.288**	0.373**	0.423**	1

Note: **, * means significant at 0.01 and 0.05 levels (2-tailed)
Source: Field Survey, 2023.

Table 6: Correlation matrix of the relationships between different adaptation strategies.

(0.373) have a substantial positive correlation, indicating that income diversification encourages farmers to invest in climate-resilient crops. Crop diversification and off-farm job opportunities (0.334) are positively correlated, implying that maize farmers with off-farm jobs may diversify crops to better manage maize production risks. The use of improved crop species and change in planting dates (0.360) are also positively correlated, indicating that maize farmers adopting improved crop species may adjust planting dates to maximize yield in changing climates.

Mixed farming with other techniques has smaller associations (ranging from 0.069 to 0.288); positive connections suggest that it complements other adaptation strategies. Mixed farming and the usage of enhanced crop species have a low correlation (0.069), which might indicate that mixed farming decisions are driven by reasons other than those driving the adoption of improved crop types. As a result, a multivariate probit (MVP) model was investigated to gain a better understanding of how different methods are implemented in tandem, taking into consideration their dependency.

Table 7 shows the result of the MVP model of climate change adaptation strategies adopted by the maize farmers. Bartlett's test of sphericity Loglikehood chi-squared tests of 176.936 was obtained and statistically significant at 1% level, null hypothesis that the residual covariance matrix is proportional to an identity matrix. The coefficient of multiple determination (R^2) shows that about 20.3% magnitude of climate change adaptation strategies adopted were explained by the independent variables included in the model, while Adjusted R^2 0.157 demonstrates the correct measurement of the model. Partial eta squared was used to measure the extent of the effect the independent variable(s) has on the dependent variable.

Crop diversification

From Table 7, age with a coefficient of -0.009 (p-value 0.010), is statistically significant at 1% and negatively impacts the probability of adopting crop diversification as climate change adaptation strategies. A unit increase in the age of the farmer could reduce the chances of adopting crop diversification by maize farmers by 0.9%, suggesting the adaptation age would enhance the chances of maize-based farmers adopting crop diversification as a climate change adaptation strategy. The negative coefficient for age shows that young maize farmers are possibly to diversify crops compared to the aged farmers, this could be a result of the young farmers being opened to innovation and curiosity about trying new adaptation strategies to enhance their maize production. This result is in agreement with Enimu and Onome (2018) who found out among farmers in Delta State that, regardless of the older farmers being aware of innovations, they are not willing to attempt new adaptation strategies. A partial eta squared of 0.027 was obtained, which indicates a small effect on the use of crop diversification as a climate change adaptation strategy. Marital status with a coefficient of 0.183 (p-value 0.004), is statistically significant at 1% and positively impacts the probability of adopting crop diversification as climate change adaptation strategies. A unit increase in the marital status of the farmer could increase the chances of adopting crop diversification by maize farmers by 18.3%, suggesting the adaptation marital status would increase the chances of maize-based farmers adopting crop diversification as climate change adaptation strategies. A partial eta squared of 0.003 was obtained, which indicates a small effect on the use of crop diversification as a climate change adaptation strategy. Household size with a coefficient of -0.031 (p-value 0.025), is statistically significant at 5% and negatively impacts

Variables	Crop diversification	Changing planting dates	Mixed farming	Planting of drought-tolerant crop species	Use improved crop species	Off-farm job opportunities
Intercept	0.408**	0.091	0.533***	0.405**	0.354*	0.535**
	(0.192)[0.018]	(0.193)[0.001]	(0.200)[0.028]	(0.195)[0.017]	(0.187)[0.014]	(0.240)[0.020]
Age	-0.009***	0.001	-0.010***	-0.003	-0.005	-0.010**
	(0.003)[0.027]	(0.003)[0.000]	(0.004)[0.031]	(0.003)[0.003]	(0.003)[0.009]	(0.004)[0.022]
Gender	0.053	-0.013	-0.144***	0.049	0.101**	0.033
	(0.053)[0.004]	(0.054)[0.000]	(0.056)[0.027]	(0.054)[0.003]	(0.052)[0.015]	(0.067)[0.001]
Marital	0.183***	-0.023	0.154**	0.042	0.043	0.087
	(0.004)[0.003]	(0.064)[0.001]	(0.066)[0.022]	(0.064)[0.002]	(0.062)[0.002]	(0.079)[0.005]
FrmExp	0.003	-0.001	0.004	0.005**	0.002	0.005*
	(0.002)[0.006]	(0.002)[0.000]	(0.002)[0.009]	(0.002)[0.017]	(0.002)[0.003]	(0.003)[0.013]
EduLev	-0.001	0.012**	-0.003	-0.006	0.001	-0.009
	(0.005)[0.000]	(0.005)[0.021]	(0.005)[0.002]	(0.005)[0.005]	(0.005)[0.000]	(0.006)[0.008]
Household size	-0.031**	0.015	0.011	-0.021*	-0.009	0.013
	(0.014)[0.021]	(0.014)[0.005]	(0.014)[0.003]	(0.014)[0.010]	(0.013)[0.002]	(0.006)[0.002]
MzFrmSiz	0.062***	0.038	0.016	-0.003	0.014	-0.060*
	(0.027)[0.022]	(0.027)[0.008]	(0.028)[0.001]	(0.027)[0.000]	(0.026)[0.001]	(0.033)[0.013]
OnFrmInc	1.5E-7	1.8E-7	-9.9E-8	-5.4E-8	-9.9E-9	-1.3E-7
	(0.001)0.003]	(0.001)[0.005]	(0.001)[0.001]	(0.001)[0.000]	(0.001)[0.000]	(2.1E-7)[0.001]
OffFrmInc	-4.6E-8	2.3E-9	-2.2E-7**	1.3E-7	1.6E-7*	1.2E-7
	(0.001)[0.001]	(0.001)[0.000]	(0.001)[0.015]	(0.001)[0.006]	(0.001)[0.008]	(1.4E-7)[0.003]
InfCC	0.555***	0.404***	0.374***	0.540***	0.542***	0.376**
	(0.112)[0.092]	(0.113)[0.050]	0.117)[0.041]	(0.114)[0.085]	(0.109)[0.092]	(0.140)[0.029]
ExtCont	0.035	0.148**	-0.048	-0.007	-0.054	-0.044
	(0.061)[0.001]	(0.062)[0.023]	(0.064)[0.002]	(0.062)[0.000]	(0.060)[0.003]	(0.077)[0.001]
AccesCred	-0.072	0.113*	0.111*	-0.097*	0.003	-0.007
	(0.059)[0.006]	(0.060)[0.014]	(0.062)[0.013]	(0.61)[0.010]	(0.058)[0.000]	(0.075)[0.000]
InsurFarm	0.214***	-0.066	0.114	0.246***	0.116	0.180*
	(0.082)[0.027]	(0.083)[0.003]	(0.086)[0.007]	(0.084)[0.034]	(0.080)[0.008]	(0.103)[0.012]
FrmAss	0.021	-0.009	0-.033	0.055	0.122**	0.129
	(0.065)[0.000]	(0.066)[0.000]	(0.068)[0.001]	(0.067)[0.003]	(0.064)[0.015]	(0.082)[0.010]

Note: ***, **, * means significant at 1%, 5%, and 10% respectively; the first figures are the betas, the bracket "( )" is the standard errors, and the parenthesis, "[ ]" is the partial eta squared; 0.01, 0.06 and 0.14 indicate small, medium and large effect of partial eta squared respectively; Bartlett's test of sphericity: Loglikehood Chi-squared = 176.936 (0.000), R^2 = 0.203, Adjusted R^2 = 0.157; Sample size = 260
Source: Field Survey, 2023.

Table 7: Parameter estimates of the Multivariate Probit (MVP) model of maize (Zea mays) farmers showing climate change adaptation strategies adopted in the study area and their determinants.

the probability of adopting crop diversification as a climate change adaptation strategy. An increase in the household size of the farmer could reduce the chances of adopting crop diversification by maize farmers in adopting crop diversification as climate change adaptation strategies. The negative coefficient of the household size implies that maize farmers with less household size are more likely to adopt crop diversification to cope with the effects of climate change. A partial eta squared of 0.021 was obtained, which indicates a small effect on the use of crop diversification as a climate change adaptation strategy. Maize farm size with a coefficient of 0.062 (p-value 0.019), is statistically significant at 5% and positively impacts the probability of adopting crop diversification as climate change adaptation strategies. An increase in the maize farm size of the farmer could increase the chances of adopting crop diversification by maize farmers in adopting crop diversification as climate change adaptation strategies. This implies that maize farmers with large farm sizes could easily adopt crop diversification as a way of minimizing the effect of climate change on their production. A partial eta squared of 0.022 was obtained, which indicates a small effect on the use of crop diversification as a climate change adaptation strategy. Access to information on climate change with a coefficient of 0.555 (p-value 0.000), is statistically significant at 1% and positively impacts the probability of adopting crop diversification as climate change adaptation strategies. A unit increase in access to information on climate change could increase the chances of adopting crop diversification by maize farmers by 55.5%, suggesting that adaptation access to information on climate change would improve the chances of maize-based farmers adopting crop diversification as climate change adaptation strategies. This implies that timely access to information on climate change could increase the rate of climate change adaptation strategies through crop diversification. The maize farmer that received information earlier could probably adopt the strategy than the farmers that may likely get the information late. This finding is in agreement with Gemeda, Korecha, and Garedew (2023) who found out that, access to climate information is correlated with crop diversification in Ethiopia. A partial eta squared of 0.092 was obtained, which indicates a medium effect on the use of crop diversification as a climate change adaptation strategy. Awareness of crop insurance with a coefficient of 0.214 (p-value 0.010), is statistically significant at 1% and positively impacts the probability of adopting crop diversification as climate change adaptation strategies. A unit increase in awareness of crop insurance could increase the chances of adopting crop diversification by maize farmers by 21.4%, suggesting that adaptation awareness of crop insurance would improve the chances of maize-based farmers adopting crop diversification as climate change adaptation strategy. This implies transferring the losses that may be encountered in maize production is possible through insurance companies. A partial eta squared of 0.029 was obtained, which indicates a small effect on the use of crop diversification as a climate change adaptation strategy. Therefore, the results of the multivariate probit (MVP) model provide sufficient indication for the simultaneous and codependent adaptation choices.

Changing planting dates

From Table 7, educational level with a coefficient of 0.012 (p-value 0.023), is statistically significant at 5% and positively impacts the probability of adopting changing planting dates as climate change adaptation strategies. An increase in years of the educational level of the farmer could increase the chances of adopting changing planting dates by maize farmers in adopting changing planting dates as climate change adaptation strategies. This implies that the more years the maize farmers spend to attain the level of education is very significant in studying and changing the planting date of maize for efficient productivity. This finding is not consistent with the result of Mwinkom, Damnyag, Abugre, and Alhassan (2021) who obtained a negative coefficient in their studies among farmers in North-Western Ghana. A partial eta squared of 0.021 was obtained, which indicates a small effect on the use of changing planting dates as a climate change adaptation strategy. Access to information on climate change with a coefficient of 0.404 (p-value 0.000), is statistically significant at 1% and positively impacts the probability of adopting change planting dates as climate change adaptation strategies. A unit increase in access to information on climate change could increase the chances of adopting changing planting dates by maize farmers by 40.4%, suggesting that adaptation access to information on climate change would improve the chances of maize-based farmers adopting changing planting dates as climate change adaptation strategies. This finding agrees with Mwinkom et al (2021) who reported that information on climate change influences the changes in planting time in Ghana. A partial eta squared of 0.050 was obtained, which indicates a small effect on the use of changing planting dates as a climate change adaptation strategy. Agricultural extension contacts with a coefficient of 0.148 (p-value 0.017), are statistically significant at 5% and positively impact the probability of adopting changing planting dates as climate change adaptation strategies. An increase in agricultural extension contacts of the farmer could increase the chances of adopting changing planting dates by maize farmers in adopting changing planting dates as climate change adaptation strategies. This implies that agricultural extension services offer very vital and accurate information on climate change and are capable of providing good agricultural and management practices to cope with climate change. Hence, farmers with better contact with the extension have a greater chance to alter planting dates for maximum yields even amid climate challenges. This finding is in agreement with Nhemachena, Hassan, and Chakwizira (2014) who noted that increasing access to free agricultural extension services delivery to farmers has the prospective to considerably enhance farmers' awareness of changes in climatic factors, and in addition adaptation strategies to adopt in response to climate changes hazards. A partial eta squared of 0.023 was obtained, which indicates a small effect on the use of changing planting as a climate change adaptation strategy. The multivariate probit (MVP) model results, consequently, afford appropriate substantiation for simultaneous adaptation choices.

Mixed farming – crop and rearing of livestock

From Table 7, age with a coefficient of -0.010 (p-value 0.006), is statistically significant at 1% and negatively impacts the probability of adopting mixed farming – crop and rearing of livestock as climate change adaptation strategies. A unit increase in the age of the farmer could reduce the chances of adopting mixed farming – crops, and rearing of livestock by maize farmers by 1%, suggesting the adaptation age would enhance the chances of maize-based farmers adopting mixed farming – crop and rearing of livestock as climate change adaptation strategies. This implies that mixed farming strategies are better capable of coping with the climate change factors through enterprise different changes in management strategies; this is possible because the younger farmers can carry out a lot of activities at or almost the same time. This finding is in agreement with Nhemachena et al (2014) who reported that mixed farming strategies are already adopted and the farmers have several alternative crops and livestock choices that could guarantee that in case one choice fails as a result of climate change the other would do well even if there are variations in climatic factors. A partial eta squared of 0.031 was obtained, which indicates a small effect on the use of mixed farming as a climate change adaptation strategy. Gender with a coefficient of -0.144 (p-value 0.010), is statistically significant at 1% and negatively impacts the probability of adopting mixed farming – crop, and rearing of livestock as climate change adaptation strategies. This implies that female maize farmers could reduce the chances of adopting mixed farming – crops, and rearing livestock, suggesting the adaptation gender would enhance the chances of maize-based farmers adopting mixed farming – crops, and rearing livestock as climate change adaptation strategies. This implies that female maize farmers may likely be affected. This finding agrees with Nyadzi, Werners, Biesbroek, Long, Franssen, and Ludwig (2019) who found that male farmers had a higher possibility of adopting climate adaptation strategies than their female farmer counterparts. A partial eta squared of 0.027 was obtained, which indicates a small effect on the use of mixed farming as a climate change adaptation strategy. Marital status with a coefficient of 0.154 (p-value 0.020), is statistically significant at 5% and positively impacts the probability of adopting mixed farming – crop and rearing of livestock as climate change adaptation strategies. An increase in the marital status of the farmer could increase the chances of adopting mixed farming – crop, and rearing of livestock by maize farmers in adopting mixed farming – crop and rearing of livestock as climate change adaptation strategies. This implies that married maize farmers could adopt mixed farming than their single farmers' counterparts. A partial eta squared of 0.022 was obtained, which indicates a small effect on the use of mixed farming as a climate change adaptation strategy. Off-farm incomes with a coefficient of -2.219E-7 (p-value 0.058), are statistically significant at 5% and negatively impact the probability of adopting mixed farming – crop and rearing of livestock as climate change adaptation strategies. An increase in off-farm incomes of the farmer could reduce the chances of adopting mixed farming – crop, and rearing of livestock by maize farmers in adopting mixed farming – crop, and rearing of livestock as climate change adaptation strategies. This implies that the maize farmers could spend their off-farm income to adapt to climate change adaptation strategies. A partial eta squared of 0.015 was obtained, which indicates a small effect on the use of mixed farming as a climate change adaptation strategy. Access to information on climate change with a coefficient of 0.374 (p-value 0.002), is statistically significant at 1% and positively impacts the probability of adopting mixed farming – crop, and rearing of livestock as climate change adaptation strategies. A unit increase in access to information on climate change of the farmer could increase the chances of adopting mixed farming – crop, and rearing of livestock by maize farmers by 37.4%, suggesting the adaptation access to information on climate change would enhance the chances of maize-based farmers adopting mixed farming – crop and rearing of livestock as climate change adaptation strategies. This implies that access to information on climate change is very crucial for productive adaptation. A partial eta squared of 0.041 was obtained, which indicates a small effect on the use of mixed farming as a climate change adaptation strategy. The multivariate probit (MVP) model results, consequently, provide appropriate substantiation for simultaneous adaptation choices.

Planting of drought-tolerant crop species

From Table 7, farming experience with a coefficient of 0.005 (p-value 0.039), is statistically significant at 5% and positively impacts the probability of adopting planting of drought tolerant crop species as climate change adaptation strategies. An increase in the farming experience of the farmer could increase the chances of adopting the planting of drought-tolerant crop species by maize farmers in adopting crop diversification as a climate change adaptation strategy. This implies that an increase in the farming experience of maize farmers could lead to more understanding of plant drought-tolerant crop species. A partial eta squared of 0.017 was obtained, which indicates a small effect on the use of drought-tolerant crop species as climate change adaptation strategies. Access to information on climate change with a coefficient of 0.540 (p-value 0.000), is statistically significant at 1% and positively impacts the probability of adopting access to information on climate change as climate change adaptation strategies. An increase in the farming experience of the farmer could increase the chances of adopting access to information on climate change by maize farmers in adopting crop diversification as climate change adaptation strategies. This implies that access to information on climate change is very crucial for productive adaptation. A partial eta squared of 0.085 was obtained, which indicates a medium effect on the use of planting drought-tolerant crop species as climate change adaptation strategies. Awareness of farm/ crop insurance with a coefficient of 0.246 (p-value 0.004), is statistically significant at 1% and positively impacts the probability of adopting planting of drought-tolerant crop species as climate change adaptation strategies. An increase in awareness of farm/ crop insurance of the farmer could increase the chances of adopting planting of drought-tolerant crop species by maize farmers in adopting crop diversification as a climate change adaptation strategy. This implies transferring the losses that may be encountered in maize production is possible through insurance companies. A partial eta squared of 0.034 was obtained, which indicates a small effect on the use of planting of drought-tolerant crop species as a climate change adaptation strategy. The multivariate probit (MVP) model results, consequently, provide appropriate substantiation for simultaneous adaptation choices.

Use of improved crop species

From Table 7, gender with a coefficient of 0.101 (p-value 0.054), is statistically significant at 5% and positively impacts the probability of adopting improved crop species as climate change adaptation strategies. This implies that both genders (male and female) can adopt improved crop species for planting. A partial eta squared of 0.015 was obtained, which indicates a small effect on the use of planting of improved crop species as climate change adaptation strategies. Access to information on climate change with a coefficient of 0.542 (p-value 0.000), is statistically significant at 1% and positively impacts the probability of adopting planting of improved crop species as climate change adaptation strategies. A unit increase in access to information on climate change of the farmer could increase the chances of adopting planting of improved crop species by maize farmers by 54.2%, suggesting the adaptation of access to information on climate change would improve the chances of maize-based farmers in adopting crop diversification as climate change adaptation strategies. This implies that access to information on climate change is very crucial for productive adaptation. A partial eta squared of 0.092 was obtained, which indicates a medium effect on the use of improved crop species as climate change adaptation strategies. Farmers association with a coefficient of 0.122 (p-value 0.056), is statistically significant at 5% and positively impacts the probability of adopting improved crop species as climate change adaptation strategies. An increase in farmers' associations of the farmer could increase the chances of adopting improved crop species by maize farmers adopting improved crop species as climate change adaptation strategies. This implies that farmers' membership in association could aid the rate of adaptation to climate change hazards. A partial eta squared of 0.015 was obtained, which indicates a medium effect on the use of improved crop species as climate change adaptation strategies. The multivariate probit (MVP) model results, consequently, afford appropriate substantiation for simultaneous adaptation choices.

Off-farm job opportunities

From Table 7, age with a coefficient of -0.010 (p-value 0.019), is statistically significant at 5% and negatively impacts the probability of adopting off-farm job opportunities as climate change adaptation strategies. An increase in the age of the farmer could reduce the chances of adopting off-farm job opportunities by maize farmers in adopting off-farm job opportunities as climate change adaptation strategies. This implies that the younger maize farmers could engage in multiple activities to cope with climate change effects. A partial eta squared of 0.022 was obtained, which indicates a small effect on the use of off-farm job opportunities as climate change adaptation strategies. Access to information on climate change with a coefficient of 0.376 (p-value 0.008), is statistically significant at 1% and positively impacts the probability of adopting off-farm job opportunities as climate change adaptation strategies. A unit increase in access to information on climate change of the farmer could increase the chances of adopting off-farm job opportunities for maize farmers by 37.6%, suggesting the adaptation of off-farm job opportunities would enhance the chances of maize-based farmers in adopting off-farm job opportunities as climate change adaptation strategies. This implies that access to information on climate change is very crucial for productive adaptation. A partial eta squared of 0.029 was obtained, which indicates a medium effect on the use of off-farm job opportunities as climate change adaptation strategies. The multivariate probit (MVP) model results, consequently, provide appropriate substantiation for simultaneous adaptation choices.

Conclusion

This research examined the analysis of determinants of maize farmers' adaptation strategies to climate change in South-South Nigeria. The result of the Variance Inflating Factor (VIF) and Tolerance level revealed that multicollinearity does not exist. The result shows that the majority of the maize farmers adopted the use of improved crop species, planting of drought tolerant crop species and changing in planting dates, crop diversification, mixed farming, and off-farm job opportunities as a means of adaptation strategies to climate change impacts. The multivariate probit (MVP) model results show that among all determinants, access to information on climate change was the most important influencing factor that enabled farmers to adopt different adaptation strategies because it was statistically significant in all the dependent variables used in the analyses.

Analyzing the determinants of adaptation strategies to climate change can aid the decision-makers and farmers to take additional mediations against the negative impacts of climate change. Declining agricultural yields and food insecurity caused by climate change continue to be the major concerns affecting farming communities' nutritional needs and food preferences. The research, therefore recommends that:

The government and NGOs should design a viable strategy to address the existing barriers to climate change adaptation strategies in the study area. Eliminating the existing barriers while supporting the farming communities with technical skills based on state-of-the-art modern science can enhance the adaptive capacity of vulnerable maize farmers to climate change.

A farmer's understanding of the impact of climate change is a fundamental requirement for designing adaptation strategies. Therefore, maize farmers should be constantly enlightened on the danger associated with climate change. This understanding of the impacts of climate change on maize farming could help policy-makers to develop appropriate adaptation and mitigation strategies.

Furthermore, institutional collaboration among the tiers of institutions is needed to improve access to credit/ finance facilities, avail affordable farm inputs (like a hybrid of maize seed), adequate extension service delivery, eliminate the risk of maize pests and disease, and provide necessary and timely information for the maize farmers.

Acknowledgments

This research was supported by funding from the Nigerian Conservation Foundation (NCF) under the Chief S.L. Edu Ph.D. research grant.

Corresponding author:
Adeyinka Richard Aroyehun
Department of Agricultural Economics and Agribusiness Management,
Faculty of Agriculture, University of Port Harcourt
East/West Road, PMB 5323 Choba, Rivers State, Nigeria
Email: +2347065528824, E-mail: aroyehun_adeyinka@unipoert.edu.ng

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Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

The Transformation From Agronomic Experiment to Practical Advice For Farmers: A Case Study with Maize in the Southern Guinea Savannah Region of Nigeria

Temitope Seun Babalola[1], Oluwadamilola Fasina[2], Olubunmi Samuel Shittu[1], Samuel Ojo Ajayi[1], Augustus Oludotun Akinmayowa Ilori[1]

[1] Department of Soil Science and Land Resources Management, Federal University Oye-Ekiti, Nigeria

[2] Department of Economics, University of Stirling, United Kingdom

Abstract

The development of recommendations that are adoptable by farmers to meet their goals is key to the introduction of improved crop management practices to farmers. An on-farm experiment was conducted to evaluate maize production under farmers (M1) and improved (M2) cultivation and management in three locations (Kabba, Ejiba, and Anyigba) of the southern Guinea Savannah zone of Nigeria. A land suitability evaluation, an evaluation of the yield of maize, and an economic analysis of the two management practices were carried out. Kabba has a potential suitability index of 32.76 and was rated S3 (marginally suitable); Ejiba and Kabba are 84 and 95, respectively; they were rated S1 (highly suitable). The yield performance of maize is in the order of Ejiba>Anyigba>Kabba for location and M2>M1 for management practices. For every \$1.00 invested in the adoption of improved cultivation and management practices, the farmer will recover the \$1.00 and get an additional \$0.4285, \$0.6850, and \$0.9349 in Kabba, Ejiba, and Ayingba, respectively. The improved management practices are recommended to farmers in the agro-ecological zone. This study established that agronomic experiments should not be limited to field experimentation levels, and the importance of the economic implications of agronomic research findings was emphasized.

Keywords

Soil, suitability, evaluation, production, economics.

Babalola, T. S., Fasina, O., Shittu, O. S., Ajayi, S. O., and Ilori, A. O. A. (2025) "The Transformation from Agronomic Experiment to Practical Advice for Farmers: A Case Study with Maize in the Southern Guinea Savannah Region of Nigeria", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 25-35. ISSN 1804-1930. DOI 10.7160/aol.2025.170202.

Introduction

Maize is an important staple crop in the world. It has a wide range of varieties adapted to different ecologies and regions of the world. It is grown in every agro ecological zones of Nigeria under rain fed and irrigation agriculture. According to FAO (2018), maize is an important traditional crop in Nigeria, ahead of millet and sorghum. An estimated 3 million hectares are cultivated, and its cultivation in the savannah continues to increase (Aduayi et al., 2002). In 2020, maize production was 11.5MMT, increasing from 0. 931 MMT in 1971 to 11.5MMT in 2020, growing at an average annual rate of 7.57%. (National Bureau of Statistics, 2020). AFEX (2024) reports that maize, Nigeria's dominant cereal crop, represented 32% of total cereal area harvested in 2023. The cultivation area declined by 7% between 2021 (6.2 million ha) and 2022 (5.8 million ha).

Maize is essential to food security in Nigeria (Adewopo, 2019). It is utilized mostly in the animal feed industry; over 60% of the local production is used for the production of animal feed. It is a food source for humans because it is a good source of carbohydrates, some protein, iron, vitamin B, and minerals. 10 to 15 percent is directly consumed by individuals as roasted, boiled, or prepared as porridge. The rest are used in pharmaceutical and confectionary industries.

Sabo et al. (2017) reported that smallholder farmers made a considerable contribution to global agricultural output. They produce the bulk of food in developing countries (IAASTD, 2009). Oke et al. (2022) and Mgbenka and Mbah (2016) reported that over 80% of farmers in Nigeria are subsistence farmers, many of whom are smallholders. This buttresses the report of Agboola and Shittu (2002) that much of the maize produced in Nigeria is produced on a subsistence basis by smallholder farmers. Smallholder farmers are characterized by marginalization in terms of accessibility, resources, information, technology, capital, and assets, but there is great variation in the degree to which each of these applies (Odoemenem and Obinne, 2010). Their farm size is less than 3 ha, however, they play a significant role in food production to the entire nation. A similar scenario is at play in Sub-Saharan Africa where it was reported that a higher percentage of maize cultivation is done by smallholder farmers (Cairns et al., 2021; Macauley, 2015; Smale et al., 2011) who depend on it for both their subsistence and livelihoods.

It was reported by Cairns et al. (2021) that maize production in sub-Saharan Africa increased from 14 metric tons to 80 metric tons from 1961 to 2017. The increase was attributed to an increase in cropped area. This implies that there has not been a significant change in crop and soil management practices among farmers for sustainable and optimum maize production.

There are myriad challenges facing maize production in Nigeria. They have been categorized into socioeconomic such as insecurity, natural disaster, high cost of labour, inadequate storage facilities, lack of access to agricultural information, resistant to modern improved technologies and limited access to capital and credit facilities (Adewopo, 2019; Abdulaleem et al., 2019; Girei et al., 2018; Mgbenka and Mbah, 2016), soil environmental and biological factors such as poor soil fertility, pests and diseases and periodic drought caused by irregular rainfall distribution Abdulaleem et al., 2019; Girei et al. 2018) and poor crop management practices such as irregular or improper plant spacing, poor seed bed preparation, poor post-harvest maize residue management and poor timing of operations (Falade and Labaeka, 2020).

There is an increase in demand for maize for human consumption, livestock and agro-allied industries. This has been attributed to population growth, industrialization, urbanization, and changing dietary habits of consumers (Egwuma et al., 2019). The local production did not meet up with local and export market demand; this has led to the importation of maize into Nigeria in recent years. An estimated 215 tonnes were imported in 2016 (FAOSTAT, 2018).

In order to increase maize production, farmers are faced with two major alternatives. The first is to increase the number of land areas cropped, and the second is to improve cultivation practices to ensure optimum and sustainable production. The first alternative has been exploited and did not give the desired result; therefore, farmers are left with the second option. The latter option is referred to as Sustainable intensification, a process whereby crop yields are increased through increased resource use and resource use efficiency, without land expansion and with minimal adverse environmental impact (Rusinamhodzi et al., 2020, Struik and Kuyper, 2017).

There has been several research on crops improvement in Nigeria, this brought about the compilation of recommended practices for important crops including maize in Nigeria by (FFD, 2002). However, the adoption of these recommended practices is low among farmers in that most of the agronomic research and recommendations did not state the economic implications of the practices. Meanwhile, farmers are more interested in the economic implications and value of adopting new management and production innovation. They are particular about the significant extent to which it is better than their current practice. The desired impact of agronomic research will be felt in the agricultural sector if the research is more of on-farm research conducted on farmers' fields and consideration is given to the economic implication of results for recommendations to end users. There is also a need for an improvement in the current farmers' practice for optimum and sustainable maize production.

The study area is important to maize production and has the potential to contribute significantly to the local demand and export, therefore, the need for this study is pertinent to efforts in the development of sustainable maize production in Nigeria.

The objectives of this study are to evaluate maize production under farmers' practice and improved management in three locations of the southern Guinea Savannah zone, Nigeria and conduct an economic analysis of the field data for farmers' recommendation.

Materials and methods

Description of the study areas

The study areas are: Kabba on 7º51'29.46"N and 6º03'45.03"E, Ejiba on 8º17'20.97" and 5º39'17.31", and Ayingba on 7º28'57.02" and 7º13'35.56" all in the southern Guinea Savannah agro ecological zone of Nigeria. The areas have a climate that is typical of the humid tropics. The majority of the population of the area is into agriculture, and they are mostly smallholder farmers.

On farm experiment

The experiment was conducted between 2021 and 2023 planting sessions. Maize farmers' field was identified and selected in each of the locations through the extension agent of the Agricultural Development Agency.

The experiment consisted of two treatments (Table 1): M1 = Maize farmers' cultivation and management practices and M2 = improved cultivation and management practices for southern guinea savannah zone of Nigeria (FFD, 2002).

The treatments were replicated four times and laid out in a randomized complete block design in each of the locations.

Soil sampling and analysis

Profile pits were dug in each of the locations, described, and sampled for laboratory analysis. The slope, flooding, drainage and texture were determined on the field. The total nitrogen, available phosphorus, pH, organic matter, exchangeable cations, cation exchange capacity and base saturation were determined in the laboratory with methods described by IITA (1979).

Data collection

At harvest, the grain yield per plot was measured with a weigh balance, and the costs of all operations were recorded in naira and converted to the naira-dollar exchange rate as of September 2022.

Land suitability evaluation

The suitability evaluation of the land in each location was conducted with the conventional parametric method (FAO, 2007; Ogunkunle, 1993). Relevant land characteristics/qualities requirements for maize (Table 2) were compared with land characteristics/qualities of each location. Five land quality groups were used: climate (c), topography (t), wetness (w), soil physical properties (s), and soil fertility (f). The final (aggregate) suitability class indicates the most limiting characteristics of the pedons and was computed using the equation: IP = A√B/100xC/100…F/100. Where: IP = index of suitability, A = the overall lowest characteristics B, C…., F = the lowest characteristics in each land quality group. The suitability classes S1 (highly suitable), S2 (moderately suitable), S3 (marginally suitable), N1 (currently not suitable) and N2 (potentially not suitable) are equivalent to index of productivity value of 100-75, 74-50, 49-25, 24-12.5 and 12.4-0 respectively.

Data analysis

Yield data was analyzed with ANOVA and means of the treatment in each location were ranked with Least Significant Difference (LSD) at the 5% level of significance.

Economic analysis

The economic analysis of maize production in the locations was done following the method suggested by the International Maize and Wheat Improvement Center (CIMMYT) (1988). It involved the computation of the following:

1. The partial budget: The adjusted yield was calculated by adjusting the yield obtained from the field downwards by 10% with the standard assumption that farmers

Cost	M1	M2
Land preparation	Plough and ridge	Plough, harrow and ridge
Seed rate per kg/ha	10-15	25
Spacing	Haphazard	75 by 25 cm at one plant per stand
Weed control	Pre-emergence + handweeding	Pre and post emergence
Fertilizer use	Based on blanket recommendation. Single application of 200kg NPK 20:10:10	Based on soil fertility map of Nigeria. First application of 300kg NPK 20:10:10 and second application of 200kg urea
Control of army worm and stem borer	Single application of control	Integrated control measures
Harvesting, shelling and packaging	Hand shelling in the house and packaging	Use of maize sheller and packaging on the farm.

Source: Agricultural Development Programme and FFD (2002)

Table 1: Comparison of treatments.

Land qualities	S1 (100-85)	S2 (84-40)	S3 (39-20)	N1 (19-0)
Climate (c):				
Annual rainfall (mm)	>850	750-600	600-500	-
Length growing season(days)	150-220	110-149	90-109	-
Mean annual temperature (°C)	22-28	18-16	16-14, 36-30	-
Relative humidity (%)	50-80	42-36	36-30, >80	-
Topography (t)				
Slope (%)	0-2	3-8	9-16	>30
Wetness (w) :				
Flooding	F0,	F1, MR	F1	Poor
Drainage	Good	imperfect	Poor	Poor
Soil physical properties (s):				
Texture	SiC, SiCL, CL, SiL, SL, C, SCL	LFS, LCS	CS, S	S
Fertility (f):				
Cation exchange capacity (cmol/kg clay)	>24	24- 16	<16	
Base saturation (%)	>50	20-35	<20	
Organic matter (%), 0-50cm	>20	8- 12	< 8	
pH (H_2O)	5.5-7.0	5.0-8.0	5.0-8.0	
Available phosphorus (mg/kg)	>22	7-13	3-7	<3
Total Nitrogen (%)	>0.15	0.08-0.10	0.04-0.08	<0.08
Extractable K (cmol/kg)	>0.50	0.20-0.30	0.10-0.20	<0.10

Note: FO – No Flooding, F1 – Seasonal Flooding, MR – Flooding Rare CL- Clay Loam, SCL- Sandy Clay Loam, SL - Sandy Loam, LS - Loamy Sand, L – Loam, LFS - Loamy Fine Sand, LCS - Loamy Coarse Sand, FS - Fine Sand, Sic - Silty Clay, Sicl - Silty Clay Loam, SC - Sandy Clay, S –Sand, S1 – Highly Suitable S2 – Moderately Suitable S3 – Marginally Suitable, N1 – Currently Not Suitable

Source: Abagyeh et al. (2016)

Table 1: Comparison of treatments.

will obtain yields lower than those obtained in the experiment. The gross field benefit is the value of one kilogram of the crop to the farmer, net of harvest costs that are proportional to yield. The cost that varies is the cost incurred in the field operations. The net benefit is calculated by subtracting the total costs that vary from the gross field benefit.

2. Marginal analysis: The dominance analysis was done by listing the treatments in order of increasing costs that vary; the treatment with net benefits that are less than or equal to those of a treatment with lower costs that vary is ranked 'dominated'. The marginal rate of return expressed in percentage was calculated by dividing marginal net benefit (the change in net benefits between the treatments) by the marginal cost (the change in cost between the treatments).

Sensitivity analysis

A sensitivity analysis was conducted to evaluate the impact of key soil properties on maize yields and land suitability. This analysis helps identify the most critical factors influencing productivity and provides insights for targeted soil and crop management interventions

Results and iscussion

Land suitability evaluation for maize

The matching of the land characteristics/qualities requirements for maize in Table 2 with the land characteristics/qualities of the study locations in Table 3 resulted in the land suitability ratings in Table 4.

Rainfall, length of growing season, and relative humidity were optimum in the three sites, therefore, they were rated highly suitable (S1). The mean annual temperature was not favourable in Kabba, it was rated marginally suitable (S3). Maize is broadly adapted to different agro-ecological zones of Nigeria; farmers can adopt farming technologies and methods that are adaptable to each agro-ecological zone based on the climatic peculiarities of each ecological zone (Egbetokun et al., 2014).

Land qualities	Kabba	Ejiba	Anyigba
Climate (c):			
Annual rainfall (mm)	1,570	1,346	1,600
Length growing season(days)	160	180	185
Mean annual temperature (°C)	30	22	25
Relative humidity (%)	60	75	73
Topography (t)			
Slope (%)	3.7	1.8	2.6
Wetness (w) :			
Flooding	F0	F0	F0
Drainage	Imperfect (mottled)	Imperfect (mottled)	Good
Soil physical properties (s):			
Texture	SCL	SL	SL
Fertility (f) :			
Cation exchange capacity (cmol/kg clay)	12.60	17.22	26.18
Base saturation (%)	90	70	75
Organic matter (%), 0-50cm	1.80	2.83	2.14
pH (H_2O)	6.05	5.74	5.90
Available phosphorus (mg/kg)	8.35	12.32	25.50
Total nitrogen (%)	0.18	0.27	0.20
Extractable K (cmol/kg)	0.51	1.16	0.82

Note: FO – No Flooding, SCL- Sandy Clay Loam, SL - Sandy Loam

Source: Metrological, field, and laboratory data

Table 3: Land characteristics/qualities of the study locations.

The major variations experienced are in the time of planting and the number of plants. In some locations, maize is planted twice (early and late planting) per annum, while it is planted once in some. The climatic condition of Ejiba and Anyigba are more favourable for the planting of maize twice per annum.

The slope is optimum for Ejiba and Anyigba. It was rated S1 while it was moderately suitable (S2) in Kabba. Jimoh et al. (2016) reported a slope range of 2% to be highly suitable for maize production in some parts of Nigeria. Fasina and Adeyanju (2007) also reported that a slope of < 3 % may favour mechanical operation.

Flooding was rated S1 in the three locations. Drainage was S1 in Anyigba and S2 in the other sites.

The soil texture of sandy clay loam and sandy loam is optimum for maize production in the three sites. The result is similar to the findings of Kefas (2016) and Jimoh et al. 2016) in other parts of the savannah zone of Nigeria.

Fertility limitations cation exchange capacity is rated below S1 in Kabba and Ejiba (S3 and S2, respectively). Organic matter is S3 in all the sites, while available phosphorus is S2 in Kabba and Ejiba. These properties constitute limitations to maize production in the study locations.

The actual suitability index ratings revealed that Kabba is currently not suitable (N1) with an actual suitability index of 10.49. Ejiba and Anyigba were marginally suitable (S3), with actual suitability indexes of 18.33 and 19.49, respectively. The soils were placed in classes l ower than S1 (highly suitable) as a result of characteristics/qualities (limiting factors) that were lower than S1. Fertility limitations for maize production are typical of Nigerian soils. A similar view was held by Orimoloye et al. (2019), Abagyeh et al. (2016), Kefas (2016), Jimoh et al. (2016, Ezeaku (2011), and Oluwatosin (2005). Fertility limitations underscore the need for sustainable soil management practices. The use of organic amendments (e.g., compost, manure) and inorganic fertilizers should be carefully balanced to avoid over-reliance on chemical inputs, which can lead to soil degradation and environmental pollution. Furthermore, conservation agriculture practices, such as minimum tillage, crop rotation, and cover cropping, can be adopted to improve soil structure,

Land qualities	Kabba	Ejiba	Anyigba
Climate (c):			
Annual rainfall (mm)	S1 (100)	S1 (100)	S1 (100)
Length growing season(days)	S1 (100)	S1 (100)	S1 (100)
Mean annual temperature (°C)	S3 (39)	S1 (100)	S1 (100)
Relative humidity (%)	S1 (100)	S1 (100)	S1 (100)
Topography (t)			
Slope (%)	S2 (84)	S1 (100)	S1 (95)
Wetness (w) :			
Flooding	S1 (100)	S1 (100)	S1 (100)
Drainage	S2 (84)	S2 (84)	S1 (100)
Soil physical properties (s):			
Texture	S1 (100)	S1 (100)	S1 (100)
Fertility (f):			
Cation exchange capacity (Cmol/Kg clay)	S3 (35)	S2 (50)	S1 (95)
Base saturation (%)	S1 (100)	S1 (100)	S1 (100)
Organic matter (%), 0-50cm	S3 (20)	S3 (20)	S3 (20)
pH (H_2O)	S1 (100)	S1 (100)	S1 (100)
Available phosphorus (mg/kg)	S2 (84)	S2 (84)	S1 (100)
Total Nitrogen (%)	S1 (100)	S1 (100)	S1 (100)
Extractable K (cmol/kg)	S1 (100)	S1 (100)	S1 (100)
Actual suitability index	N1 (10.49)	S3 (18.33)	S3 (19.49)
Potential suitability index	S3 (32.76)	S1 (84)	S1 (95)

Note: S1 – Highly Suitable S2 – Moderately Suitable S3 – Marginally Suitable N1 – Currently Not Suitable
Source: Land suitability evaluation analysis

Table 4: Land suitability ratings of the locations for maize.

enhance water retention, and reduce erosion, thereby promoting long-term soil health. These will ameliorate fertility limitations. Under this consideration, the potential suitability ratings of the locations improved, with Kabba having a potential suitability index of 32.75 and rated S3 (marginally suitable) while Ejiba and Anyigba were highly suitable with an index of 84 and 95, respectively. The improvement in the suitability ratings is a pointer that agronomic practices targeted towards improving soil fertility will lead to improved maize production. For improved and sustainable maize production, the adoption of improved cultivation and management practice is inevitable by farmers in the study locations. However, the adoption of these practices by farmers could be hindered by socio-cultural barriers. Addressing these barriers is critical to ensuring the successful implementation of sustainable agricultural practices (Barbosa Junior, 2022).

Sensitivity analysis of limiting properties that can be altered by management

The sensitivity analysis (Table 5) indicates that organic matter, soil pH, and total nitrogen significantly affect crop yields, while CEC, available phosphorus, and extractable potassium also play essential roles. By concentrating on interventions that target these key properties, farmers can improve soil fertility, increase yields, and promote sustainable agricultural production. Continuous monitoring and adaptive management are vital for preserving soil health and productivity over the long term.

Yield of maize

The data on the yield of maize is presented in Table 6. There was significant difference ($P>0.05$) between yield obtained from farmers' practice (M1) and that of the improved cultivation and management practice (M2). M2 was significantly higher than M1 with average yield of 4530, 5950 and 5860 compared to 3500, 4530 and 4410 at Kabba, Ejiba and Ayingba respectively. This can be attributed to higher seeding rate, defined spacing, effective weed and pest control and higher fertilizer doses in M2 than M1. The low adoption of improved crop production practices, as highlighted by Obiechina (2012) and Mgbenka and Mbah (2016), is a significant factor contributing

Soil Property	Kabba			Ejiba			Anyigba		
	BV	C	IY (%)	BV	C	IY	BV	C	IY
Cation exchange capacity (Cmol/kg clay)	12.60	11.34–13.86	±5–10	17.22	15.50-18.94	±5–10	26.18	23.56–28.80	±5–10
Base saturation (%)	90	81–99	M	70	63-77	±5–10	75	67.5–82.5	±5–10
Organic matter (%), 0-50 cm	1.80	1.62–1.98	±8–12	2.83	2.55-3.11	±8–12	2.14	1.93–2.35	±8–12
pH (H2O)	6.05	5.44–6.66	±10–15	5.74	5.17-631	±10–15	5.90	5.31–6.49	±10–15
Available phosphorus (mg/kg)	8.35	7.52–9.19	±5–10	12.32	11.09–13.55	±5–10	25.50	22.95–28.05	±5–10
Total Nitrogen (%)	0.18	0.16–0.20	±10–15	0.27	0.24–0.30	±10–15	0.20	0.18–0.22	±10–15
Extractable K (cmol/kg)	0.51	0.46–0.56	±5–10	1.16	1.04–1.28	±5–10	0.82	0.74–0.90	±5–10

Note: BV = Base line; C = ±10% Change; IY = Impact on Yields, m = minimal
Source: Economics analysis

Table 5: Summary of sensitivity analysis result of soil properties.

Treatment	2021	2021	2023	Average yield (kg/ha)
KabbaM$_1$	3615b	3450b	3435b	3500
KabbaM$_2$	4540a	4655a	4395a	4530
EjibaM$_1$	4654b	4238b	4458b	4450
EjibaM$_2$	6007a	5965a	5878a	5950
AyingbaM$_1$	4390b	4650b	4190a	4410
AyingbaM$_2$	5940a	5895a	5745b	5860

Note: Means in a column or row followed by the same letters are not significantly different at 5% level of probability.

Source: Field data and statistical analysis

Table 6: Maize yield in the locations.

to the low yield output of arable crops in Nigeria. This challenge is further compounded by environmental factors (such as climate variability and soil degradation) (Olumide, 2022) and socio-cultural barriers (such as traditional practices and limited access to resources) (Salisu, 2022).

The yield varies slightly by the year for all the treatments in the locations, and this can be attributed to environmental and biological factors, which vary by year. Between the locations, Ejiba had a higher average yield for each of the treatments than the other locations, this is not surprising because most land qualities are more suitable for maize in Ejiba than other locations. The rank of the yield performance of maize in the location is as follows: Ejiba>Ayingba>Kabba. The result on yield was in agreement with the land suitability ratings of the location in this study. The actual suitability rating was reflected in the yield of maize under farmer's management (M1), while M2 revealed the potential suitability.

Economic analysis of maize production in the locations

The partial budget analysis is presented in Table 7. The gross field benefits of the plots that received the recommended management practices by FFD (2002) (M1) were higher than those that were cultivated with the farmer's practice (M1). Kabba is $1,916.19 and $1,480.50, Ejiba is $2,516.85 and $1,882.35 while Anyigba is $2,478.78 and $1865.43 for M2 and M1 respectively. There is variation in the cost of land preparation, seed, herbicide, fertilizer, pest control, and shelling due to different intensities of operations and quantities required by each practice. Labour also varies. An average Nigerian earns a minimum of $2.6 in a day, which amounts to the minimum wage of $77 in a month (National Bureau of Statistics, 2020), therefore, the cost of labour in the three locations is not below the minimum wage, although it is lower in Kabba than others. This explained the lowest total cost that varies of $388 and $693 for M1 and M2 at Kabba. The highest for M1, $430, is at Ayingba, and the highest for M2 is $768 at Ejiba. The net benefit revealed that there is a higher benefit in M2 than M1 in all the locations. $1,092.5 and $1223.19, $1493.35 and $1748.85, and $1,435.43 and $1,731.78 were recorded for M1 and M2 at the three locations, respectively. It is noted that subsistence farmers participate in farm operations along with the members of their family and friends in some cases. Alabi and Abdulazeez (2018) affirm that In most agrarian communities of Nigeria, family size is seen

Cost	KabbaM$_1$	KabbaM$_2$	EjibaM$_1$	EjibaM$_2$	AnyigbaM$_1$	AnyigbaM$_2$
Average Yield (kg/ha)	3500	4530	4450	5950	4410	5860
Adjusted Yield (kg/ha)	3150	4077	4005	5355	3969	5274
Gross field Benefits ($/ha) at $0.47/kg*	1,480.50	1,916.19	1,882.35	2,516.85	1,865.43	2,478.78
Land preparation	79.00	129.00	68.00	120.00	66.00	92.00
Seed at $1.31 per kg	15.00	35.00	20.00	35.00	20.00	35.00
Planting	40.00	70.00	45.00	80.00	45.00	90.00
Herbicide ($/ha)	12.00	24.00	20.00	40.00	22.00	45.00
Labour for application of herbicide ($/ha)	11.00	22.00	14.00	28.00	16.00	30.00
Labour for hand weeding ($/ha)	28.00	0	30.00	0	35.00	0
Cost of fertilizer ($/ha)	78.00	150.00	78.00	150.00	78.00	150.00
Cost of fertilizer application ($/ha)	30.00	60.00	30.00	80.00	40.00	80.00
Control of Army worm and stem borer	30.00	68.00	30.00	85.00	38.00	85.00
Shelling	65.00	135.00	60.00	150.00	70.00	140.00
Total cost that vary ($/ha)	388	693	395	768	430	747
Net Benefit ($/ha)	1,092.5	1,223.19	1,493.35	1,748.85	1,435.43	1,731.78

Note: Computation was made based on the exchange rate of naira to dollar as at September, 2022
*Price as at September 2022
Source: Economics analysis

Table 7: Partial budget.

as an advantage to the household head as it signifies the availability of farm labour. Therefore, farmers in the study locations can beat the cost of labour through family labour.

The high benefits and lower total costs that vary in Ayingba for M2 in comparison with the other locations led to the tagging of Ayingba M2 as the dominated (D) site in comparison to others (Table 8) in this study. This implies that Ayingba has comparative advantage over the other locations for maize production. is a location to be sought after for maize production within the southern guinea savannah zone of Nigeria.

Treatment	Total costs that vary ($/ha)	Net benefits($/ha)
KabbaM$_1$	388	1,092.50
EjibaM$_1$	395	1,493.35
AyingbaM$_1$	430	1,435.43
KabbaM$_2$	693	1,223.19
AyingbaM$_2$	747	1,731.78
EjibaM$_2$	768	1,748.85

Source: Economics analysis

Table 8: Dominance analysis.

The marginal rates of return are presented in Table 9. Kabba had a marginal rate of return of 42.85%, Ejiba had 68.50%, and Ayingba had 93.49%. This implied that for farmers to deviate from their usual practice, adopt and invest $1.00 in the improved cultivation and management practice for maize production used in this study, they will recover the $1.00 and get an additional $0.4285, $0.6850, and $0.9349 in Kabba, Ejiba and Ayingba, respectively. Alabi and Abulazeez (2018) reported lower return on investment by maize farmers in Kaduna, northern guinea savannah agro ecological zone of Nigeria. Lower returns were also reported from other locations in Nigeria (Girei et al., 2018; Abdulaleem et al., 2017). All the reports were for farmers' practice. It may be necessary for farmers to obtain loans in other to be able to make extra investment on the improved practice. According to the guideline of CIMMYT (1988), the minimum rate of return is set between 60% to 100% considering the 5% to 8% bank interest rate for agricultural loan in Nigeria.

Treatment	Kabba	Ejiba	Ayingba
Difference in Cost that varies($/ha)	305	373	317
Difference in net benefits ($/ha)	130.39	255.50	296.35
Marginal rates of return (%)	42.85	68.50	93.49

Source: Economics analysis

Table 9: Marginal rates of return.

Sensitivity analysis of the components of economic analysis

The sensitivity analysis of the components of economic analysis (Table 10) shows that maize yield and fertilizer costs have the most significant impact on profitability. By focusing on improving yields and implementing cost-saving measures in fertilizer use, farmers can greatly enhance their net profitability. Furthermore, optimizing

Cost	BV	C %	IMGB	IMTC %
Maize Yield (kg/ha)	3500-5860	±10	±10%	-
Land preparation	66.00-129.00	±10		±2–3
Seed at $1.31 per kg	15.00-35.00	±10		±1–2
Planting	40.00-90.00	±10		±1–2
Herbicide ($/ha)	12.00-45.00	±10		±1–2
Labour for application of herbicide ($/ha)	11.00-30.00	±10		±1–2
Labour for hand weeding ($/ha)	28.00-35.00	±10		±1–2
Cost of fertilizer ($/ha)	78.00-150.00	±10		±3–5
Cost of fertilizer application ($/ha)	30.00-80.00	±10		±1–2
Control of Army worm and stem borer	30.00-80.00	±10		±1–2
Shelling	60.00-150.00	±10		±2–3

Note: BV= Baseline values; C= ±10% Change; IMGB = Impact on Gross Benefits; IMTC = Impact on Total Costs
Source: Land suitability evaluation analysis

Table 10: Summary of sensitivity analysis of economic evaluation variables.

land preparation, shelling, and other cost factors can improve overall cost efficiency. Continuous monitoring and adaptive management are crucial for maintaining profitability and ensuring sustainable maize production.

The findings of this study have significant long-term implications for improving maize productivity, enhancing food security, and promoting sustainable agriculture in the southern Guinea Savannah zone of Nigeria. However, the variability in yields and suitability across locations underscores the need for site-specific recommendations and adaptive management practices. Sustainable practices to resolve fertility problems can also reduce environmental degradation, such as soil erosion and nutrient depletion, ensuring that farmland remains productive for future generations. The findings from the southern Guinea Savannah zone can be scaled to other regions with similar agro-ecological conditions, such as the northern Guinea Savannah and Sudan Savannah zones of Nigeria and neighboring countries in West Africa. However, scaling up the adoption of improved practices requires addressing socio-cultural barriers, providing institutional support, and leveraging technology to ensure that innovations reach smallholder farmers. Scaling up requires adaptation to local conditions, including soil types, rainfall patterns, and socio-cultural contexts.

Conclusion

The conduction of the experiment on the farmer's field allowed farmers to have a firsthand experience of the implication of their practices and the recommended practices for maize production. Limitations to maize production in the study area are mean annual temperature, slope, drainage, low cation exchange capacity clay, low organic matter, and low available phosphorus. For every $1.00 invested in the adoption of the improved cultivation and management practice, the farmer will recover the $1.00 and get an additional $0.4285, $0.6850, and $0.9349 in Kabba, Ejiba, and Ayingba, respectively. The improved management practice is recommended to farmers in the agro ecological zone. However, achieving environmental sustainability and overcoming socio-cultural barriers to adoption require a multifaceted approach that integrates technical, economic, and social interventions. By addressing soil fertility limitations, promoting climate-smart practices, and engaging farmers in participatory decision-making, stakeholders can create an enabling environment for sustainable agricultural development. Additionally, addressing socio-cultural barriers, such as limited access to resources and risk aversion, is essential to ensure the widespread adoption of improved practices and the long-term resilience of farming communities. Further research on the assessment of other important crops in agro ecological zones of Nigeria in other to identify locations that has comparative advantage for specific crops in the zone is also recommended.

Acknowledgments

The authors are grateful to the Extension Agents of the Kogi State Agricultural Development Project and the Farmers for granting permission to use their farms for the field experiment and also sharing their experience.

Corresponding author:
Babalola Temitope Seun, Ph.D.
Department of Soil Science and Land Resources Management, Faculty of Agriculture
Federal University Oye-Ekiti, P. M. B. 373,. Km 3 Oye – Afao Road, Ekiti State, Nigeria
E-mail: seun.babalola@fuoye.edu.ng

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Volume XVII Number 2, 2025

Economic Development and Diet Composition: Cross-Continental Insights into Bennett's Law

Bartłomiej Bajan , Magdalena Piechocka

[1] Faculty of Economics, Poznan University of Life Sciences, Poland

Abstract

The study assesses Bennett's Law, which posits that higher incomes lead to reduced consumption of starchy staples in favor of more diverse, nutrient-dense diets, and its relevance across various global regions. Using regression models, the research examines the relation between GDP per capita and the share of starchy staple foods in caloric intake across continents. The findings indicate significant regional variations in adherence to Bennett's Law. For instance, while South America aligns with Bennett's predictions, Europe deviates, showing increased starchy staple consumption with rising incomes, potentially due to cultural and eco-conscious dietary trends. Africa and parts of Asia display limited dietary diversification, often due to structural barriers and economic constraints. Contrarily, Oceania and North America exhibit a mixed relationship, influenced by income inequality and health trends. These results suggest that Bennett's Law's applicability is region-specific and influenced by socioeconomic, cultural, and policy factors, underscoring the complexity of dietary transitions and cautioning against one-size-fits-all assumptions about the impacts of economic development on food consumption.

Keywords

Food consumption patterns, diet composition, Bennett's Law.

Bajan, B. and Piechocka, M. (2025) "Economic Development and Diet Composition: Cross-Continental Insights into Bennett's Law", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 37-49. ISSN 1804-1930. DOI 10.7160/aol.2025.170203.

Introduction

As conceptualized by Merrill Bennett in 1941, Bennett's Law highlights a fundamental shift in dietary patterns as household incomes rise. Specifically, it states that the share of calories derived from starchy staples - such as grains, roots, and tubers - decreases with increasing income. At the same time, the consumption of more nutrient-dense and diverse foods, including meats, dairy, fruits, and vegetables, rises (Bennett, 1941). Bennett's is an extension of Engel's Law, which asserts that the share of total income spent on food declines as income grows, with Bennett's Law focusing specifically on the composition of food expenditure (Grigg, 1996; Manannalage et al., 2023). A dietary transition imposed by Bennett's Law is part of the broader "nutrition transition" seen as economies develop, where populations move away from cheap, energy-dense foods towards higher-quality, diverse diets (Drewnowski and Popkin, 1997).

Over the past few decades, major macroeconomic trends such as globalization, urbanization, and rising incomes have significantly changed what people eat, especially in developing countries. These changes are central to verifying whether Bennett's Law still holds in a globalized and increasingly interconnected world. A striking trend, mainly since the 1960s, is the growing convergence of global food consumption patterns, a phenomenon primarily driven by globalization (Bajan and Sowa, 2019). As economies develop and become more integrated into the global market, diets in wealthier regions tend to influence those in developing areas, resulting in what many researchers refer to as the "Westernization" of diets (Pingan, 2007). This shift toward processed foods, high sugar intake, and animal products is most noticeable in urban areas, where access to various food products has become the norm (Rae, 1998). Such urbanization processes and income growth support Bennett's Law as diets transition from traditional to more diverse compositions (Huang and Bouis, 2001).

Nonetheless, the verification of Bennett's Law is complicated by regional disparities. For instance, while food consumption patterns in many Asian and Latin American countries have indeed moved toward a more Westernized model, African countries present an outlier (Bajan et al., 2021). In Africa, the dietary shift has not been as pronounced, and in some cases, it has even diverged from global trends. The food consumption structure in Africa remains heavily dependent on staple cereals, even as incomes rise (Bajan and Sowa, 2019). This divergence calls into question the extent to which Bennett's Law applies universally, especially in regions where economic growth does not translate into the widespread availability of higher-quality food products. Moreover, rising environmental and health concerns have led to a countertrend in some high-income countries, with a growing preference for plant-based and environmentally sustainable diets (Janssen et al., 2016). This shift, driven by consumer preferences and policy interventions, could lead to a reversal of the trend predicted by Bennett's Law, as wealthier populations reduce their intake of animal products and processed foods in favor of diets more aligned with environmental sustainability goals.

The main goal of this article is to empirically test whether Bennett's Law still holds, given the changes in the population's food consumption patterns over the past half-century. To achieve this, we analyze Bennett's Law on a global scale by examining the relationship between GDP per capita, as a proxy for income (wealth), and the share of starchy staples in total caloric intake across different continents. We employ a panel regression model and perform a time-series regression analysis for each continent, offering a comprehensive, region-specific perspective on how economic development influences dietary composition. The novelty of this study lies in its global scope, using the newest data on food consumption patterns, revealing how the wealth-diet dynamic may differ across regions, and providing insights into the socioeconomic drivers of dietary shifts worldwide.

Literature review

Empirical evidence from various regions affirms Bennett's Law. However, some findings through the years are mixed. Studies show that Bennett's Law holds true in many contexts; however, several factors can moderate its effects, leading to variations in the rate of dietary transition. For instance, Manannalage et al. (2023) discussed that calorie deprivation may slow the dietary shift from starchy staples to nutrient-dense foods. Households with unsatiated calorie needs prioritize inexpensive, calorie-rich staples, delaying the transition to a more diverse diet. Geographic and infrastructural barriers also play a role in moderating Bennett's Law. For instance, households in rural areas with limited access to markets may be slower to adopt more diverse diets, even as their incomes rise (Ansah et al., 2020).

In some regions, cultural preferences for certain foods, particularly starchy staples, persist even as incomes grow. For example, Filippini and Srinivasan (2019) noted that in India, where vegetarianism is prevalent, rising incomes do not necessarily lead to a shift toward animal-based proteins. Instead, dietary diversification occurs within the bounds of cultural norms, especially for members of religious groups. Such findings are further supported by Gouel and Guimbard (2019), who found that food consumption patterns in culturally conservative societies are less elastic and less influenced by income, leading to a slower transition away from starchy staples.

Another factor contributing to the slow transition of food consumption patterns is government intervention. For instance, Pingali (2007) and Timmer et al. (1984) highlight how government policies in countries like India and China have maintained low prices for rice and wheat, distorting the natural food demand pattern expected under Bennett's Law. As a result, even wealthier households may continue to consume a high proportion of starchy staples because they are economically attractive relative to other food options (Reardon and Timmer, 2014).

While Bennett's Law traditionally emphasizes a shift toward animal-based proteins and other nutrient-dense foods as incomes rise, modern food technology is introducing new, affordable alternatives to these products, potentially altering the expected dietary transition. For instance, Drewnowski (2024) examined the rising availability of plant-based proteins and processed foods, which are becoming more affordable and accessible, even in low- and middle-income countries (LMICs). Another factor influencing food consumption patterns in LMICs is the lack of nutrition education. Choudhury et al. (2019) demonstrated that many households do not diversify their diets despite rising incomes due to limited food literacy and knowledge about the benefits of more expensive food groups like meat, fruits, and vegetables.

Historical dietary shifts in 19th-century Europe and North America mirror Bennett's Law.

As incomes rose, populations moved away from cheap staples like potatoes toward more diverse, high-quality foods such as meat and dairy (Fuglie, 2004). Grigg (1996) also proves that caloric intake from starchy staples remains high in poorer countries but declines as incomes grow. This trend has been observed consistently in developing regions like Africa and Asia, where staples dominate diets but are gradually replaced by more nutrient-dense foods. Drewnowski and Popkin (1997) documented how rising incomes in Africa have led to a gradual reduction in the consumption of traditional starchy staples, like maize and cassava, with increased spending on processed foods, oils, and animal products.

Further evidence is provided by Ansah et al. (2020), who found that in Ghana, dietary patterns shift away from starchy staples towards more diverse food groups, including fish, meat, and dairy. This pattern is consistent across urban and rural settings, though urban households tend to spend a higher share of their budget on non-starchy foods. The study also confirms that female-headed households in Ghana allocate more of their food budget to diverse, nutrient-rich foods than their male counterparts.

Choudhury et al. (2019) extended the analysis of Bennett's Law to infant diets, showing that wealthier households tend to introduce more diverse and nutrient-dense foods to their children earlier than poorer households. In the aforementioned studies in Sri Lanka, Manannalage et al. (2023) found that once calorie demands are satisfied, households reduce their consumption of staples and increase spending on non-starchy foods, thus affirming Bennett's Law. Also, Drewnowski (2024) argues that despite the growing presence of alternative plant-based proteins, the aspirational demand for animal proteins remains strong, particularly in developing regions where rising incomes continue to drive demand for high-quality animal-sourced proteins.

Material and methods

Data and its limitations

All the data used in this article come from the open-source data of the Food and Agriculture Organization of the United Nations (FAO). We used data from the FAO food balance sheets to determine the proportion of starchy staples in the average diet (FAO, 2024). It's important to note that while FAO data reflect the food supply available on the market, we refer to it as 'consumption' throughout this paper for simplicity. However, this term doesn't account for food losses at the household level. Despite this limitation, FAO data remain a dependable source for understanding consumption trends, as confirmed by studies that have successfully used food balance sheets to analyze dietary patterns (Unar-Mungala et al., 2019; Bajan et al., 2021).

We used GDP per capita in constant prices as a proxy for the income (wealth) of households in the region. It offers an average income figure but has limitations in the consumption patterns analysis. The main concern is that GDP per capita may not accurately represent food access differences and income disparities within a population. However, a comparison of starchy staple consumption and GDP per capita gives reliable macro trend approximation, which is confirmed by previous studies. The most famous example of such study was probably done by Grigg (1996), who plotted Gross National Product per capita against starchy staple ratios in a long-run analysis of several regions in the world.

Estimation strategy

Our calculation strategy was to first regress GDP per capita with a share of starchy staples based on panel data for six continents and then to regress it for each continent separately. The first step was to ensure the robustness of the models through a series of statistical tests, and after that, the regressions were run.

We employed the Fisher-type panel unit root test to assess the stationarity of GDP per capita in the panel data, which aggregates individual augmented Dickey-Fuller (ADF) test results across panels (Maddala and Wu, 1999). The ADF equation is specified as follows:

$$\Delta y_{it} = \alpha_i + \rho y_{i,t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{i,t-j} + \epsilon_{it} \tag{1}$$

where: y_{it} represents GDP per capita for panel i at time t, Δy_{it} is the first difference to address potential non-stationarity, α_i is a panel-specific intercept, ρ tests for a unit root (with $\rho = 0$ indicating non-stationarity), $\sum_{j=1}^{p} \gamma_j \Delta y_{i,t-j}$ includes lagged terms to control for autocorrelation, and ϵ_{it} is the error term.

The null hypothesis H_0: $\rho = 0$ (all panels contain a unit root) was tested against

H_1: $\rho < 0$ (stationarity in at least some panels). This step confirmed whether differencing was required to ensure reliable estimation results (Levin et al., 2002).

We next examined serial correlation in the residuals using the Wooldridge test for autocorrelation (Wooldridge, 2002). The test assumes a first-order autoregressive process in the error terms:

$$\epsilon_{it} = \rho\epsilon_{i,t-1} + u_{it} \quad (2)$$

where: ϵ_{it} is the residual for panel i at time t, ρ is the coefficient that indicates first-order autocorrelation, and u_{it} is a white-noise error term.

The null hypothesis H_0: $\rho = 0$ (no autocorrelation) was tested against H_1: $\rho \neq 0$ (presence of autocorrelation). Clustering or alternative adjustments are warranted if serial correlation is present to obtain accurate standard errors.

To determine the appropriate panel model, we performed a Hausman test (Hausman, 1978), comparing the fixed-effects (FE) and random-effects (RE) specifications. The Hausman test statistic is calculated as follows:

$$H = (b_{RE} - b_{FE})'[Var(b_{RE}) - Var(b_{FE})]^{-1}(b_{RE} - b_{FE}) \quad (3)$$

where: b_{RE} and b_{FE} are the coefficient vectors for the RE and FE models, respectively. A significant H value indicates a correlation between the random effects and regressors, validating the use of an FE model.

To verify the presence of homoskedasticity across groups in our panel model, we employed the Modified Wald test for groupwise heteroskedasticity. The test statistic for the Modified Wald test for fixed effects is calculated as (Wooldridge, 2010):

$$W = \sum_{i=1}^{N}(\frac{e_i'e_i}{\sigma^2} - T_i)^2 \quad (4)$$

where: e_i is the vector of residuals for group i, σ is the hypothesized common variance across groups under the null hypothesis of homoskedasticity, T_i is the number of periods for group i, and N is the total number of groups.

To verify the presence of homoskedasticity (constant error variance across groups) with the alternative hypothesis that heteroskedasticity is present (error variances differ across groups).

We tried to keep the same approach as the panel model in the time series models (model for each continent). Similarly, we first employed a stationarity check using the Dickey-Fuller test, as in equation 1, and adjusted it for time series data. To verify the absence of autocorrelation in the time series, we conducted the Durbin-Watson (DW) test for first-order autocorrelation in the residuals from a regression model, as follows (Durbin and Watson, 1971):

$$DW = \frac{\sum_{t=2}^{T}(\epsilon_t - \epsilon_{t-1})^2}{\sum_{t=1}^{T}\epsilon_t^2} \quad (5)$$

where: ϵ_t represents the residuals.

A DW statistic close to 2 suggests no first-order autocorrelation, while values significantly different from 2 indicate potential positive or negative autocorrelation (Durbin and Watson, 1951).

To detect potential heteroskedasticity in our time series models, we used the Breusch-Pagan / Cook-Weisberg test. The Breusch-Pagan test statistic is derived from the regression residuals and calculated as follows:

$$\chi^2 = \frac{1}{2}(\sum_{i=1}^{n}\frac{\hat{\epsilon}_i^2}{\sigma^2} - n)^2 \quad (6)$$

where: n is the sample size, $\hat{\epsilon}_i^2$ represents the squared residuals from the initial regression model, and σ^2 is the assumed constant variance under the null hypothesis.

The Breusch-Pagan test evaluates the null hypothesis that the error variance is homoskedastic against the alternative hypothesis that the variance changes with the independent variables.

Detecting autocorrelation or heteroskedasticity would suggest a need for additional adjustments in the error structure to ensure reliable inference. Therefore, we use robust standard errors with the Newey-West procedure in such cases. The estimator corrects for both heteroskedasticity and autocorrelation, providing consistent standard errors when serial correlation exists in time series data. The Newey-West estimator modifies the Ordinary least squares (OLS) variance-covariance matrix by incorporating weighted autocovariances up to a specified lag q (lag(1) in our case). The formula for the Newey-West covariance matrix is (Newey and West, 1987):

$$\hat{\Sigma}_{NW} = \hat{\Sigma}_{OLS} + \sum_{k=1}^{q}(1 - \frac{k}{q+1})(\Gamma_k + \Gamma'_k) \quad (7)$$

where:

$\widehat{\Sigma}_{OLS} = \frac{1}{T}\sum_{t=1}^{T} \epsilon_t^2 X_t X_{t-k}'$ is the traditional OLS covariance matrix,

$\Gamma_k = \frac{1}{T}\sum_{t=k+1}^{T} \epsilon_t \epsilon_{t-k} X_t X_{t-k}'$ is the lag-k autocovariance of the residuals, T is the total number of observations, ϵ_t is the residual at time t, X_t is the vector of regressors at time t.

Model specification

Based on statistical tests conducted for the panel data, we established strong evidence of unit root for GDP per capita and share of starchy staples (Table 1). Therefore, we applied the first difference to our variables and reran the Fisher-type unit-root test. The results for differentiated data showed stationarity, assuming a significance level of 0.05 (Table 1).

Then, we employed the rest of the statistical tests as described in the estimation strategy, interpreting it at the 5% significance level. We found that in our data, there is no autocorrelation based on the high p-value of the Wooldridge test (Table 2.). The heteroskedasticity is present, based on the low p-value of the Wald test (Table 2.), and the fixed effects model is more appropriate, based on the low p-value for the Hausman test (Table 2.).

To address potential heteroskedasticity, we applied robust clustered standard errors. The FE model is specified as:

$$\Delta Share\ of\ starchy\ staples_{it} = \alpha_1 + \beta \cdot \Delta GDP\ per\ capita_{it} + \epsilon_{it} \tag{8}$$

where: Δ represents the differentiation of variable, α_i represents time-invariant fixed effects, β is the estimated coefficient for GDP per capita, and ϵ_{it} is the error term.

In the case of time series data, we established a high probability of unit root for GDP per capita and share of starchy staples, except for Oceania in the latter case (Table 3). Therefore, we applied the first difference to our variables and reran the ADF test. After the differentiation, there is no evidence of unit root in the data.

Durbin-Watson's test for autocorrelation showed no autocorrelation issues in Africa, Europe, Asia, and North America. We based our interpretation on a well-established view that d-statistic between 1.5 and 2.5 is proof of the absence of strong autocorrelation (Green, 2018). Thus, autocorrelation is detected in the case of Oceania and South America. Moreover, in the case of South America, we detected heteroskedasticity based on the low p-value of the Breusch-Pagan test (Table 3). Therefore, to adjust for autocorrelation or/and heteroskedasticity, we used robust standard errors with the Newey-West procedure in the case of Oceania and South America.

Variable	Statistical Measure	Statistic			
		Inverse chi-squared (P)	Inverse normal (Z)	Inverse logit t(L*)	Modified inv. chi-squared (Pm)
GDP_per_capita	value	1.5300	2.6610	2.5911	-2.1372
	p-value	0.9999	0.9961	0.9926	0.9837
d_GDP_per_capita	value	115.0726	-8.4480	-13.1062	21.0396
	p-value	0.0000	0.0000	0.0000	0.0000
Share_of_Starchy_Staples	value	12.3925	0.8365	0.7484	0.0801
	p-value	0.4147	0.7986	0.7703	0.4681
d_Share_of_Starchy_Staples	value	144.6216	-10.4335	-16.5276	27.0713
	p-value	0.0000	0.0000	0.0000	0.0000

Source: own computation in the STATA 15, based on FAO data

Table 1: Results of the Fisher-type unit-root test for panel data.

Test	Statistic	value	p-value
Wooldridge test for autocorrelation	F	0.1080	0.7555
Hausman FE/RE model	Chi-squared	9.4100	0.0022
Modified Wald test	Chi-squared	28.7300	0.0001

Source: own computation in the STATA 15, based on FAO data

Table 2: Statistical tests for panel data.

Region	Africa	Europe	Asia	Oceania	South America	North America
ADF test GDP_per_Capita	0.9486	0.7416	1.0000	0.9670	0.6091	0.9116
ADF test d_GDP_per_Capita	0.0000	0.0000	0.0017	0.0000	0.0000	0.0000
ADF test Share_of_Starchy_Staples	0.5905	0.6128	0.9804	0.0123	0.7385	0.7398
ADF test d_Share_of_Starchy_Staples	0.0000	0.0000	0.0000	-	0.0000	0.0000
Durbin-Watson d-statistic	1.8163	1.7149	2.3056	0.7136	2.5098	1.8148
Breusch-Pagan / Cook-Weisberg	0.6630	0.6197	0.7387	0.7022	0.0289	0.9233

Source: own computation in the STATA 15, based on FAO data

Table 3: P-values of statistical tests for time series data.

Results and discussion

The African continent has the lowest GDP per capita, with a maximum of around 2 thousand USD. Over the years, a distinct upward trend in GDP per capita is observed across Asia, Europe, Oceania, and North America. North America reached the highest GDP per capita in 2021, exceeding 46 thousand USD, which is more than twenty times that of Africa (Figure 1). A clear opposite trend between GDP per capita and the share of starchy foods in the diet could be observed in Asia and South America during the study period. To some extent, Europe is also characterized by such relations. However, it was primarily significant in the 1970s and 1980s. After the collapse of the Soviet Union, the relation between GDP per capita and starchy staples consumption in newly shaped Europe is unclear. The highest proportion of starch in total caloric intake is found in less economically developed regions, such as Africa, where starch accounts for more than 60% of the diet, and Asia, where the share of starchy staples in the diet was even higher for an extended period.

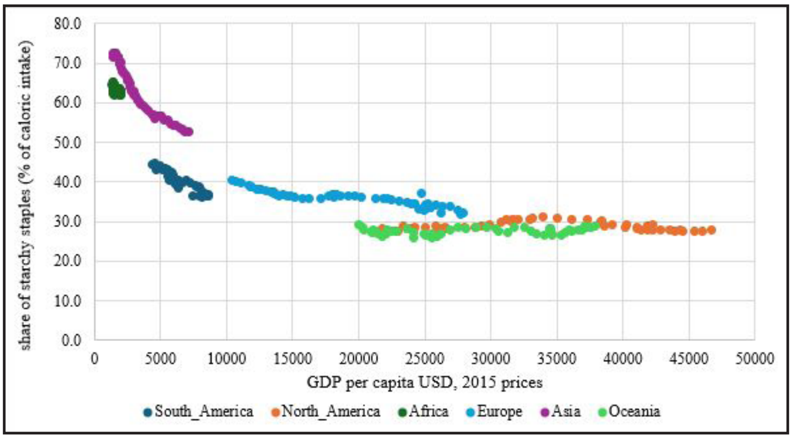
Oceania serves as a contrasting example, with the lowest proportion of starch-rich foods in the diet; here, the share of starchy foods consistently remained below 30% during the study period, reaching a minimum value of 26%. North America is the second continent with the lowest proportion of starch-rich foods in the overall diet, with values ranging between 27% and 31%, alongside the highest GDP per capita among all continents. In both cases, there is no evident trend in the percentage of starchy staple consumption, as it fluctuates.

The panel regression analysis indicates that the change in GDP per capita is not significantly associated with changes in the share of starchy staples, as shown by a non-significant coefficient (0.0000675, $p = 0.354$) (Table 4). The model's within-group R2 is 0.0099, suggesting that changes in GDP per capita within continents explain a minimal variation in the dependent variable. The constant is significant (-0.1461, $p < 0.001$), reflecting a baseline decline in d_Share_of_Starchy_Staples across groups, though this result does not imply a causal effect given the independent variable's non-significance.

An OLS regression was conducted to analyze the relationship between the GDP per capita change and the share of starchy staples in Africa. Table 4 shows that the coefficient for d_GDP_per_Capita is -0.0009683 ($p = 0.509$), indicating no statistically significant relationship (Table 4). The model's R2 is 0.0089, suggesting that less than 1% of the variation in d_Share_of_Starchy_Staples is explained by changes in GDP per capita. The constant term is also not significant.

In Asia, the coefficient for d_GDP_per_Capita is -0.0005761 ($p = 0.399$), indicating no statistically significant association (Table 4). The model's R2 is 0.0145, suggesting that only 1.45% of the variation in d_Share_of_Starchy_Staples is explained by changes in GDP per capita. However, the constant term is significant ($p = 0.002$), indicating a baseline trend in the dependent variable.

For North America, the coefficient for d_GDP_per_Capita is -0.0001105 ($p = 0.133$), suggesting no statistically significant relationship (Table 4). The model's R2 is 0.0455, indicating that approximately 4.55% of the variation in d_Share_of_Starchy_Staples is explained by changes in GDP per capita. The constant term is also not significant.



Source: Own elaboration based on FAOstat data.

Figure 1: Relationship between GDP per Capita and Share of Starchy Staples in Caloric Intake Across Continents.

Variable	Panel	Africa	Asia	North America	Europe	Oceania	South America
d_GDP_per_Capita	0.000067 (0.000066)	-0.00097 (0.001456)	-0.000576 (0.0006777)	-0.0001105 (0.0000723)	0.0001333*** (0.0000313)	0.0000945 (0.0003424)	-0.0008728*** (0.0002805)
Constant	-0.1461*** (0.0152)	-0.03964 (0.061262)	-0.326816*** (0.0987807)	0.0476612 (0.0604273)	-0.2141*** (0.0477)	27.5257*** (0.1830)	-0.0965* (0.0540)
Nr. of Observations	306	51	51	51	51	51	51
F-Statistic	1.04	0.44	0.72	2.34	18.09	0.08	9.68
Prob > F	0.3543	0.5092	0.3994	0.1327	0.0001	0.7837	0.0031
R-squared	0.0148	0.0089	0.0145	0.0455	0.2696		

Note:*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (standard errors in parentheses)
Source: own computation in the STATA 15, based on FAO data

Table 4: Results of regression models for Starchy Staples Share and GDP per Capita.

For Europe, the coefficient for d_GDP_per_Capita is 0.0001333 ($p = 0.000$), indicating a statistically significant positive relationship (Table 4). This suggests that increases in GDP per capita are associated with increases in the share of starchy staples in Europe, contrary to Bennett's Law. The model's R2 is 0.2696, meaning that about 27% of the variation in d_Share_of_Starchy_Staples is explained by changes in GDP per capita. The constant is also significant and negative, indicating a baseline downward trend in the share of starchy staples, independent of GDP growth. Together, these results imply that while GDP growth may positively impact the share of starchy staples, a broader downward trend remains in place.

A regression with Newey-West standard errors was conducted to assess the relationship between GDP per capita growth (d_GDP_per_Capita) and the share of starchy staples (Share_of_Starchy_Staples) in Oceania, accounting for potential autocorrelation with a lag of 1. The coefficient for d_GDP_per_Capita is 0.0000945 ($p = 0.784$), indicating no statistically significant relationship (Table 4). The constant term is significant ($p < 0.001$), with a coefficient of 27.5257, suggesting an average level of starchy staples share that remains consistent over time.

The same type of regression was conducted for South America. However, Share_of_Starchy_Staples was differentiated. The coefficient for d_GDP_per_Capita is -0.0008728 ($p = 0.003$), indicating a statistically significant negative relationship (Table 4).

This suggests that increases in GDP per capita are associated with a decrease in the share of starchy staples, confirming that Bennett's Law holds in South America. The constant term is not significant at the 5% significance level. However, it is significant at a 10% significance level ($p = 0.080$), indicating a slight downward trend in starchy staples shares.

Confirming Bennett's Law in South America aligns with established theories on dietary transitions in developing regions. Economic growth in South

America has spurred increased access to various foods, leading to diversified diets less reliant on starchy staples (Pingali, 2007). Urbanization has further contributed to this shift; as people move to urban areas, they gain exposure to diverse food markets, with greater availability of non-staple foods like fruits, vegetables, and animal products, encouraging dietary shifts as incomes rise (Rae, 1998). Additionally, in several South American countries, dietary policies and food subsidies have made it economically feasible for households to opt for more nutrient-dense foods, accelerating the departure from starchy staples (Huang and Bouis, 2001).

Another significant factor is the aspiration for Western dietary patterns, which are common in many developing regions experiencing income growth and globalization. Studies indicate that as urban middle-class populations grow, so does the influence of Western diets high in protein-rich animal products, processed foods, and fresh produce (Azzam, 2021). This Western influence reinforces Bennett's Law in South America by shifting consumer preferences away from starchy staples as symbols of lower socioeconomic status toward diversified diets that signal upward mobility (Gouel and Guimbard, 2019).

Contrary to expectations, Europe presents increased starchy staple consumption with rising incomes, a phenomenon that runs counter to Bennett's Law. This deviation may stem from several unique socio-cultural and economic factors. Notably, contemporary dietary trends in Europe - such as vegetarianism, veganism, and plant-based diets - are partly influenced by environmental and ethical concerns, driving an increasing demand for plant-based foods, including whole grains and other starchy staples, often as substitutes for animal-based products (Jansen et al., 2016). This eco-conscious dietary shift aligns with broader trends in high-income societies where a reduction in meat consumption has coincided with a renewed focus on grain-based and other starchy staple foods (Meixner et al., 2024).

Additionally, the European market has seen significant growth in low-cost, processed starchy foods that appeal to health-conscious and budget-conscious consumers (Monteiro et al., 2013; Vandevijvere et al., 2019). Unlike in developing regions, where increased income typically shifts preferences away from staples, European consumers may prioritize sustainable, affordable, and versatile options, often opting for plant-based diets emphasizing starchy staples as primary energy sources.

Lastly, cultural preferences and established dietary patterns play a role. Europe's historical reliance on staples such as bread, pasta, and potatoes remains culturally ingrained, even among wealthier populations. Unlike in South America, where income growth shifts dietary preferences toward more Westernized patterns, Europe's entrenched culinary traditions persist, contributing to continued high consumption of starchy staples, albeit in varied forms adapted to modern dietary sensibilities (Dokova et al., 2022).

In examining Asia, Africa, North America, and Oceania, we observe that Bennett's Law does not exhibit significant applicability in these regions, as the expected relationship between rising income levels and reduced starchy staple consumption does not manifest consistently. We explore potential explanations, grounded in socioeconomic, cultural, and policy-related contexts, for why Bennett's Law may not hold firmly in these continents.

In the case of Asia, despite rapid economic growth and urbanization, it displays unique dietary dynamics that may inhibit the effects of Bennett's Law. In particular, cultural factors, including the high prevalence of vegetarianism, especially in South Asia, contribute to sustained high levels of starchy staple consumption (Lipoeto et al., 2015). Studies indicate that in Asian countries, dietary shifts towards animal proteins and other nutrient-dense foods are moderated by cultural preferences, which strongly rely on cereals, legumes, and rice as primary dietary components even as incomes rise (Chang et al., 2018). Economic policies and market conditions also play a role. Many Asian governments have historically supported the production and subsidization of staple grains like rice and wheat, making these foods more affordable relative to other options reinforcing their position as dietary mainstays (Mughal and Fontan Sers, 2020). Such policies create a price-sensitive market where, despite income growth, consumers continue to prioritize these low-cost staples over higher-priced animal products or imported foods. Starchy staples' affordability and cultural integration make them resilient against the dietary shifts predicted by Bennett's Law (Pingali, 2007).

In Africa, structural economic and market barriers moderate the application of Bennett's Law. Although certain regions experience rising incomes, persistent poverty in rural areas restricts many households from achieving the income levels required to diversify diets substantially. Consequently, most of the population remains heavily dependent on starchy staples such as maize, cassava, and sorghum, which are both locally available and affordable (Zhou and Staatz, 2016). Studies suggest that households in resource-limited settings prioritize meeting caloric needs with cost -effective staples, delaying or even negating the transition to nutrient-dense foods (Ansah et al., 2020). Additionally, limited access to diverse food markets, especially in rural areas, hampers dietary diversification (Douyon et al., 2022). Infrastructure deficiencies, such as poor transportation networks, limit access to various food products, keeping starchy staples the primary option. Unlike in more urbanized continents, Africa's infrastructural constraints restrict the influence of Bennett's Law, as even rising income fails to facilitate access to non-staple foods in many regions (Sibhatu et al., 2015; Fraval et al., 2019).

North America demonstrates a complex relationship between income and food consumption patterns, resulting in weak evidence for Bennett's Law. This complexity stems mainly from a bifurcated food market influenced by socioeconomic inequality (Otero et al., 2015). On one hand, wealthier segments of the population have shifted towards nutrient-dense, diverse diets in line with Bennett's predictions. On the other hand, lower-income households remain dependent on affordable, calorie-rich foods, which often include starchy staples but also highly processed options (Ricciuto and Tarasuk, 2007). As a result, dietary polarization undermines a consistent trend across income groups, complicating the broad applicability of Bennett's Law in this region.

Furthermore, there has been a rise in health-conscious diets favoring whole grains, increasing the demand for staple grains even among affluent consumers (Mancino and Kuchler, 2012). This dietary shift, driven by concerns about health, sustainability, and dietary fiber intake, aligns with rising interest in plant-based diets, leading to a maintained or even increased intake of starchy foods. Therefore, North America's mixed dietary landscape, influenced by economic disparity and health trends, creates an environment where Bennett's Law only partially applies, as both high- and low-income groups exhibit different staple consumption patterns (Liu et al., 2020).

Oceania includes both high-income countries, such as Australia and New Zealand, and smaller Pacific island nations with varying economic statuses. This economic diversity limits the general applicability of Bennett's Law because dietary shifts tied to income growth may manifest differently across these diverse settings. Smaller island nations often face geographic and infrastructural constraints that restrict access to imported or nutrient-diverse foods and lead to continued reliance on locally available starchy staples. Additionally, the high cost of importing fresh produce and animal-based proteins to island nations sustains the preference for affordable, energy-dense starchy foods (Thow et al., 2011). However, Australia has the most considerable influence on trends in the entire region. The historical emphasis on staple crops, particularly wheat, underlines Australia's cultural reliance on grains, a result of both British influence and longstanding agricultural practices (Argent, 2002). Wheat remains central to Australian farming due to its established role in local diets and export markets. This cultural and economic connection to grains persists, even as income rises, aligning with the arguments that productivism - focused on staple output - does not necessarily encourage dietary diversification (Lawrence et al., 2013). Deregulation and a competitive export market lead to heavy reliance on cost-efficient staple crops, limiting policy incentives for diversified food production that could otherwise shift consumption patterns away from staples as incomes rise (Dibden and Cocklin, 2005).

Conclusion

Our analysis supports Bennett's Law to varying degrees across different continents, confirming that economic development often correlates with dietary diversification away from starchy staples. In line with Bennett's prediction, continents with higher GDP per capita, such as North America and Oceania, display significantly lower consumption of starchy foods compared to less economically developed continents. In Africa and parts of Asia, however, starchy staples continue to dominate diets, reflecting persistent structural and economic limitations that restrict access to diverse food options even as incomes rise.

In South America, the study finds a clear inverse relationship between GDP per capita and the proportion of calories from starchy staples, suggesting that economic growth encourages dietary shifts toward higher-quality, nutrient-dense foods. This aligns well with Bennett's Law and may be influenced by urbanization, market accessibility, and changing consumer preferences toward Western dietary patterns. Europe presents an unexpected deviation from Bennett's Law, where an increase in starchy food consumption accompanies rising income. This phenomenon may reflect unique cultural factors, such as the rise in health and environmental consciousness, which promote plant-based diets that include a substantial share of grains and other starches.

Overall, the findings emphasize the importance of region-specific factors - including cultural dietary preferences, infrastructure, policy interventions, and socioeconomic conditions - that influence the applicability of Bennett's Law in different contexts. While economic growth broadly supports dietary diversification, as Bennett's Law suggests, local variables often modify this relationship, leading to distinct regional dietary trends. The study thus reinforces that while Bennett's Law provides a valuable framework for understanding global dietary transitions, its applicability must be viewed within individual regions' complex socioeconomic and cultural landscapes. Future research should investigate these factors further, particularly in areas where economic development alone does not predict dietary shifts, to enhance our understanding of food security and nutrition transitions in a rapidly globalizing world.

Corresponding author:
Bartłomiej Bajan
Poznan University of Life Sciences, Wojska Polskiego 28, 60-637 Poznań
Phone: +48 61 846 6379, E-mail: bartlomiej.bajan@up.poznan.pl

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Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

The Impact of Governance and Digital Competitiveness on Agriculture Sectors Amid Global Uncertainty

Ernawati[1], Muhammad Syarif[1], Mansyur Asri[2]

[1] Department of Economics and Development Studies, Halu Oleo University, Indonesia

[2] Department of Information System, STMIK Catur Sakti, Indonesia

Abstract

In the last five years, the world has faced several events that have driven global uncertainty, namely pandemics and geopolitical events. Governments in various countries determine strategic policies to face global uncertainty. Governance has a crucial role in dealing with economic conditions amidst uncertainty. On the other hand, digital developments since the pandemic have also increased, which is expected to have positive externalities for society and the government in making economic decisions under uncertainty. This research examines the impact of governance and digital competitiveness on economic performance. This research uses secondary data from IMD publications for 2019–2023, covering a total of 58 countries. The data were analyzed using panel data regression. The research results show that there are disparities in digital competitiveness and governance in the group of countries with GDPs of more than $20,000 and less than $20,000, respectively. This difference leads to differences in economic performance between the two groups of countries. The governance dimension that affects macroeconomic performance is government governance, while for the agricultural sector it is business governance. The digital competitiveness dimension that worsens macroeconomic performance is future readiness, while for the agricultural sector it is the digital technology dimension. In a period of global uncertainty, infrastructure variables can drive economic performance, but on the other hand, they actually reduce the share of the agricultural sector. The more flexible anticipatory business behavior (due to more complete information) in the face of global uncertainty restrains the motivation for business expansion, which ultimately reduces economic performance. This research recommends to the government the importance of developing a strategy for handling future readiness and digital technology to support economic and agriculture stimulus policies in conditions of global uncertainty.

Keywords

Digital, technology, economic, government, agriculture.

Ernawati, Syarif, M. and Asri, M. (2025) "The Impact of Governance and Digital Competitiveness on Agriculture Sectors Amid Global Uncertainty", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 51-62. ISSN 1804-1930. DOI 10.7160/aol.2025.170204.

Introduction

The COVID-19 pandemic has increased reliance on technology and digital communications, accelerated remote work and e-commerce trends, caused disruption to traditional news media and increased misinformation, expanded online education and virtual events, and raised concerns over privacy and cyber security (Lu et al., 2023). One of the biggest developments affecting society and industry at a time when firms and nations are coping with the fallout from COVID-19 is digitalization (Hornungová and Petrová, 2023). Thus, the pandemic has changed the behavior of society and businesspeople in making decisions based on the massive amount of information received. When countries in the world experienced a post-pandemic economic recovery in 2021, geopolitical events, especially the Russia-Ukraine war in early 2022, threatened the global economy. Geopolitical risk causes natural resource prices to be more sensitive to geopolitical uncertainty (Khurshid et al., 2024). Based on a counterfactual scenario, the GDP decrease seen in EME nations during the 2008–2009 crisis would have been lessened by about 2% if there had been no uncertainty shocks (Miescu, 2023). Geopolitical risks cause a sharp decline in economic growth (Jiao et al., 2022) and agriculture sectors. The Russian and Ukraine war has caused disruption to the global agricultural supply chain (Aizenman et al., 2024). The findings of Polat et al. (2023) show the dynamic interlinkages between geopolitical stress and agricultural commodity market. Higher geopolitical risk causes stock price falls to occur more frequently, but companies that are more involved in ESG governance practices are more resistant to the adverse impacts of geopolitical risk (Fiorillo et al., 2024). Apart from geopolitical factors, the COVID-19 crisis has also led to a worsening of the agricultural system (Blazy et al., 2021).

Governance is an important variable in this global uncertainty. A country with an abundance of resources but not supported by efficient resource management institutions is unable to manage them optimally. Entele (2021) examines why countries rich in natural resources have not shown the same economic growth due to institutional performance, which, in several groups of countries, confirms the existence of a resource curse and an institutional curse. The findings of Pazouki and Zhu (2022) show that an increase in oil dependence volatility in democratic countries causes an increase in government spending, but vice versa in non-democratic countries, where government spending in response to oil dependence volatility fluctuates between positive and negative depending on its quality, political institutions; the more visible democratic attributes, the greater the spending. However, it is the volatility of oil revenues and poor government response to volatility that drives the resource curse paradox, not the abundance of oil revenues (El-Anshasy et al., 2017).

The potential to escape the resource curse exists if a country can develop human resources, adopt ICT services, and build quality institutions. Weak public and private institutions, as one of the inefficiencies, can also weaken economic performance. Palei (2015) shows that institutions have a significant effect on global competitiveness. Poor institutions encourage the proliferation of inefficiencies and high-cost economies, such as corruption. Khodapanah et al. (2022) found an inverted U relationship between GDP and corruption in Asian countries where, in the early stages of economic development, economic activities expanded but there were no institutional changes; therefore, at this stage, along with As economic development increases, corruption also increases. Enhancements in the quality of institutions in the domains of law, rules, and regulations frequently follow further economic progress. These establishments will boost output while decreasing corruption.

The findings of Abilda et al. (2024) show that corporate governance is an important key for companies in the agricultural sector in facing difficulties during the Covid-19 pandemic. Strict corporate governance mechanisms have a beneficial influence on cost and total efficiency (Agyapong and Xusheng, 2024). This cost efficiency will ultimately drive aggregate economic performance. Findings of Palei (2015) show that labor market efficiency has a significant effect on national competitiveness, while goods market efficiency is not significant. On the other hand, good governance will increase business resilience to geopolitical risks. The findings of Fiorillo et al. (2024) show that companies can mitigate the impact of geopolitics through ESG governance, where companies that are more involved in ESG practices are more resistant to the negative impact of geopolitical risks on the risk of falling stock prices.Governance that adopts information technology also has a positive impact on the economy. Studies for a sample of 103 countries in the period 2003–2018 show that e-government development is a positive determining factor for a country to achieve sustainable development, especially in developing and transition countries (Castro and Lopes, 2022).

Decision-making under conditions of uncertainty requires symmetric information to avoid inappropriate decisions. The use of ICT is very helpful for business people in making business decisions. ICT has a positive impact on financial capital, human capital, physical capital, social capital and natural capital (Sarkar et al., 2022). Bussy and Zheng (2023) research regarding the pressure of geopolitical risks for multinational companies in making investments shows that good governance mitigates the negative impact of perceived risk and geopolitical uncertainty, while symmetric information strengthens this negative impact by reducing investment motivation to avoid risk.

The use of ICT services in countries experiencing crises or rich in resources optimizes economic performance. In the case of the European Union for the period 1995–2019, there was a positive effect of ICT investment on total employment (Santos et al., 2023). Oikonomou et al. (2023) found that in regions where companies adopted more IT before the pandemic, unemployment rates increased less in response to social distancing, and IT protected all individuals, regardless of gender and race, except those with the lowest levels of education. Meanwhile, at the industry level, research by Ma et al. (2024) shows that there is an inverted U-shaped relationship between the digital economy and industrial agglomeration. Study of Mascagni et al. (2021) found that ICT can increase tax compliance, where tax revenues increase by at least 12% for income tax and 48% for VAT.

Previous research shows that conditions of global uncertainty are avoided through the availability of governance and information. However, previous studies have placed governance and information variables interacting with geopolitical instability, as in research by Bussy and Zheng (2023). Several previous studies placed global instability as an exogenous variable as per research Khurshid et al. (2024); Adra et al. (2023); Wang et al. (2022); and Ali et al. (2023). Meanwhile, studies examining the impact of ICT on economic performance show inconsistent results in boosting the economy, especially during the COVID-19 period. This paper estimates the influence of governance and digital information on agriculture sectors in a period of global uncertainty due to the pandemic and geopolitics. This study differs from previous ones because uncertainty is not included in the estimates. This article also differentiates between digital as part of human capital, technology, and company adaptation in driving economic performance in times of global uncertainty. The research results will reveal forms of digital competitiveness that need to be considered in efforts to encourage the benefits of digital progress as well as support government and business governance to improve economic performance and value-added agriculture.

Materials and methods

The research uses secondary data resulting from the publication of the IMD digital competitiveness and world economic competitiveness report for the 2019–2023 period and World Bank. Based on data availability, the estimated number of countries is 58. According to the IMD, digital variables have three dimensions: knowledge, technology, and future readiness. Governance data consists of two dimensions: government and private institutions. Government efficiency serves as a proxy for government governance, while corporate efficiency serves as a proxy for private governance.

The data were analyzed using comparison test analysis and panel data analysis. Comparison test analysis is applied to test differences in groups of countries based on IMD World Competitiveness in 2023, namely GDP greater than $20,000 (hereinafter referred to as higher GDP in this study) and the group of countries with GDP less than $20,000 (hereinafter referred to as lower GDP). There are 38 countries with a higher GDP and 20 countries with a lower GDP. Before the comparison test was applied, a Kolmogorov-Smirnov normality test was carried out with a $p > 0.05$.

The comparison test is applied to all variables for each year estimated using the Statistical Package for the Social Sciences data processing. Testing the influence of digital and institutional competitiveness on economic performance uses panel data regression. The first model of panel data analysis is presented as equation (1). The economic performance equation (Ec) in Model 1 is influenced by digital competitiveness (Dc), infrastructure (Inf), and governance (government efficiency, *Ge*, and business efficiency, *Be*). The coefficient α01 is the constant of model 1, $b_{11},\ldots, b_{14}$ is the variable coefficient of model 1, and e_1 is the error term of the model. The symbol *i* is the country, which is estimated to consist of 58 countries, and *t* is the estimation period of 2019–2023.

$$Ec_{1it} = \alpha_{01} + b_{11}Ge_{it} + b_{12}Be_{it} + b_{13}Inf_{it} + b_{14}Dc_{it} + + e_{1it} \quad (1)$$

Equation (2) describes the factors that influence economic performance, where digital competitiveness is derived into 3 variables, namely: knowledge (*Kn*), digital technology (*Dt*), and future readiness (*Fr*). The coefficient α_{02} is a constant of model 2; $b_{21},..,b_{26}$ are the variable coefficients of model 2, and e_2 is the error term of the model.

$$Ec_{2it} = \alpha_{02} + b_{21}Ge_{it} + b_{22}Be_{it} + b_{23}Inf_{it} + b_{24}Kn_{it} + + b_{25}Dt_{it} + b_{26}Fr_{it} + e2_{it} \quad (2)$$

Equations (3) present the influence of digital competitiveness and governance on the share of the agricultural sector on GDP (SA).

$$SA_{it} = \alpha_{04} + b_3Ge_{it} + b_{32}Be_{it} + b33Inf_{it} + b_{34}Kn_{it} + + b_{35}Dt_{it} + b_{36}Fr_{it} + e3_{it} \quad (3)$$

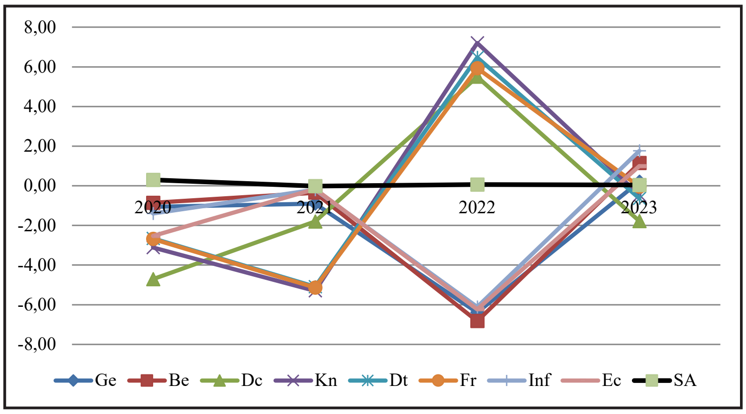
Model estimation (1) and (2) use balanced panel for 58 countries for the period 2019-2023. Based on complete data, model estimation (3) is conducted for 57 countries using unbalanced panel data. The panel data model estimation stage begins with selecting the best model. The Chow test is used to select the best model between the Common Effect Model (CEM) and the Fixed Effect Model (FEM). If the probability (prob.) in cross-section F < 0.05, then the best model for estimating panel data is FEM, and vice versa, if prob. > 0.05, the best model is CEM. The Hausman test is used to select the best model between the Random Effect Model (REM) and the Fixed Effect Model (FEM). If the probability (prob.) in the random cross-section is <0.05, then the best model for estimating panel data is FEM, and vice versa, if prob. >0.05, the best model is REM. To select the best model between the Random Effect Model (REM) and the Common Effect Model (CEM), the Lagrange

Multiplier (LM) Test is used. If the Breusch-Pagan probability is <0.05, then the best model for estimating panel data is REM, and vice versa, if prob. >0.05, the best model is CEM. The CEM and FEM models are OLS, followed by testing the classical model assumptions. On the other hand, the REM estimation model is a GLS estimate; no classical assumption tests are carried out.

Results and discussion

Figure 1 presents changes in variables (compared to the previous year): governance, digital competitiveness, infrastructure, economic performance, and agricultural value added. All of the estimated variables showed negative changes throughout the pandemic-induced economic recovery period in 2021, with the digital knowledge and future readiness variables experiencing the steepest fall. In 2022, when there is global uncertainty due to geopolitics, digital competitiveness and its dimensions show positive changes, but governance, infrastructure, and economic performance variables experience a deep decline. The opposite condition shows that in 2023, economic performance, governance, and infrastructure will experience positive changes. However, digital competitiveness and its dimensions are experiencing negative changes. However, Figure 1 shows that the average share of the agricultural sector continued to decrease during the estimation period.

Figure 2 presents governance variables measured by government and business efficiency and economic performance by country group. In the group of countries with higher GDP (Figure 2a), the development of government efficiency has a downward trend for the entire estimated period, while business efficiency declines in 2022 and increases in 2023. Economic performance shows a downward trend for the first three years, with the highest decline in 2022. This implies that the pandemic has worsened the economies of countries with higher GDP, which reached their peak at the beginning of geopolitical uncertainty in 2022.



Source: Authors

Figure 1: Changes in governance, digital competitiveness, infrastructure, economic performance, and share of agriculture in 2020-2023.

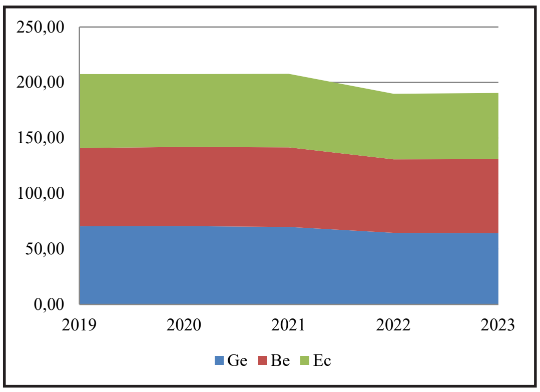


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Figure 2a: Government efficiency, business efficiency, and economic performance in the group of countries with a higher GDP.

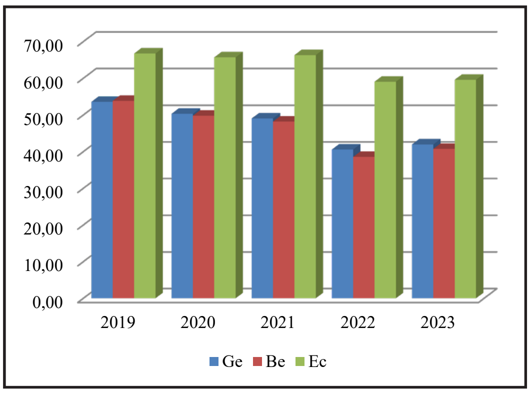

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Figure 2b: Government efficiency, business efficiency, and economic performance in the group of countries with a lower GDP.

The lower GDP group (Figure 2b) shows that the pandemic has worsened economic performance but recovered in 2021, decreased again during global uncertainty due to geopolitics in 2022, and adjusted in 2023. This pattern of movement in economic performance in the lower GDP group seems to be in line with developments in governance, which have a downward trend from 2020 to 2022 and an increase in 2023.

Figure 3 presents the development of economic performance and digital competitiveness of the two groups of countries studied: countries with a higher GDP (Figure 3a) and a lower GDP (Figure 3b). Figure 3 presents the relationship in the opposite direction between digital competitiveness and economic performance. In the higher GDP group, it shows that the relationship in the opposite direction occurs for the entire research period,

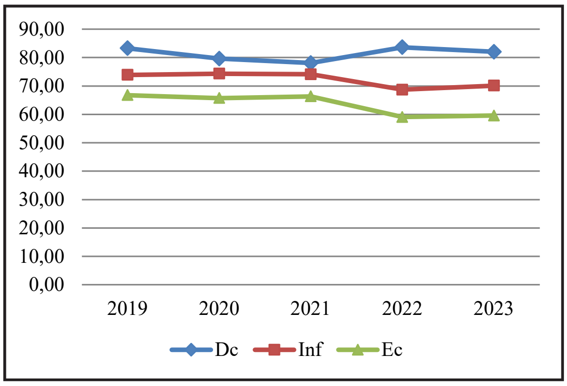

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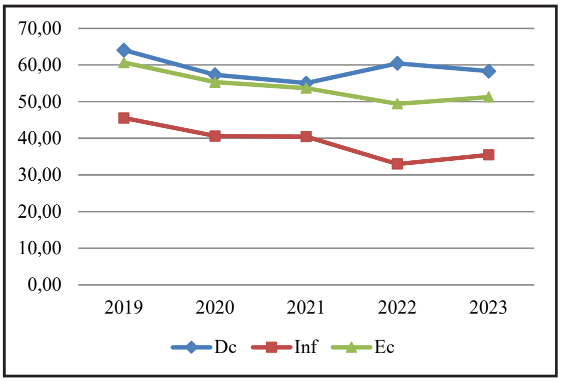
Figure 3a: Digital competitiveness, infrastructure and economic performance for countries with a higher GDP.



Source: Authors

Figure 3b: Digital competitiveness, infrastructure and economic performance for countries with a lower GDP.

Variable		2019	2020	2021	2022	2023
Dc	Mean Difference	-19.215	-22.321	-23.053	-23.205	-23.741
	t	-6.858	-6.899	-6.855	-7.555	-7.376
	Sig.	.000	.000	.000	.000	.000
Kn	Mean Difference	-18.380	-19.844	-21.913	-23.067	-23.591
	t	-6.183	-5.831	-6.477	-7.636	-7.271
	Sig.	.000	.000	.000	.000	.000
Dt	Mean Difference	-18.110	-21.679	-22.771	-22.678	-23.077
	t	-6.119	-6.502	-6.377	-6.447	-6.233
	Sig.	.000	.000	.000	.000	.000
Fr	Mean Difference	-21.203	-25.439	-25.968	-23.680	-24.520
	t	-6.853	-6.682	-6.722	-6.760	-6.888
	Sig.	.000	.000	.000	.000	.000
Ge	Mean Difference	-16.852	-20.196	-20.787	-23.975	-22.147
	t	-4.308	-4.637	-4.792	-5.642	-5.149
	Sig.	.000	.000	.000	.000	.000
Be	Mean Difference	-16.609	-21.486	-23.389	-27.693	-26.095
	t	-3.620	-4.377	-4.650	-5.334	-4.529
	Sig.	.001	.000	.000	.000	.000
Inf	Mean Difference	-28.372	-33.725	-33.667	-35.710	-34.624
	t	-8.300	-8.875	-8.922	-9.520	-8.807
	Sig.	.000	.000	.000	.000	.000
Ec	Mean Difference	-6.068	-10.413	-12.649	-9.662	-8.329
	t	-1.948	-3.519	-4.060	-3.301	-2.702
	Sig.	.056	.001	.000	.002	.009

Source: Authors

Table 1: Comparison test between groups of countries with lower and higher GDP.

while in the group with lower GDP, the relationship in the opposite direction occurs in 2021–2023. On the other hand, both the higher and lower GDP groups have infrastructure development that is in line with the development of economic performance. In the group of countries with higher GDP, digital competitiveness reached its highest point at the beginning of conditions of geopolitical uncertainty and decreased again in 2023. In the group of countries with lower GDP, the highest point of digital competitiveness occurred in the period before the pandemic, in 2019. The data presented in Figures 3a and 3b illustrates the discrepancy in digital and infrastructure competitiveness among the nations in this group. Countries with lower GDP are also associated with lower digital and infrastructure competitiveness indices as well as worse economic competition, as demonstrated by the comparison test between countries with lower and higher GDP, as presented in Table 1.

The comparison test results, as presented in Table 1, show significant differences in all variables and estimation years. All estimated variables have a negative mean difference in the group of countries with lower GDP. The difference in digital competitiveness continues to increase during the estimation period, which is in line with the increase in the knowledge gap. Digital technology in general is experiencing an increasing trend, except in 2022, as is future readiness. The difference in government efficiency will increase in 2020–2022 and decrease again in 2023, which is in line with the gap in business efficiency. Meanwhile, infrastructure inequality decreased in 2021 and 2023. Differences in economic performance between groups of countries increased on average in 2020 and 2021, until they decreased again in 2022 and 2023.

The selection of the best panel data regression model is presented in Table 2. The Chow Test results for Model 1 show that, at cross-section F 0.000 < 0.05, the correct model between CEM and FEM is FEM. Hausman Test Model 1 shows a random cross-section probability value of 0.071>0.05, where the best model between FEM and REM is REM. The LM Test results for Model 1 show the Breusch-Pagan (Both) probability of 0.000 <0.05, thus the best model for Model 1 is REM. Research Model 2 shows that the best model for estimating panel data is REM, and the best model for estimating research Model 3 is FEM. Based on the Glejser test, the research model contains symptoms of heteroscedasticity, and testing cross-section dependence shows the probability of Pesaran CD < 0.05. Estimation of Model 3 was carried out with Cross-section seemingly unrelated regressions (SUR) .

The research findings shown in Table 3 reveal that the business efficiency variable is not significant in Model 1, but infrastructure, digital competitiveness, and government efficiency variables have a significant impact on economic performance. An increase of 1 percentage point in government efficiency will increase 0.230 percentage points of economic performance, and an increase of 1 percentage point in infrastructure will increase 0.359 percentage points of economic performance. The research results show that a 1 percentage point increase in digital competitiveness reduces economic performance by 0.207 percentage points. In Model 1, the factor that has the highest elasticity in influencing economic performance is the infrastructure variable.

The results of the research data estimation for Model 2 show that the business efficiency variable still has no significant effect on economic performance, while the government efficiency and infrastructure variables have a significant effect. In Model 2, digital competitiveness is described in three variables: knowledge, digital technology, and future readiness. The estimation results of Model 2 show that of these 3 variables, only the future readiness variable is significant at alpha 0.10. An increase of 1 percentage point in future readiness will reduce economic performance by 0.146.

No	Testing	Criteria	Model 1	Model 2	Model 3
1	Chow Test	Cross-section F	12.592	12.686	56.209
		Prob.	0.000	0.000	0.000
2	Hausman Test	Cross-section random	8.633	9.34	20.693
		Prob.	0.071	0.155	0.002
3	LM Test	Breusch-Pagan (Both)	269.976	271.436	-
		Prob.	0.000	0.000	
	Best Model		REM	REM	FEM

Source: Authors

Table 2: Panel data model selection.

Variable	Model 1	Model 2	Model 3
C	37.963	35.805	5.697
	(8.453)	(8.657)	(17.331)
	0.000***	0.000***	0.000***
Ge	0.230	0.230	0.000008
	(3.101)	(3.076)	(0.065)
	0.002***	0.002***	0.948
Be	0.027	0.058	0.005
	(0.395)	(0.804)	(1.942)
	0.693	0.422	0.053*
Inf	0.359	0.349	-0.024
	(4.837)	(4.643)	(-4.408)
	0.000***	0.000***	0.000**
Dc	-0.207		
	(-2.676)	-	-
	0.008***		
Kn		0.097	0.003
		(0.995)	(0.960)
		0.320	0.338
Dt		-0.1611	-0.016
		(-1.644)	(-3.840)
		0.101	0.000***
Fr		-0.146	-0.002
		(-1.651)	(-0.960)
		0.099*	0.337
S.E. of regression	5.341	5.305	0.585
F-statistic	31.085	21.325	749.528
Prob(F-statistic)	0.000***	0.000***	0.000***

Note: *** p <0.01, ** p <0.05, * p <0.1.

Source: Authors

Table 3: Estimation results.

On the other hand, in Model 3, the business efficiency variable is significant positive effect, whereas infrastructure has a negative effect. An increase of 1 percentage in business efficiency will increase 0.005 percentage points of share in agriculture, and an increase of 1 percentage in infrastructure will decrease 0.024 percentage points of share in agriculture. In addition, model 3 shows that the digital competitiveness dimension that plays a role in agriculture is digital technology with coefficient -0.016. An increase of 1 percentage in digital technology will decrease 0.024 percentage points of share in agriculture. The comparison regression coefficients between Models 2 and 3 show lower coefficient in Model 3. This implies a greater role of digital competitiveness for other economic sectors compared to the agricultural sector.

According to the research findings, countries with a higher GDP have higher digital competitiveness than those with a lower GDP. This finding is in line with Lu et al. (2023), who found that per capita income drives informational globalization. The research results show that government governance manifested through government efficiency will encourage economic performance. This research is in line with previous research, as with the findings of Ayana et al. (2024). A larger government will be detrimental to economic growth (Nirola and Sahu, 2019). The quality of governance broadly and positively facilitates economic performance (Adedeji et al., 2024). A study by Qureshi et al. (2021) found that economic growth and corruption have a positive bidirectional relationship for developing countries and a negative unidirectional relationship for developed countries.

The research results show that infrastructure will encourage economic performance. This research is in line with research by Mao et al. (2024), which shows that transportation and financial infrastructure influence trade. Infrastructure is a factor that stimulates economic development, although in some cases, infrastructure investment can pose a direct threat to project-affected communities Kadyraliev et al. (2022). Zhang and Cheng (2023) findings show that transportation infrastructure has a positive effect on the economy in the long term of development, but in the short term, it has a negative impact. Transport infrastructure opens up the potential for regional transit traffic and promotes connectivity between Central Asian countries that lack land and shipping routes (Japarov et al., 2022). This connectivity will ultimately encourage trade between countries and increase GDP. Pokharel et al. (2021) study shows that transportation facilitates urbanization, and higher urbanization leads to higher regional GDP per capita. The research results of Yusufu et al. (2023) show that communication infrastructure encourages an increase in manufacturing industry exports. Numerous academics have also come to other conclusions that corroborate the beneficial impact of infrastructure on the economy, including Sun and Kauzen (2023); Palei (2015); Rehman et al. (2020); Tsaurai and Ndou (2019); and Yu and Luu (2022).

IMD defines digital competitiveness as consisting of three dimensions: knowledge, technology, and future readiness. The knowledge dimension consists of talent, training, education, and scientific concentration. The technology dimension consists of three indicators, namely: regulatory framework, capital, and technological framework, while the future readiness dimension consists of three indicators: adaptive attitudes, business agility, and IT integration. The research results show that digital competitiveness reduces economic performance. Research model 2, which describes these three dimensions as variables, shows that digital technology and knowledge variables have no significant influence on economic performance. The results of Park and Choi (2019) show that digital technology innovation capabilities take time to show their impact on economic growth. The future readiness variable harms economic performance. The findings of Leibrecht et al. (2023) for the case of OECD and EU countries show that increasing automation is positively related to unemployment in countries that have weak worker collective bargaining. On the other hand, Zhang and Qu (2024) shows that the digital economy has a negative impact on the consumption of poor people and subsistence households, mainly by exacerbating the uncertainty they face in the labor market (higher risk of unemployment and uncertainty in expected income) and inequality in the distribution of wealth.

On the other hand, the negative relationship between economic performance and digital competitiveness is very visible during the pandemic period and after, as presented in Figures 1a and 1b. Srisathan and Naruetharadhol (2022) found that people struggled to transform their digital behavior during the COVID-19 pandemic. This pandemic not only leads to increased use of technological tools but also affects various organizational aspects, such as employee attitudes towards technology and organizational culture towards innovation. Increased digital transformation has proven to be beneficial to companies affected by the pandemic. As a result, this pandemic has affected the spirit of innovation and accelerated the pace of digital transformation (Moser-Plautz and Schmidthuber, 2023). The COVID-19 pandemic has encouraged people to work from home. This encourages increased demand for telecommunications services and, on the other hand, reduces demand for the transportation sector, thereby increasing unemployment. Mack et al. (2021) findings show that workers in the transportation sector are 20.6% more likely to be unemployed due to the pandemic than workers in non-transportation industries. Figure 1 shows changes in research variable data, showing that during global uncertainty in 2021–2022, there was an increase in digital competitiveness, followed by a decline in economic performance. Effective information, when paired with digital competitiveness—particularly future readiness —will lower corporate actors' incentives to invest, which will lower overall economic performance. This is in line with research by Bussy and Zheng (2023) regarding the pressure of geopolitical risks for multinational companies, showing that good information motivates multinational companies to avoid geopolitical risks by reducing investment, but foreign investment in the form of technology is still being increased because it is more resistant to geopolitical risks. After all, intangible assets are more easily transferred across national borders.

The business efficiency variable has a positive effect on agriculture share. The business efficiency variable has a positive effect on the share of agriculture. Macro business efficiency drives the rapid development of the agricultural sector more than others. Business governance that drives competitive and efficient markets strengthens the agricultural sector. The achievement of high corporate efficiency in the banking sector, for example, actually provides incentives to contribute to the agricultural sector in uncertainty. Digital technologies play a critical role in empowering resilience through farm-scale operations, industrial transformation, and technological advancement (Quan et al., 2024). Digital agricultural technologies in food crop production have an impact of up to 60% reduction in fertilizer use and an 80% reduction in pesticide use with Variable Rate Technology (VRT). VRT also shows a 62% increase in crop yields, and robotic systems or intelligent machines can reduce labor energy by up to 97% and diesel consumption by up to 50% (Papadopoulos et al., 2024). However, research findings show that digital technology and infrastructure have a negative impact on agricultural share.

In a global uncertainty period, the government is required to make decisions to save the economy by utilizing finances for macroeconomic recovery. Research findings show that the governance implemented by the government is able to improve the macro economy but not for the agricultural sector. This is due to the lack of focus on governance for this sector. Research findings of Boughton et al. (2021) show that the rural sector only received a very small allocation from the government's initial fiscal response to mitigate the economic impact of COVID-19.

Conclusion

Digital competitiveness can reduce economic performance, while government governance and infrastructure will boost economic performance. The negative impact of digital competitiveness, which reduces economic performance, lies in the future readiness dimension. Future readiness is a company's ability to anticipate and adapt to external changes, both in terms of adaptive attitudes, business agility, and IT integration. The anticipatory behavior of businesses in global uncertainty that occurs when they have better information appears to reduce economic performance. The behavior of business actors in facing uncertainty reduces motivation to expand their business. Business efficiency drives the share of the agricultural sector, but infrastructure has a negative effect on the agricultural sector. Digital technology worsens agricultural sector during global uncertainty period.

The author recommends that future researchers study the behavior of business actors in facing geopolitical uncertainty in making business decisions that have an impact on the aggregate economy. The author also recommends how these governance and digital variables interact to drive the country's economy in a period of global uncertainty. This research also recommends for policymakers how to develop a digitalization policy strategy, especially for future readiness, which strengthens government and private governance to support economic stimulus policies in conditions of global uncertainty.

Corresponding author:
Ernawati
Department Economics and Development Studies, Halu Oleo University
Kampus Hijau Bumi Tridharma, Anduonohu, Kendari City, South East Sulawesi, Indonesia 93232
Phone: +628219250762, E-mail: ernawaty@uho.ac.id

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Bridging Digital Gaps: Optimizing Marketing Strategies and Branding for Sustainable Growth in Farmers' Household Businesses

Nurliza[1], Siti Sawerah[2], Morteza Muthahhari[3], Tatang Abdurrahman[4]

[1] Doctoral Studies in Agricultural Sciences, Agriculture Faculty, University of Tanjungpura, Kalimantan Barat, Indonesia

[2] Department of Agribusiness, Agriculture Faculty, University of Tanjungpura, Kalimantan Barat, Indonesia

[3] Department of Informatics Engineering, Engineering Faculty, University of Tanjungpura, Kalimantan Barat, Indonesia

[4] Department of Agrotechnology, Agriculture Faculty, University of Tanjungpura, Kalimantan Barat, Indonesia

Abstract

Farmers' household enterprises in developing economies often operate under structural constraints such as limited digital literacy, scarce resources, and entrenched socio-cultural norms—factors that collectively hinder market access and brand development. This study investigates the interplay between entrepreneurial traits, digital marketing practices, socio-cultural context, and branding strategies in shaping business sustainability and competitiveness. Drawing on data from 98 rural enterprises in West Kalimantan, Indonesia—where internet access lags behind the national average and cultural identities of Dayak and Malay communities influence business behavior—a mixed-methods approach was employed, combining surveys with qualitative interviews to capture both patterns and lived realities. The findings reveal that while traits like age, gender, and digital platform preferences guide strategic decisions, adoption is often constrained by low digital proficiency, outdated technologies, and vague performance indicators; yet, these businesses persist with resilience, underscoring the urgent need for culturally attuned marketing, digital infrastructure investment, and targeted capacity-building initiatives.

Keywords

Digital marketing, branding, farmers' household businesses, sustainable agriculture.

Nurliza, Saverah, S., Muthahhari, M. and Abdurrahman, T. (2025) "Bridging Digital Gaps: Optimizing Marketing Strategies and Branding for Sustainable Growth in Farmers' Household Businesses", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 63-77. ISSN 1804-1930. DOI 10.7160/aol.2025.170205.

Introduction

Agriculture remains a cornerstone of development across many low- and middle-income countries —not only as a contributor to national GDP but as the livelihood core of rural communities. In Indonesia, household-run farming enterprises operate at this critical intersection of economy and identity. These smallholder businesses —often informal, inherited across generations, and deeply entwined with local traditions —sustain rural livelihoods and preserve cultural continuity. Globally, such enterprises account for nearly 70% of the world's food production (WBG, 2022). Yet despite their significance, they remain systematically marginalized from digital economies. Structural barriers like capital limitations, weak infrastructure, and entrenched socio-cultural norms continue to hinder their engagement with the tools and platforms reshaping modern markets (Touch et al., 2024).

Nowhere is this exclusion more visible than in the widening gap between smallholder enterprises and digital marketing ecosystems. While digital tools—particularly social media and e-commerce —have unlocked new pathways for product visibility, narrative building, and customer interaction, their uptake among rural agribusinesses has been uneven. Some entrepreneurs have found in these platforms a means of differentiation and expansion. But for many, digital branding remains out of reach, limited not just by access or technical know-how, but by layers of uncertainty shaped by generational habits, gender roles, communal expectations, and varying degrees of cultural resonance (Kumar and Agrawal, 2023; Yuan and Sun, 2024).

This study asks a deceptively question: how do entrepreneurial capacity, digital marketing strategies, and socio-cultural forces interact to influence branding effectiveness and business sustainability in household agribusinesses? Rather than treating these domains as isolated variables, the research adopts a multi-framework perspective—both to guide inquiry and to structure interpretation. While prior studies have explored each domain separately, few have examined how they operate in concert, particularly in rural contexts where identity and tradition infuse every layer of economic decision-making (Zollo et al., 2021; Vărzaru, 2022).

To ensure theoretical integrity throughout the research process, three frameworks were selected not for rhetorical framing but for analytical deployment: the Resource-Based View (RBV), the Technology Acceptance Model (TAM), and Social Identity Theory (SIT). Each was embedded in the study's empirical architecture—guiding instrument design, informing data collection, and anchoring the interpretation of results. These frameworks are not merely cited in the literature review; they are activated in the analysis and used to make sense of patterns, outliers, and emergent dynamics.

RBV is used to assess the internal resources and capabilities that smallholders mobilize to compete in digital spaces. Constructs such as branding knowledge, platform use proficiency, digital literacy, and social capital are translated into measurable indicators—allowing us to test how specific resource bundles influence branding outcomes (Kero and Bogale, 2023). TAM offers a lens into the cognitive and perceptual dimensions of technology adoption, using established constructs like perceived ease of use and perceived usefulness. These were operationalized into behavioral metrics—ranging from posting frequency to platform diversification—thereby tracing how users' beliefs shape their digital engagement patterns (Boustani and Chammaa, 2023).

SIT brings an essential socio-cultural depth to the study, moving the analysis beyond capacity and perception to explore how identity and belonging shape platform behavior. Constructs such as in-group affiliation, cultural conformity, and normative expectations were integrated into the survey design and qualitative instruments. This allowed for a nuanced interpretation of how digital marketing decisions are mediated by gendered expectations, ethnic belonging, and generational worldviews—particularly in community settings where social reputation and collective coherence often outweigh individual entrepreneurial ambition (Zollo et al., 2021).

Importantly, the use of theory extends beyond the construction of the model—it shapes the reading of results. Findings are not presented as decontextualized statistics but are interpreted through these frameworks, drawing links between observed behaviors and the theoretical mechanisms presumed to underpin them. When training efforts fall short, for example, the analysis moves past performance metrics to examine where in the RBV, TAM, or SIT dimensions friction may be occurring—whether due to misalignment between resources and task complexity, low perceived relevance, or social resistance to behavioral change.

To deepen this evaluative lens, the study also employs the Kirkpatrick model to assess the impact of digital literacy interventions across four dimensions: reaction, learning, behavior, and results. This enables a layered understanding of not just whether training worked, but how participants responded to it, what they internalized, how they applied it, and what outcomes emerged. For instance, low learning scores were contextualized through open-ended responses revealing mismatched expectations, linguistic barriers, and limited post-training support (Nurliza and Fauyan, 2021).

By threading theory into every phase of the research—from design to analysis—this study moves decisively beyond descriptive mapping. It offers a theoretically informed, empirically grounded account of how digital transformation unfolds within the lived realities of smallholder entrepreneurs. In doing so, it positions household agribusiness branding not as a technical upgrade but as a socio-cultural negotiation—where internal capacity, technological perception, and identity-based norms intersect in ways that shape both constraints and possibilities. Ultimately, the study contributes a robust analytic model for understanding rural digital engagement—one that is contextually sensitive, methodologically rigorous, and globally relevant for those seeking inclusive models of innovation and development.

Materials and methods

This study used a convergent mixed-methods design (Creswell and Creswell, 2018) This study applied a convergent mixed-methods design (Creswell and Creswell, 2018) to explore how entrepreneurial characteristics, digital marketing practices, and socio-cultural contexts shape branding strategies in household agribusinesses. By combining descriptive data with thematic insights from interviews, it revealed patterns such as generational differences in platform use and motivational clusters, while also unpacking the deeper narratives behind them—like learning through trial and error, peer influence, and trust-building. The region presents a unique context, with only 59% of households having internet access—below the national average of 73% (Muazir et al., 2022)—and a diverse social landscape shaped by multi-ethnic communities and smallholder farming. The integration of quantitative trends and qualitative stories allowed for a richer understanding not just of what digital engagement looks like, but why it unfolds the way it does (Fetters et al., 2013).

Sampling

A purposive sampling approach was used to select 98 household agribusiness entrepreneurs from three agriculturally intensive districts. These districts were intentionally chosen to reflect variation in market connectivity, ethnic composition, and access to extension services. Participants were identified through collaboration with local cooperatives, farmer groups, and agricultural extension agents, which ensured both contextual credibility and logistical feasibility (Palinkas et al., 2015). To be included, respondents needed to meet three criteria: (1) operate an agribusiness enterprise for at least one year; (2) be engaged in household-based agricultural production; and (3) demonstrate some level of digital engagement, either current or aspirational.

Data collection

Data were collected over three months through two complementary modalities. 59 participants completed online surveys via Google Forms, while 39 participated through face-to-face interviews. This dual-mode strategy was not incidental but intentional, grounded in the digital realities of the region. Internet coverage and digital fluency varied considerably by location and demographic; thus, the bifurcation enabled inclusivity without compromising methodological rigor (Roberts et al., 2021). To ensure data equivalence, both instruments were structurally identical in content, phrasing, and scoring logic. Interviewers used a read-aloud protocol and visual Likert scales for in-person administration, mitigating literacy constraints without sacrificing methodological consistency.

Instrument design

Survey and interview instruments were adapted from validated tools in digital marketing, technology adoption, and rural entrepreneurship (Yueh and Zheng, 2019; Boustani and Chammaa, 2023), then refined through a three-stage process to ensure clarity and contextual fit. First, an expert review was conducted with two digital marketing researchers, a rural sociologist, and two agribusiness practitioners, who evaluated the instruments for conceptual and cultural relevance. Next, pilot testing with ten respondents from a nearby village led to adjustments in language—replacing jargon with local terms—and response formats, such as using pictograms for Likert scales. Finally, reliability testing showed acceptable internal consistency across constructs, with Cronbach's alpha ranging from 0.74 to 0.88. To support respondent comprehension, especially in low-literacy settings, the survey included visual scales and analog examples. Key constructs measured included digital branding and performance (e.g., platform use, engagement, brand recall) (Yueh and Zheng, 2019); entrepreneurial motivation, both intrinsic (learning, creativity) and extrinsic (income, visibility), based on Self-Determination Theory (Ryan and Deci, 2000); and brand identity and personality, assessed through tone, narrative coherence, and emotional appeal (Boustani and Chammaa, 2023).

Research steps and analytical tools

The instrument captured five core domains across three analytical subsections, and the discussion mirrors this structure to ensure continuity between research design and findings. First, entrepreneurial characteristics, digital marketing strategies, and the socio-cultural environment. This study first examined participants' demographic and socio-cultural backgrounds using descriptive statistics and percentage distributions. It covers age, gender, education, internet familiarity, and community ties (Ryan and Deci, 2000). While the numbers provided an overview, interviews added depth by showing how identity and social context shape digital engagement (Zollo et al., 2021). In terms of digital marketing, survey data detailed platform use, posting habits, and performance metrics like click-through rates and brand recall. Qualitative reflections highlighted how training influenced actual marketing behavior (Boustani and Chammaa, 2023). Motivations for adopting digital tools were also explored, combining statistical insights with personal stories framed by self-determination theory (Ryan and Deci, 2000).

Second, assessing the effectiveness of digital tools and branding training for farmers' household businesses. It focused on the impact of training, framed by Kirkpatrick's four-level evaluation model using descriptive statistics and percentage distributions. This involved assessing participants' reactions to training in terms of satisfaction with facilitation and relevance, measuring learning gains in digital literacy and branding knowledge, evaluating behavioral changes reflected in the adoption of new marketing strategies, and finally, examining results in terms of customer base growth, revenue changes, and increased peer engagement (Kirkpatrick, 1998). The qualitative part uses semi-structured interviews and storytelling to understand how the training truly affected participants' behavior—like how they started using new marketing strategies, boosted their digital skills, and put branding knowledge into practice in their everyday business.

Third, business overview, branding strategies, and digital marketing approaches. It offers a snapshot of each business—what they aim to do, how they operate, and where they're headed. It helps us see how entrepreneurs navigate competitive, often limited-resource environments and how they shape their strategies to stay relevant. By looking at these patterns, we can better understand how different business types emerge and adapt within their local contexts. The quantitative side helps show what's happening—like which platforms are used, how often, or what strategies are common across businesses with descriptive statistics. Meanwhile, the qualitative side helps explain why or how those things happen—through people's stories, experiences, and reflections with the guide was informed by three theoretical frameworks: Social Identity Theory (Zollo et al., 2021), Resource-Based View (Kero and Bogale, 2023), and the Technology Acceptance Model (Boustani and Chammaa, 2023). This ensured alignment between conceptual framing and empirical questioning. Interviews were audio-recorded, transcribed, and analyzed, following Braun and Clarke (2006) six-phase thematic approach. The integration of theory with empirical narrative enabled interpretation beyond surface-level description, providing nuanced insights into how branding and digital performance are shaped by lived experience, resource availability, and cultural framing.

By combining quantitative breadth with qualitative depth, the study offers a grounded view of how rural entrepreneurs navigate the promises and pitfalls of digital branding. It underscores that while digital tools are increasingly within reach, the capacity to use them strategically remains deeply shaped by identity, experience, and context.

Results and discussion

Entrepreneurial characteristics, digital marketing strategies, and the socio-cultural environment

The demographic landscape of digital platform engagement among household agribusiness entrepreneurs reveals significant variation shaped by gender, generation, and behavioral preferences.

Entrepreneurs' Characteristics	%
Female	60.24
<20	21.69
Gen Z (1997-2012)	21.69
Facebook, Instagram	3.61
Facebook, Instagram, Pinterest, TikTok	4.82
Instagram, TikTok	3.61
TikTok	9.64
20-25	4.82
Gen Z (1997-2012)	4.82
Facebook, Instagram, YouTube, Pinterest, TikTok	4.82
25-30	13.25
Gen Z (1997-2012)	13.25
Facebook	9.64
YouTube	3.61
30-35	20.48
Gen X (1965-1980)	4.82
Facebook	4.82
Millennials (1981-1996)	15.66
Facebook	12.05
Facebook, Instagram, Pinterest, TikTok	3.61
Male	39.76
<20	7.23
Gen X (1965-1980)	3.61
Instagram, YouTube	3.61
Gen Z (1997-2012)	3.61
Facebook	3.61

Source: Author's

Table 1: Characteristics of entrepreneurs (to be continued).

Entrepreneurs Characteristic´s	%
20-25	14.46
Gen Z (1997-2012)	14.46
Facebook	7.23
Facebook, Instagram, YouTube, TikTok	3.61
Instagram	3.61
25-30	7.23
Milenial (1981-1996)	7.23
Facebook	3.61
Facebook, Instagram, YouTube, TikTok	3.61
30-35	10.84
Gen X (1965-1980)	3.61
Facebook	3.61
Milenial (1981-1996)	7.23
Facebook, Instagram, TikTok	3.61
Facebook, YouTube, Wa	3.61
Grand Total	100.00

Source: Author's

Table 1: Characteristics of entrepreneurs (Continuation).

Table 1 illustrates distinct demographic patterns and digital engagement behaviors among household agribusiness entrepreneurs, with clear generational and gendered tendencies in social media use. Women make up the majority (60.24%) of entrepreneurs, a trend particularly pronounced in micro and small-scale operations. This aligns with wider patterns observed in rural digital entrepreneurship, where women often occupy central roles in household-based business strategies, especially in contexts where flexibility and informal capital are central to participation (Meagher, 2021).

Generational segmentation reveals that Generation Z (born 1997–2012) comprises the largest share of respondents (40.97%). Their platform choices reflect this generational positioning—favoring TikTok (9.64%) or blended usage patterns that include combinations such as Facebook, Instagram, and TikTok (4.82%). These younger entrepreneurs are clearly drawn to dynamic, short-form, visually oriented content, characteristic of platforms that reward immediacy and creative presentation (Van Dijk, 2020). Millennials (1981–1996) make up 33.73% of the sample, showing a strong preference for Facebook, both as a standalone platform and in hybrid use cases, while Gen X (1965–1980) is less represented (4.82%) and primarily reliant on Facebook. Aggregated platform data indicate Facebook as the most dominant overall (49.40%), particularly among older users and male entrepreneurs, who tend to prefer simpler, more functionally familiar platforms.

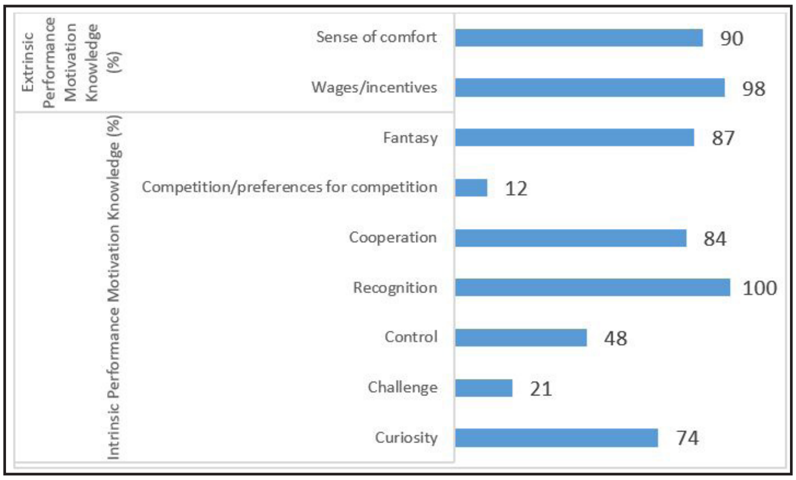
A deeper look into gendered platform preferences reveals telling differences in how male and female entrepreneurs navigate the digital space. Male respondents tend to stick with single-platform usage—7.23% use only Facebook—suggesting a more streamlined, possibly utilitarian approach. In contrast, women are more likely to engage across multiple platforms, with combinations like Facebook–Instagram–TikTok appearing more frequently. This suggests not just broader digital exposure, but potentially greater adaptability and experimentation in how female entrepreneurs reach and relate to their audiences. Such differences may stem from varying levels of digital literacy, audience targeting approaches, or even the nature of products marketed within household enterprises (Zhao et al., 2022; Hu et al., 2023).

Generational differences add important context to these patterns. Gen Z's strong use of TikTok and Millennials' preference for Facebook go beyond simple platform choice—they reflect deeper comfort zones shaped by the way each generation grew up with technology and communicates online. These connections aren't accidental; the data shows that digital engagement is closely linked to both generational identity and gender. This means it's not just about which platforms people use, but also how social and cultural influences shape their digital habits in consistent and meaningful ways.

Transitioning to Figure 1, which explores intrinsic and extrinsic motivations for entrepreneurship, these behavioral insights begin to cohere.

Younger entrepreneurs, especially Gen Z, tend to be driven more by intrinsic motivators like creativity, autonomy, and self-fulfillment, while older cohorts—Gen X and older Millennials—lean toward extrinsic goals such as financial security and social recognition. Though not directly linked to platform use, these motivational differences shed light on why Gen Z gravitates toward visually rich, expressive platforms like TikTok and Instagram, whereas Facebook appeals more to those with practical, outcome-focused intentions. This suggests that platform choice reflects a complex interplay of entrepreneurial identity, motivation, and strategy (Bhargava et al., 2022). Together, these insights reveal underlying generational, gendered, and motivational dynamics shaping digital engagement.

Digital marketing strategies are organized into three key areas—channels, engagement, and performance metrics—offering a clear framework to understand how entrepreneurs select, use, and assess their digital tools. The first dimension, marketing channels, highlights communication approaches, implementation hurdles, and cost factors, as detailed in Table 2.



Source: Author's

Figure 1: Knowledge of intrinsic and extrinsic work motivation (%).

Digital Marketing Channels	%
Content marketing	7.23
Social media	7.23
Branding capital	3.61
Limited understanding of social media changes	3.61
Paid advertising	3.61
Social media	3.61
Digital platform	3.61
Social media marketing	59.04
Multimedia advertising	3.61
None	3.61
Social media	51.81
Internet, old-fashioned mobile phone	7.23
Limited understanding of social media changes	12.05
None	28.92
Old-fashioned mobile phone	3.61
Website/blog, multimedia advertising, social media	3.61
Promotion	3.61
Social media marketing, content marketing	3.61
Social media	3.61
Old-fashioned mobile phone	3.61
Social media marketing, content marketing, paid advertisement, video marketing	4.82
Social media	4.82
None	4.82
Social media marketing, content marketing, video marketing	9.64
Social media	9.64
Limited understanding of social media changes	9.64
Social media marketing, mobile marketing	8.43
Social media	8.43
Limited understanding of social media changes	8.43
Social media marketing, mobile marketing, video marketing	3.61
Social media	3.61
Limited understanding of social media changes	3.61
Total	100.00

Source: Author's

Table 2: Digital marketing channels.

Table 2 reveals that most respondents (59%) primarily use social media for marketing, while content marketing (7%) and paid advertising (4%) remain limited. Alarmingly, nearly 29% have no digital marketing strategy, and 12% struggle with understanding digital tools, highlighting ongoing knowledge gaps. To clarify patterns, responses were grouped into three typologies: High-Integration, Low-Integration, and Non-Adopters.

The preference for social media seems driven more by ease of access and peer familiarity than strategic choice, with platforms like Facebook and WhatsApp dominating due to their simplicity. This aligns with earlier findings on how limited digital literacy constrains adoption in rural settings (Rachmawati, 2024). These insights underscore the need for tailored support—not just platform access, but training focused on strategic use, multi-channel storytelling, and basic analytics to help entrepreneurs move beyond mere presence.

The next domain, social media engagement, examines interactions, trust, outcomes, and content creation, as detailed in Table 3.

Social Media Engagement	%
Once a day	21.69
Yes	21.69
Attract clients to the physical store	3.61
Instagram and Facebook ads	3.61
Drive traffic to the website or social media platforms for ad revenue and build an online presence	18.07
Advancement in SEO, social media, YouTube and Google ads, Instagram and Facebook ads, LinkedIn marketing, brand introduction, and brand enhancement	9.64
Advancements in SEO and social media	4.82
SEO optimization and social media	3.61
Once a week	3.61
Yes	3.61
Attract clients to the physical store	3.61
Instagram and Facebook ads	3.61
Rarely/Never	3.61
Yes	3.61
Drive traffic to the website or social media platforms for ad revenue and build an online presence	3.61
YouTube and Google ads	3.61
Several times a day	56.63
Not confident	13.25
Attract clients to the physical store	13.25
Brand introduction and enhancement	8.43
Instagram and Facebook ads	4.82
Yes	43.37
Attract clients to the physical store	12.05
Brand introduction and enhancement	12.05
Drive traffic to the website or social media platforms for ad revenue and build an online presence	31.33
Advancement in SEO, social media, YouTube and Google ads, Instagram and Facebook ads, LinkedIn marketing, brand introduction, and brand enhancement	4.82
Brand introduction and enhancement	22.89
YouTube and Google ads, brand introduction, and brand enhancement	3.61
Several times a week	14.46
Yes	14.46
Drive traffic to the website or social media platforms for ad revenue and build an online presence	14.46
Advancement in SEO, social media, YouTube and Google ads, Instagram and Facebook ads, LinkedIn marketing, brand introduction, and brand enhancement	7.23
Brand introduction and enhancement	3.61
SEO optimization and social media	3.61
Total	100.00

Source: Author's

Table 3: Social media engagement.

Table 3 reveals distinct patterns in digital engagement among agribusiness entrepreneurs. While over half (57%) access social media multiple times daily, a notable minority (13%) remain less confident or infrequent users, highlighting uneven digital literacy and strategic capacity. This gap underscores the need to enhance digital presence through better website performance and targeted social strategies. As Sayudin (2023) emphasizes, optimizing user experience and search visibility can expand market reach, while integrating organic and paid channels across platforms like Instagram and Google boosts returns (Mero and Karjaluoto, 2015). Using analytics to refine campaigns and collaborating with influencers further deepen audience connections (Akintayo et al., 2022). Consistent, interactive content remains key to sustaining long-term growth.

The study identifies three digital marketing profiles: visibility-focused entrepreneurs (23%) who prioritize brand awareness through visual storytelling but often stop short of conversion; transaction-oriented entrepreneurs (31%) driven by immediate sales and leads, sometimes at the expense of deeper engagement; and content-driven entrepreneurs (10%) who employ integrated SEO and multimedia strategies to build trust and community, reflecting greater digital maturity. Yet, frequent engagement does not always mean effective marketing—many underuse content qualities, targeting, and timing.

These strategies reflect a tension between transactional goals and relational depth, echoing the Technology Acceptance Model and Social Influence Theory. While ease of use and utility drive adoption (Boustani and Chammaa, 2023), social trust and norms strongly influence behavior in rural settings where social capital often outweighs technology (Zollo et al., 2021; Sayudin, 2023).

The next focus, digital metrics, assesses revenue growth, brand positioning, and messaging effectiveness (Table 4).

Digital Performance Metrics	%
Click-Through Rate (CTR)	12.05
>20%	4.82
Improvement in search engine rankings	4.82
Image ads	4.82
2-5%	3.61
Increased website traffic	3.61
Image ads, video ads, story ads	3.61
2-5%	3.61
Increased website traffic	3.61
Video ads, story ads	3.61
Click-through rate, average session duration, social media engagement	3.61
2-5%	3.61
Increased website traffic	3.61
Image ads, video ads, story ads	3.61
Cost per acquisition	3.61
5-10%	3.61
Increased leads/sales	3.61
Video ads	3.61
Cost per acquisition, social media engagement	3.61
2-5%	3.61
Increased leads/sales, social media engagement, and positive customer feedback/reviews	3.61
Image ads, video ads, slideshow ads	3.61
Impressions, cost per acquisition	3.61
2-5%	3.61
Increased leads/sales	3.61
Image ads, video ads	3.61

Source: Author's

Table 4: Digital performance metrics (to be continued).

Digital Performance Metrics	%
Impressions, cost per acquisition, social media engagement	
10-20%	
Increased website traffic, improved leads/sales, brand awareness, enhanced search engine rankings	
Image ads, video ads, story ads	
Social media engagement	
>20%	
Positive customer feedback/reviews	
Image ads, video ads, collection ads	
Video ads, collection ads	
10-20%	
Increased website traffic	
Image ads, video ads, carousel ads, slideshow ads, story ads	
10-20%	
Increased website traffic	
Image ads, video ads, carousel ads, slideshow ads, story ads	
2-5%	
Brand awareness	
Video ads	
Increased leads/sales	
Image ads, video ads, story ads	
2-5%	
Increased website traffic	
Image ads, video ads	
Uncertain	37.35
Increased website traffic	3.61
Image ads, video ads, story ads	3.61
Increased website traffic, brand awareness	3.61
Video ads, story ads	3.61
Positive customer feedback/reviews	30.12
Image ads	4.82
Image ads, video ads	25.30
Total	100.00

Source: Author's

Table 4: Digital performance metrics (continuation).

Table 4 presents key digital performance indicators shaping marketing strategies among agribusiness entrepreneurs. About 12% prioritize click-through rates (CTR), with nearly 5% achieving rates above 20%, mainly through image, video, and story ads that boost website traffic by 10–20%. While promising, these figures lack rigorous statistical backing, suggesting the need for more robust analysis. Only a small group (3.6%) focuses on improving cost-per-acquisition (CPA) through video and social engagement, signaling a gradual shift toward cost-efficient creativity. Lead generation and sales tend to rely on visually rich ad formats, while brand awareness benefits from sustained video campaigns.

Interestingly, 13% use visual content to gather customer feedback, reflecting a growing emphasis on listening as much as persuading. Social media engagement remains central, with nearly 69% prioritizing it and 13% reporting engagement rates over 20%. Yet, over a third of businesses struggle to measure campaign impact clearly, highlighting persistent challenges in aligning KPIs and evaluating success. Figure 3 further illustrates sectoral differences in digital strategy maturity, revealing not just what entrepreneurs prioritize, but how uneven and selective their measurement approaches remain. This underscores the ongoing need for clearer metrics and integrated analytics frameworks.

Assessing the effectiveness of digital tools and branding training for farmers' household businesses

An assessment of the effectiveness of digital tools and branding training for farmers' household businesses showed diverse outcomes across the four evaluation categories—reaction, learning, behavior, and outcomes, as detailed in Figure 2.

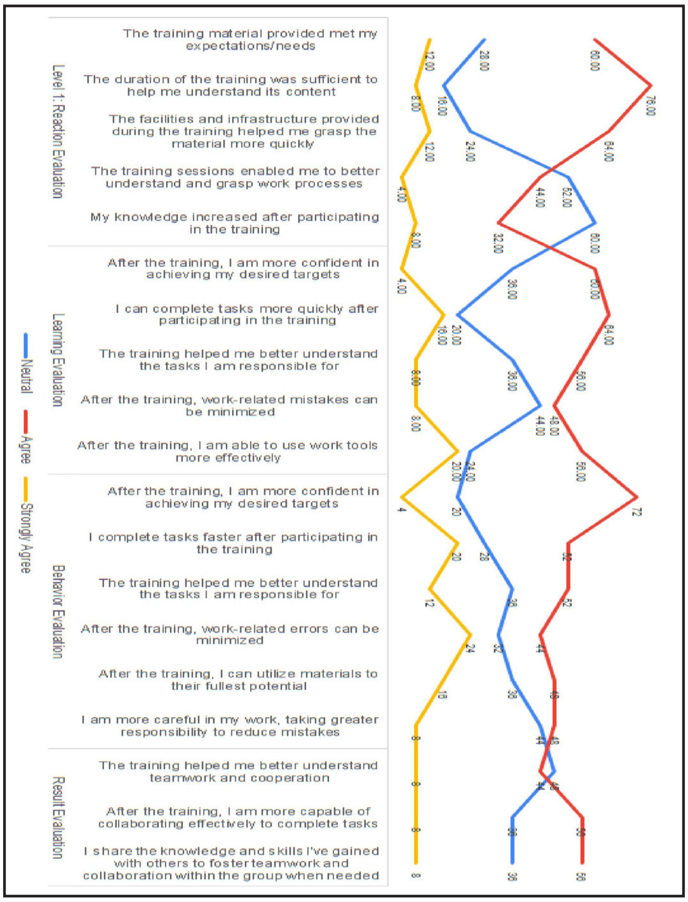
Figure 2 illustrates training outcomes through Kirkpatrick's four-level model, revealing a distinct gap between participant satisfaction and deeper learning. While 88% expressed satisfaction with the training delivery, only 44% reported improved understanding of work processes. This suggests that engagement alone does not ensure cognitive gains, pointing to the need for more immersive, application-oriented learning. A similar pattern appears in behavioral outcomes: 72% felt more confident in pursuing business goals, yet only 44% demonstrated increased responsibility in practice. Behavioral outcomes reflected a similar duality. While 72% felt more confident pursuing business goals, only 44% reported greater responsibility in task execution.

Digital readiness emerged as a key moderating factor. Those with prior exposure to digital tools showed more consistent gains across all evaluation levels. Although formal statistical tests were not applied, the pattern suggests a potential interaction worth exploring in future work through stratified or regression-based analyses.

Figure 2 reinforces a key insight: training is well-received, but its impact varies significantly by participant readiness. As Bujang et al. (2020) emphasize, real-world tasks, modular delivery, and collaborative formats are likely to support more meaningful transformation—especially for those navigating early stages of digital adoption. A more tailored, experiential learning approach may better meet the varied needs of farmers' household businesses in adapting to digital environments.

Business overview, branding strategies, and digital marketing approaches

Table 5 offers a snapshot of business purpose, operations, and strategic direction, revealing



Source: Author's

Figure 2: Assessing the effectiveness of digital tools and branding training (%).

Business Overview	
Unique Story	Trial and error, hobby, availability of abundant natural resources
Business Target Niche/Segment	No specific niche/target, accessible to all social classes
Main Competitors:	Existing similar products
Differentiation from Main Competitors:	Uniqueness, price, taste
Market Positioning	Following market trends
Products/Services:	Vegetables, chicken, goats, VOC oil, agricultural products, knitted bags and wallets, craft bracelets, and cakes.
Commitment to Customers:	Fast delivery, high-quality products, satisfying service, good taste, neat presentation
Business Slogans:	- "If you haven't tried it, you don't know." - "Delicious crab, you know." - "Greenhouse, thriving business." - "You buy, we sell." - "Unlimited shopping, endless profit." - "Fresh vegetables, healthy living." - "Coconut in my business, prosperity in my village."
Business Challenge:	Capital, knowledge and skills, profit, and digital marketing
Social Media Formula:	X, Facebook, WhatsApp, Instagram, TikTok, Shopee
Focused Social Media Platforms:	Facebook, WhatsApp, Instagram, TikTok, Shopee
Marketing Strategy:	Order-based
Business Strengths:	Taste, price, quality, service

Source: Author's

Table 5: Business overview.

how entrepreneurs position their ventures within competitive landscapes. Most businesses emphasize flexibility and accessibility, drawing on personal experience and available resources rather than formal planning. While this organic approach fosters adaptability, the absence of clearly defined objectives or targeted market segments may limit long-term strategic growth. Still, the overview reflects a foundational awareness of value creation—particularly through taste, quality, and service—that can be refined with more structured business development support.

As shown in Table 5, entrepreneurs differentiate their businesses primarily through taste, price, and product quality. While this emphasis supports broad appeal, the absence of clear market positioning may hinder long-term brand consolidation. The diversity of offerings —from agriculture to handmade crafts—adds resilience but also calls for a more coherent brand narrative to foster customer loyalty and identity (Zia, 2013; Tan & Ludwig, 2016).

Brand development, as shown in Tables 6 and 7, presents a varied picture of maturity among entrepreneurs. While some clearly express a strong visual identity and convey emotional depth, many others find it challenging to craft consistent and compelling brand stories. This contrast underscores both the budding strengths within these businesses and the ongoing struggles they face in shaping meaningful brand narratives. It points to a clear need for more tailored support—rooted in strategic thinking, authentic storytelling, and deeper customer engagement—to help entrepreneurs build brands that resonate and endure.

Entrepreneurs in this study display growing competence in crafting visual and emotional brand identities; however, many lack coherent brand narratives. Key elements such as conflict, character, and resolution are often missing, revealing a disconnect between surface-level branding and deeper value-driven storytelling. From this gap, three archetypes emerge—Functionally Focused, Emotionally Driven, and Narratively Undeveloped—providing a practical framework to assess current practices and guide branding support. Prior studies affirm that authentic, emotive branding—particularly when co-created with customers—strengthens trust and long-term engagement (Kirumirah et al., 2021; Tian et al., 2022).

Although entrepreneurs actively utilize platforms like WhatsApp, Shopee, and TikTok, many struggle to align brand personality with digital content. The inconsistency across touchpoints suggests an enthusiasm for digital tools that is not yet matched by strategic branding literacy. These findings echo earlier calls for branding interventions

Target audience	
Ideal customers	General public
General public	All ages
Customer online location	Cafés, anywhere with social media
Customer contact methods	Direct message, chat, live
Customer priorities	Taste/quality, affordable prices, easy access
Brand personality	
Emotions related to the brand	Happy
Brand location	Shopee
Brand image	Innovative and inspiring
Preferred brand colors	Black-white, pink-white, brown-white, green, rainbow, red
Brand	
Words describing the brand's appearance	Luxurious, elegant, simple, relaxed, modern, warm, friendly, fun
Brand personality	Serious, colorful, fun, classic, modern, professional, approachable, relaxed-elegant
Word group describing the brand	Honest, humble, healthy, trustworthy, cheerful
Chosen brand fonts	Modern, serif, classic
Selected brand colors	Dark, blue, green, pink, gray

Source: Author's

Table 6: Brand discovery.

Brand personality creation	
Brand Representative	Business identity, product name
Strongest Brand Motivation	Uniqueness of process and product
Brand Recall	Name, logo
Brand Story Development	
The story theme	Health
The story plot	None
The backstory	None
The primary conflict	None
The brand's role	None
How the story resolves	None
The moral/lesson	None
The brand character	None
Other characters	None

Source: Author's

Table 7: Brand personality.

that go beyond aesthetics to address story structure, audience alignment, and platform-specific adaptation (Kirby and Kent, 2010; Suprayitno, 2017).

Despite some limitations—such as a modest sample size and reliance on self-reported data—these findings provide valuable insight into the branding challenges faced by rural entrepreneurs. Future studies would benefit from exploring regional differences and the socio-cultural factors that shape digital marketing adoption, as well as the long-term impact of branding and digital initiatives on smallholder business growth. It remains critical to assess the effectiveness of digital literacy programs and to better understand how local infrastructure, training methods, and cooperative support contribute to success. Creating inclusive, narrative-driven, and digitally empowered entrepreneurial ecosystems will require thoughtful strategy alongside ongoing collaboration between entrepreneurs, educators, and policymakers.

Conclusion

This study examines how entrepreneurial traits, digital marketing strategies, socio-cultural factors, and branding interact within farmers' household businesses in Indonesia. The findings emphasize the significant influence of traits such as age, gender, and platform preferences on digital marketing strategies, highlighting the need for tailored, multi-platform approaches. While social media remains the primary channel, challenges like limited digital literacy, outdated tools, and unclear performance metrics hinder its full potential. Training evaluations show improvements in confidence, collaboration, and task efficiency, but also reveal gaps in understanding work processes and practical application. Despite adaptability in product offerings and multi-platform engagement, businesses face barriers such as limited capital, digital skills, and marketing knowledge. Overcoming these challenges requires targeted digital literacy programs, accessible funding, and strategic collaborations with local partners, e-commerce platforms, and influencers. Strengthening brand storytelling around health, quality, and emotional connections can build loyalty and expand market reach. Effective training, performance evaluations, and the adoption of advanced digital tools, combined with employee motivation and strong partnerships, are essential for driving sustainable growth, competitiveness, and long-term success in an evolving market.

Corresponding author:
Nurliza
Doctoral Studies in Agricultural Sciences, Agriculture Faculty
University of Tanjungpura, Jl. Hadari Nawawi, Pontianak 78124, Kalimantan Barat, Indonesia,
Phone:+6281345249199, E-mail: nurliza.spmm@gmail.com

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The Size of Czech Agricultural Enterprises: Implications for Economic Efficiency

Radka Redlichová[1], Vojtěch Tamáš[1], Kristina Somerlíková[1], Jana Hlaváčková[2]

[1] Faculty of Regional Development and International Studies, Mendel University in Brno, Czech Republic

[2] Department of Agro-Environmental Policy, Institute of Agricultural Economics and Information, Brno, Czech Republic

Abstract

This study analyses the economic efficiency and size structure of agricultural enterprises in the Czech Republic, focusing on differences between organic and conventional farming systems during the 2016-2022 period. Key objectives include evaluating farm size distribution, profitability, and efficiency under varying conditions. Results reveal that organic farms are generally smaller and more reliant on subsidies, achieving lower production per hectare compared to conventional farms. However, their profit becomes comparable when subsidies are included. Conversely, conventional farms demonstrate greater efficiency, particularly among larger enterprises. These insights are pivotal for shaping agricultural policy with respect to production efficiency and food self-sufficiency.

Keywords

Farm structure, farm size, farm results, profitability, organic agriculture, conventional agriculture.

Redlichová, R., Tamáš, V., Somerlíková, K. and Hlaváčková, J. (2025) "The Size of Czech Agricultural Enterprises: Implications for Economic Efficiency", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 79-93. ISSN 1804-1930. DOI 10.7160/aol.2025.170206.

Introduction

Agriculture is a complex sector characterized by intricate relationships and interconnections among various actors within the supply chain. Over the past decade, alternative farming systems have gained importance, with a greater focus on factors related to natural conditions and sustainability. Organic and conventional agriculture represent two entirely distinct farming systems that respond to these challenges in different ways. Conventional agriculture is traditionally associated with intensive production and effective use of technology, while organic agriculture emphasizes sustainability and minimal reliance on chemical inputs.

Diversification of agricultural production systems can enhance sustainability and resilience, particularly by reducing inputs (Dumont et al., 2020) and leveraging synergies among agricultural components in organic farming (Ponisio et al., 2015). Furthermore, the increasing demand for organic agricultural products among consumers in high-income countries strengthens support for the organic farming system. Consumers in these regions associate organic products with sustainable development and environmental quality (Brătulescu et al., 2019).

Although conventional agriculture is generally more economically efficient, certain crops demonstrate long-term profitability in organic agriculture even without subsidies (Tudor et al., 2022). As such, exploring organic and conventional agricultural practices is key to understanding the broader economic and environmental implications of agriculture today.

This article focuses on changes in the size structure of agricultural enterprises in the Czech Republic that operate under these two systems. The objective is to determine whether there are differences in the size structure of these enterprises and, if so, how these differences translate into economic efficiency. Given the growing interest in organic products and changing market conditions, it is also important to understand how these factors influence the distribution of profitability and economic sustainability of the respective companies.

Previous studies suggest that the size of a farm can influence input utilization and the overall productivity of the enterprise and, by extension, the agricultural sector. For instance, Cheng et al.

(2018) highlight that smaller farms tend to utilize more labor and non-productive inputs per unit of land compared to larger farms, achieving higher labor productivity due to intensive usage and precision in agricultural techniques. A report by the International Fund for Agricultural Development (IFAD) demonstrates that larger farms often exhibit stronger labor productivity and highlights the influence of regional variations and policy frameworks. Similarly, Norboo and Dolma (2023) found that smaller farms are frequently more productive per unit of land due to incentives for intensive farming practices.

These findings underline the complex dynamics of farm size in relation to input utilization and productivity, suggesting that smaller farms may excel in productivity per unit of land, whereas larger farms often demonstrate superior labour productivity. However, there is limited research that integrates the economic efficiency and resilience of farms under different farming systems, particularly in the context of varying market and policy conditions. Studies have shown that organic farming practices often yield lower economic returns without subsidies but perform better in terms of environmental sustainability (Ponisio et al., 2015).

Under favourable economic conditions, even small-scale farmers can prosper and expand. However, small-scale farming can also impede the sustainable development of agriculture, particularly in countries where smallholders predominate. Previous research has indicated that fertilizer application per hectare tends to decrease as farm size increases (Ren et al., 2019), illustrating the challenges faced by smaller farms in optimizing input use. The efficiency of smaller farms compared to larger agricultural enterprises in most low-income countries can be attributed to labour market transaction costs. At the same time, increases in machine capacity with operational scale globally led to larger sizes of agricultural enterprises (Foster and Rosenzweig, 2022).

Several factors determine the susceptibility of agriculture and the food system to disturbances, leading to elevated levels of uncertainty, risks, and subsequent effects on economic performance. Natural influences, including weather patterns, diseases, pests, climate change, and environmental pollution, prominently affect this susceptibility. Additionally, the configuration and alterations in agricultural policy, farm size structure, the economic cycle, market concentration (Blažková and Chmelíková, 2015), and the overall economy play pivotal roles (Rosero et al., 2023).

This article specifically addresses changes in the size structure of agricultural enterprises certified for organic production in the Czech Republic in comparison to conventional agriculture. Farm size structure directly influences not only the economic performance of agriculture but also its environmental performance and sustainability (Ren et al., 2019). In fact, farm size structure is essential when considering ownership dynamics of agricultural land, as small-scale farms globally cover up to 40% of agricultural land (Lesiv et al., 2018). Small-scale farmers are commonly characterized as operating on less than 2 hectares, although the specific definition of a "smallholder" varies significantly in national censuses (Rigg et al., 2016).

Despite the nuanced economic advantages associated with large-scale agriculture, there are multiple vulnerabilities, some of which have exerted substantial influence during economic crises and the recent pandemic (Dudek and Piewak, 2022). This duality highlights a research gap in understanding how different farm sizes and systems adapt to economic shocks and changes in agricultural policy. The need to explore the interplay between profitability, environmental performance, and farm size is critical to informing future agricultural policy and supporting sustainable development (Zhou et al., 2022).

The interplay between farm size and the efficiency of resource utilization, particularly under organic and conventional systems, remains a largely underexplored topic, with limited studies addressing this issue, such as those by Nehring et al. (2021) and Durham and Mizik (2021). In the study by Durham and Mizik (2021), farm size is not the main focus of analysis; however, the authors mention that the economic efficiency and profitability of different agricultural systems (conventional, organic, and alternative) may be influenced by farm size. Conversely, Nehring et al. (2021) place greater emphasis on farm size, analyzing differences between small and large dairy farms in both organic and conventional systems. Their findings indicate that larger farms in both systems generally achieve higher productivity and efficiency due to better technologies and more effective utilization of fixed costs. This presents an opportunity for deeper investigation into how farm size mediates economic efficiency. Further research is needed to evaluate the comparative profitability of organic and conventional farms under changing economic and policy landscapes, particularly in Central Europe (Wang et al., 2022). Such analysis is crucial for identifying strategies that enhance resilience and sustainability across diverse farming systems.

Research gap and questions

Based on the above findings, this article aims to provide a new perspective on how different farming systems manage economic challenges and how the size of an enterprise can contribute to its efficiency and profitability. The research questions guiding this investigation are:

1. Are there differences in the size structure of organic and conventional farms?
2. What are the differences in profit levels for farms of different sizes and farming systems?
3. What are the differences in efficiency levels for farms of different sizes and farming systems?

Materials and methods

Based on these research questions the following hypotheses have been formulated:

1. H0 (1): There is no difference in the size structure of conventional and organic agricultural enterprises.
2. H0 (2): There is no difference in the level or development of profit between agricultural enterprises of different sizes and different farming systems.
3. H0 (3): There is no difference in the level or development of efficiency between agricultural enterprises of different sizes and different farming systems.

To address the research questions and assess the economic efficiency of agricultural enterprises, the following indicators were selected and defined. Economic efficiency, in this context, refers to the ability of an enterprise to achieve maximum output (or profitability) from a given set of inputs while minimizing costs. This approach aligns with widely accepted definitions in the literature (Foster and Rosenzweig, 2022; Ren et al., 2019).

Profit is one of the fundamental indicators used in economic analyses of enterprises, both at the company level and across industries. It is defined as:

Profit = Total Revenue − Total Cost

where:

Revenue = Crop Production + Livestock Production + Other Production + Operating Subsidies

Since subsidies are a significant part of the profit in agricultural enterprises (Cimpoieș and Coșalîc, 2024; Ponisio et al., 2015), we evaluated the profit in two variants:

- **With subsidies:** Includes all revenues, capturing the enterprise's ability to utilize both market returns and state support.
- **Without subsidies:** Excludes operating subsidies, focusing on the enterprise's intrinsic performance without external financial support.

This distinction allows for the assessment of an enterprise's capacity to generate sufficient revenue to cover its costs independently of subsidy policies:

Profit = Production Profit + Operating Subsidies

Production efficiency measures the output achieved relative to the inputs used. This is a core aspect of economic efficiency and is generally expressed as:

$$\text{Production Efficiency} = \frac{Inputs}{Production}$$

This approach has been widely used in studies assessing the sustainability of enterprises (Ray, 2024; Arbelo, 2020; Azizi, 2016). Specific ratios used to evaluate production efficiency include:

- $\frac{Profit}{Total\ Costs}$: Evaluates profitability per unit of cost.
- $\frac{Operating\ Profit}{Total\ Costs}$: Measures profitability while accounting for operational performance.
- $\frac{Total\ Production}{AWU}$: Assesses the productivity of labour, where:

Total Production = Crop Production + Livestock Production + Other Production

AWU = Annual Working Unit (labour input)

These indicators collectively provide a comprehensive measure of economic efficiency, capturing both the financial viability (profitability) and the productivity of resource use (efficiency). Similar approaches to measuring production efficiency have been applied in comparative studies of conventional and organic farming systems (Ponisio et al., 2015; Dumont et al., 2020).

The information used in this article was derived from the literature on the subject, data from the Institute of Agricultural Economics and Information (IAEI), and publicly available data and information on ecological and conventional agriculture at FADN CZ (Farm Accountancy Data Network – Czech Republic), which is managed by IAEI.

Data are collected by inspectors from each inspection organization directly on the farm during routine inspections. The foundation for this collection is a questionnaire prepared by IAEI, updated annually in accordance with the requirements of the European Commission/Eurostat and the Ministry of Agriculture. A web application is used for data collection, allowing inspectors to input farm-related information online. Since 2009, this application has significantly streamlined data collection, particularly in light of the growing number of organic farmers. An additional benefit is the ability for the IAEI to verify, allowing correction or supplementation of information provided by individual inspection organizations.

An additional information source is the Register of Ecological Entrepreneurs (REP) accessible on the Ministry of Agriculture's website: The Register of Ecological Entrepreneurs (eagri.cz), providing data on the count of ecological entities.

The time series 2016-2022 (the latest data available at the time of the research in the FADN CZ database) was chosen to evaluate the development. The time series data are expressed in current prices. The groups of enterprises by size follow the FADN CZ methodology, i.e., they are based on the designated standard output (SO) as follows:

Enterprise Category	Total Standard Output (SO) in EUR
Small enterprises	8,000 – less than 50,000
Medium enterprises	50,000 – less than 500,000
Large enterprises	500,000 – less than 1,000,000
Very large enterprises	1,000,000 and more

Source: FADN CZ, 2024

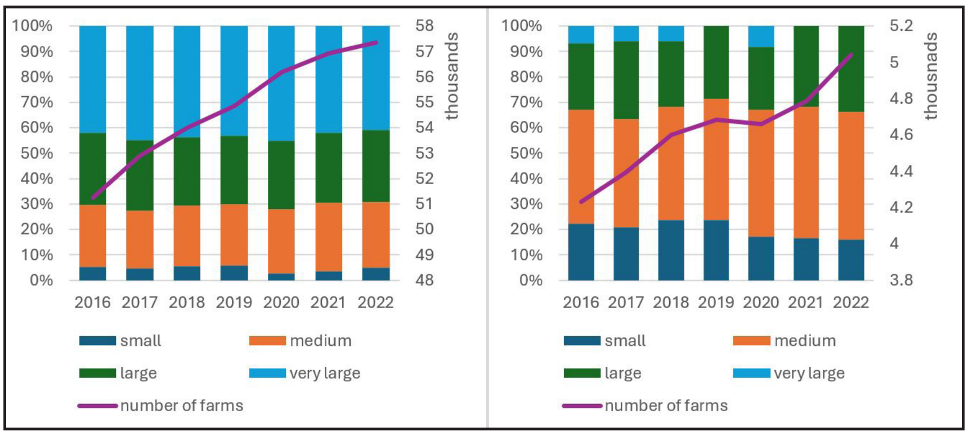
Table 1: Size categories of enterprises.

The data were subjected to statistical processing using the Statistica 14 software. Given the nature of the data, statistical hypothesis testing was employed. The specific proposed null hypotheses were tested at a significance level of $\alpha = 0.05$. Due to the nature of the data, one-way and two-way ANOVA were used. The processed data meet the assumptions of normality and homogeneity of variance. Statistically significant results were further verified using post hoc testing methods, specifically Tukey's test for unequal sample sizes.

Results and discussion

Hypothesis 1 – size structure

In the period 2016-2022, the number of farms in the Czech Republic increased, both conventionally and organically (see Figure 1). The share of organically grown farms increased slightly (8.2 - 8.8%). In the case of the size structure, differences are noticeable between the two farming systems, with conventionally farmed farms being rather larger in size (large and very large farms have around 70% share), while in the case of organic farms, around 70% are made up of small and medium-sized farms.



Source: authors, 2024 (data: FADN CZ)

Figure 1: Number and structure of enterprises - conventional (left), organic (right).

Based on the first hypothesis, we tested the differences in size structure between groups of conventional and organic enterprises. The results of the analysis of variance (ANOVA) showed that the differences in the relative numbers of enterprises by size are statistically highly significant ($p < 0.01$) (Table 2).

To identify specific differences between individual groups, we used post-hoc testing methods, specifically Tukey's test for unequal sample sizes.

Tukey's test provided detailed insights into the results of the analysis of variance mentioned above (Table 3).

The test confirmed differences between individual groups of enterprises. For instance, differences between small organic enterprises and most other categories (e.g., medium-sized organic enterprises, small conventional enterprises) are highly significant ($p < 0.01$). Conversely, differences between large organic enterprises and medium-sized conventional enterprises were not statistically significant ($p > 0.05$).

Hypothesis 2 - profit

In terms of total production per hectare, conventional farms are more efficient than organic farms, by a factor of approximately 2 to 3 (Figure 2). It can be said that the ratio of total production of conventional farms to organic farms increases with increasing size.

However, for conventional farms, in recent years, the larger the farm, the higher its productivity per hectare. An interesting trend is that the productivity of small farms is decreasing, even though the productivity of the whole set of conventional farms is increasing. The initial identical productivity level (about 2000 EUR/ha in 2016) of small and very large enterprises has gradually changed in favour of very large enterprises, which in 2022 reach almost double the value of production per hectare compared to small enterprises (2800 EUR/ha and 1700 EUR/ha, respectively).

Small farms are generally the best performers in terms of production per hectare, by around 30%, as could be also seen in Figure 2.

In the evolution of farm profits there is no clear trend over time (Figure 3) that can be applied to the whole set of farms studied.

When analysing profit (EUR/ha) (Figure 4) small and medium-sized farms generally exhibit higher levels compared to the large and very large farms, with conventional farms achieving higher profits compared to organic farms.

In terms of profit net of subsidies (Figure 4 – right side), it becomes evident that organic farms of all sizes operate at a loss. Similarly, among conventional farms, very large enterprises are the least profitable, aligning with the earlier findings

	SS	DF	MS	F	p
intersection	714.2857	1	714.2857	3,009.690	0.000000
size	81.4394	3	27.1465	114.383	0.000000
standard error	11.3918	48	0.2373		

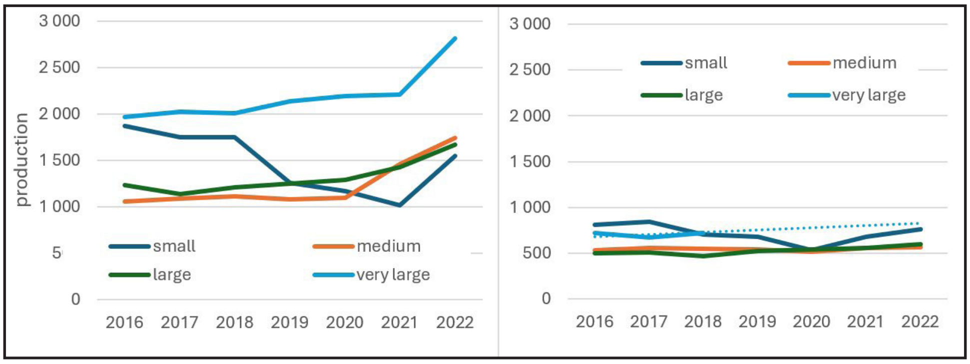
Source: authors, 2024 (data: FADN CZ)

Table 2: ANOVA test H0 (1).

	small organic	medium organic	large organic	very large organic	small conven.	medium conven.	medium conven.	large conven.
small organic		0.000134	0.000881	0.000134	0.000134	0.272891	0.006131	0.000134
medium organic	0.000134		0.000134	0.000134	0.000134	0.000134	0.000134	0.396665
large organic	0.000881	0.000134		0.000134	0.000134	0.362873	0.997685	0.000134
very large organic	0.000134	0.000134	0.000134		0.999861	0.000134	0.000134	0.000134
small conventional	0.000134	0.000134	0.000134	0.999861		0.000134	0.000134	0.000134
medium conventional	0.272891	0.000134	0.362873	0.000134	0.000134		0.775548	0.000134
large conventional	0.006131	0.000134	0.997685	0.000134	0.000134	0.775548		0.000134
large conventional	0.000134	0.396665	0.000134	0.000134	0.000134	0.000134	0.000134	

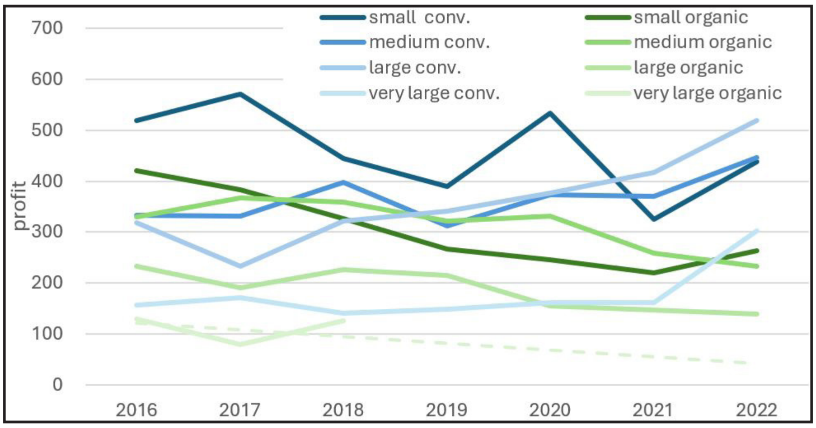
Source: authors, 2024 (data: FADN CZ)

Table 3: Tukey HSD test H0 (1)



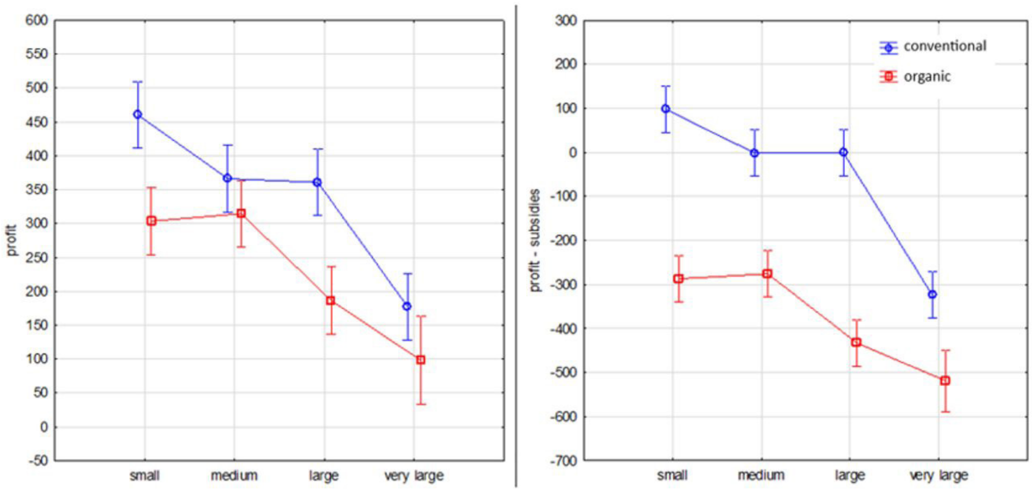
Source: authors, 2024 (data: FADN CZ)

Figure 2: Total production of conventional (left) and organic (right) farms based on their size (EUR/ha).



Note: data for 2019, 2021 and 2022 were not available for very large organic companies, so a linear trend is indicated.
Source: authors, 2024 (data: FADN CZ)

Figure 3: Profit per hectare (EUR/ha).



Source: authors, 2024 (data: FADN CZ)

Figure 4: Profit and profit without subsidies per hectare (EUR/ha).

on profit including subsidies. A clear inverse relationship is observed between farm size and profitability per hectare in both farming systems.

A detailed overview of the basic characteristics of the profit of agricultural enterprises of different size categories and farming systems is provided by descriptive statistics (See Table 4). These data allow comparisons between conventional and organic farms and reveal differences in the distribution of profit values.

The statistical analysis of differences in profitability (ANOVA test of mean equality) between different sizes and farming systems showed the following results (Table 5).

Based on the probability result ($p < 0.01$), we reject the null hypothesis and confirm the existence of significant differences in profitability between different sizes and farming systems (Table 6).

The results of the post hoc testing using Tukey's test confirm statistically significant differences between different sizes of enterprises as well as between conventional and organic systems.

Hypothesis 3 - efficiency

The structure of revenues and total cost coverage (efficiency) did not differ significantly throughout the period under review for any of the business types. For this reason, only the last year, 2022, is shown in Figure 5. The data show a higher share of subsidies in total revenues for organic farms. The differences between size groups are not significant.

From previous results it is also possible to derive an indicative ratio of profit to total inputs (Figure 6). Small and medium enterprises can be said to be more efficient than very large enterprises in evaluating their input. In the last year, large enterprises have been the most successful. Excluding operating subsidies, the level of efficiency would have fallen by around 20-30 percentage points, with more significant differences (i.e. around 30 percentage

	average	SS	Min	Max	Q1	median	Q3
small conventional	460.3326	86.9645	324.5302	571.5795	389.7039	445.1129	534.0616
small organic	303.4439	74.8833	219.9128	420.1579	246.1437	266.4872	382.4769
medium conventional	366.2065	46.1497	312.3597	446.9884	331.851	370.345	396.9702
medium organic	314.4485	49.9685	233.3148	366.8928	259.1117	329.8703	359.3843
large conventional	360.8675	90.3497	232.0667	519.8749	318.3119	341.0612	416.5326
large organic	186.3387	39.1507	138.9961	231.9625	147.1019	190.4422	225.546
very large conventional	177.4598	56.0925	141.1559	302.8129	148.653	160.591	170.8208
very large organic	98.109	34.2265	60.043	128.8069	69.2142	101.7929	127.0038

Source: authors, 2024 (data: FADN CZ)

Table 4: Descriptive statistics (profit/ha).

	SS	SV	MS	F	p
profit	594,712.8	7	84,958.98	20.40654	0.00000
standard error	187,349.4	45	4,163.321		

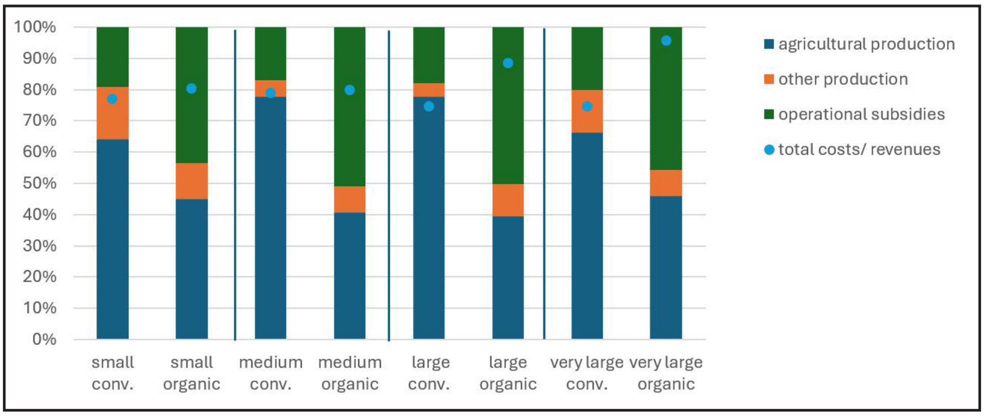
Source: authors, 2024 (data: FADN CZ)

Table 5: ANOVA test H0 (2)

		medium organic	large organic	very large organic	small convent.	Medium convent.	Large convent.	very large convent.
small organic		0.000134	0.000881	0.000134	0.000134	0.272891	0.006131	0.000134
medium organic	0.000134		0.000134	0.000134	0.000134	0.000134	0.000134	0.396665
large organic	0.000881	0.000134		0.000134	0.000134	0.362873	0.997685	0.000134
very large organic	0.000134	0.000134	0.000134		0.999861	0.000134	0.000134	0.000134
small convent.	0.000134	0.000134	0.000134	0.999861		0.000134	0.000134	0.000134
medium convent.	0.272891	0.000134	0.362873	0.000134	0.000134		0.775548	0.000134
large convent.	0.006131	0.000134	0.997685	0.000134	0.000134	0.775548		0.000134
very large convent.	0.000134	0.396665	0.000134	0.000134	0.000134	0.000134	0.000134	

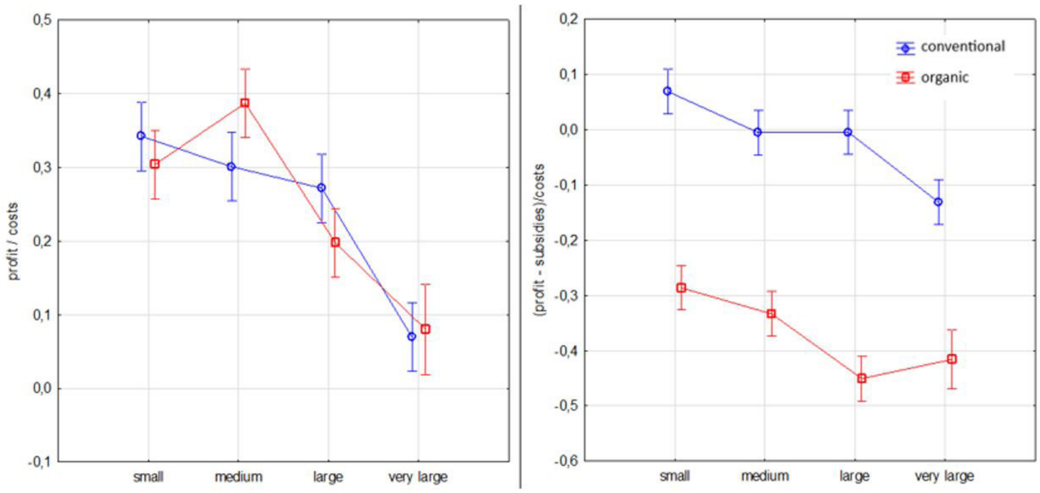
Source: authors, 2024 (data: FADN CZ)

Table 6: Tukey HSD test H0 (2).



Note: 100% = revenues (agricultural production + other production + operational subsidies); data for very large organic are from 2021.
Source: authors, 2024 (data: FADN CZ)

Figure 5: The Structure of revenues and costs (year 2022).



Source: authors, 2024 (data: FADN CZ)

Figure 6: Profit /costs ratio.

points) for smaller enterprises. It is therefore evident that for these size groups, subsidies account for a more significant part of revenues (which is also evident from the structure of revenues in the previous figure).

Subtracting subsidies has more than twice the impact on efficiency reduction for organic enterprises than for conventional enterprises, i.e. by 50-70 p.p. compared to the variant with subsidies. Again, this impact is more pronounced for smaller companies.

To verify the differences between the various groups of enterprises, statistical testing was performed using analysis of variance (ANOVA). The results indicate that the differences in the profit-to-cost ratio among the examined groups of enterprises are statistically significant ($F = 22.8336$; $p < 0.0001$).

Differences in the ratio of "profit after subsidies/ costs" were also tested, and significant differences were also found ($F = 95.1466$; $p < 0.0001$) (Table 7).

The Tukey HSD test revealed significant differences between specific pairs of groups. The most pronounced differences were found between small organic enterprises and very large conventional enterprises, as well as between small and medium-sized groups of organic enterprises. In conventional enterprises, the differences were less pronounced, with the proportion of subsidies to total income being an important factor (Table 8 and 9).

	SS	SV	MS	F	p
profit / costs	0.5944	7	0.0849	22.8336	0.0000
standard error	0.1673	45	0.0037		
(profit – subsidies) / costs	1.8581	7	0.2654	95.1466	0.0000
standard error	0.1255	45	0.0028		

Source: authors, 2024 (data: FADN CZ)

Table 7: ANOVA test H0 (3)

	small conven.	small organic	medium conven.	medium organic	large conven.	large organic	very large conven.	very large organic
small conventional		0.936202	0.907475	0.861918	0.394397	0.001537	0.000131	0.000131
small organic	0.936202		1	0.201902	0.973683	0.040778	0.000131	0.00014
medium conventional	0.907475	1		0.16806	0.984906	0.051416	0.000131	0.00015
medium organic	0.861918	0.201902	0.16806		0.019607	0.000142	0.000131	0.000131
large conventional	0.394397	0.973683	0.984906	0.019607		0.332194	0.000133	0.000344
large organic	0.001537	0.040778	0.051416	0.000142	0.332194		0.006563	0.064555
very large conventional	0.000131	0.000131	0.000131	0.000131	0.000133	0.006563		0.999993
very large organic	0.000131	0.00014	0.00015	0.000131	0.000344	0.064555	0.999993	

Source: authors, 2024 (data: FADN CZ)

Table 8: Tukey HSD test H0 (3) – profit / costs.

	small conven.	small organic	medium conven.	medium organic	large conven.	large organic	very large conven.	very large organic
small conventional		0.000131	0.172109	0.000131	0.182411	0.000131	0.000131	0.000131
small organic	0.000131		0.000131	0.712077	0.000131	0.000142	0.000172	0.007111
medium conventional	0.172109	0.000131		0.000131	1	0.000131	0.001415	0.000131
medium organic	0.000131	0.712077	0.000131		0.000131	0.003475	0.000131	0.227275
large conventional	0.182411	0.000131	1	0.000131		0.000131	0.001304	0.000131
large organic	0.000131	0.000142	0.000131	0.003475	0.000131		0.000131	0.963572
very large conventional	0.000131	0.000172	0.001415	0.000131	0.001304	0.000131		0.000131
very large organic	0.000131	0.007111	0.000131	0.227275	0.000131	0.963572	0.000131	

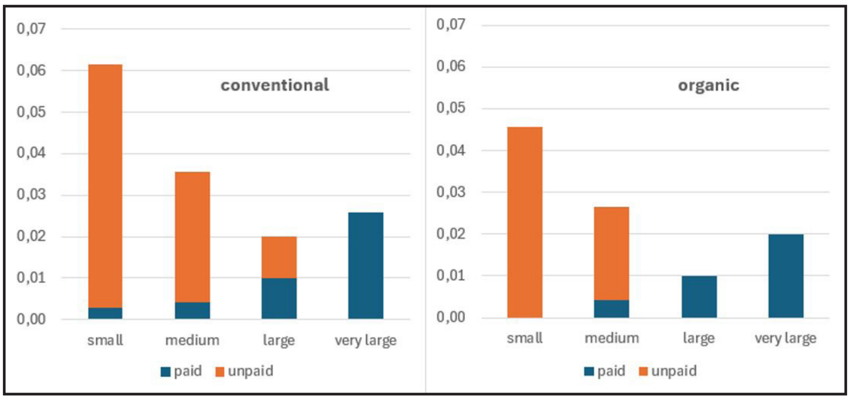
Source: authors, 2024 (data: FADN CZ)

Table 9: Tukey HSD test H0 (3) – (profit – subsidies) / costs

In terms of efficiency of the labour factor of production, organic farms, whose farming system is to some extent based on a higher proportion of manual labour, could be expected to have a higher number of workers per hectare and a related lower labour efficiency. However, the number of workers per hectare counted is slightly lower for organic farms of all sizes than for conventional farms (see Figure 7 below). There is no significant trend in the time series, so the graph below presents average values for 2016-2022, distinguishing between paid and unpaid labour. The results can be assessed that small enterprises, regardless of the farming method, have a higher number of workers per hectare than large enterprises. This can be explained by the lower ability to take advantage of the factor of production capital (technology), which can be very costly for small enterprises and less profitable due to the smaller size of the cultivated land.

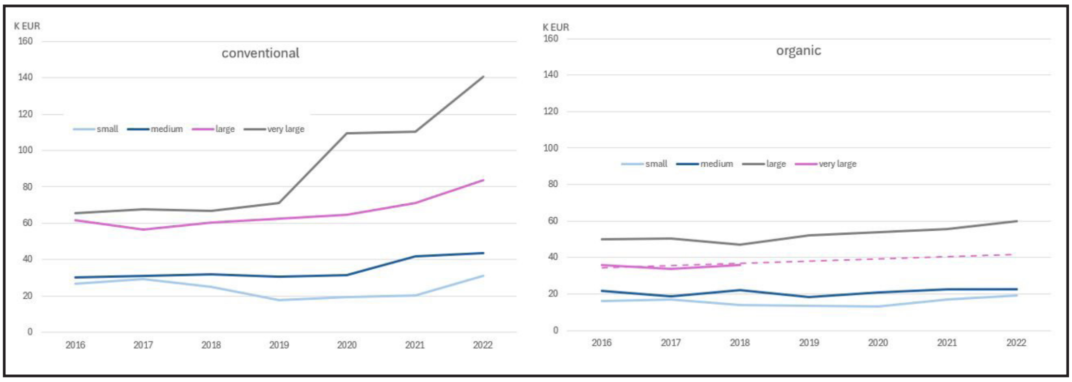
Unlike conventional farms, small organic farms have no paid labour and the amount of unpaid labour per hectare is lower.

The total factor productivity of labour is also lower for organic farms in all size groups (see Figure 8 below). Some of the lower productivity is very likely linked to the farming system, where organic farms rely to a greater extent on manual labour, which they prefer to use, for example, over pesticides. Their lower capital endowment is probably also an influence. Another factor that may influence this result is the different structure of production. Conventional farms are more focused on intensive livestock production that requires a larger number of workers. Livestock production



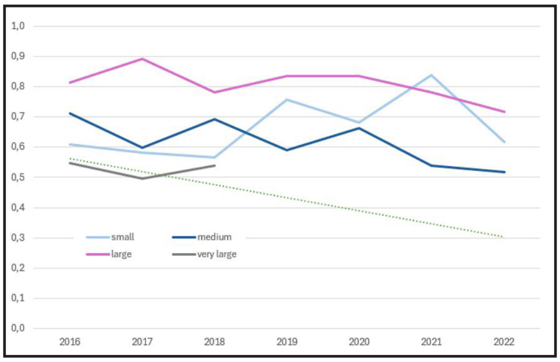
Source: authors, 2024 (data: FADN CZ)

Figure 7: Number of workers per hectare.



Note: data for 2019, 2021 and 2022 were not available for very large organic companies, so a linear trend is indicated.
Source: authors, 2024 (data: FADN CZ)

Figure 8: Total production per worker.



Note: data for 2019, 2021 and 2022 were not available for very large organic companies,
so a linear trend is indicated.
Source: authors, 2024 (data: FADN CZ)

Figure 9: The organic / conventional ratio of labour productivity.

on organic farms tends to take the form of grazing on permanent grasslands and is therefore not as labour intensive.

The efficiency ratio between organic and conventional farms can be seen in 9 (above).

In general, from the data presented it can be inferred that the differences between the productivity of organic and conventional companies tend to widen over time. The most balanced efficiency is found in large enterprises (about 80 %), while the largest difference is found in very large enterprises (50 %). Here, roughly twice as many workers are needed to produce one unit of output. Small and medium enterprises are between 60 and 70 %. Baser and Bozoğlu (2019) reached similar conclusions regarding low productivity in Turkish beef farms and highlighted the necessity of addressing this issue. They propose state-level support to increase farm size. The relation of farm size on its efficiency has been proven by Ren et al. (2019) based on whom economic efficiency is deeply connected to the economy of scale that is reached by larger farms.

Ecological farms, despite growing interest and support due to environmental considerations (Ponisio et al., 2015), often operate at a productivity disadvantage. This is seen in lower yields per hectare compared to conventional farms, attributed to differing input and farming methodologies. Despite this, Ponisio et al. (2015) argue for the potential of organic practices to close yield gaps through techniques such as crop rotations and polycultures, potentially increasing ecological farm productivity. Baudron et al. 2022 lean towards diversification practices in their global research take, as do Tudor et al. (2022). Dumont et al. (2020) and Ren et al. (2019) also emphasize resilience through diversity and farm-level innovation. Their insights are particularly relevant as ecological farms often rely on diverse cropping systems and innovative practices to improve resilience against both economic and environmental shocks. Such strategies are imperative for smaller ecological farms in the Czech Republic, which need to leverage their adaptability to ensure economic viability and competitive positioning against larger conventional counterparts.

According to Mizik (2023), Karunathilake et al. (2023) or John et al. (2023), precision farming practices may be a pathway to improved productivity, but they have some constraints, especially financial, as is pointed out by Quaicoe et al. (2023) when implemented in small farms. Similarly, Choruma et al. (2024) or Lu et al. (2024) consider digitalization as a key factor to increase the productivity and sustainability of small and medium farms. The problem of labor productivity as one of the development factors was already highlighted by Rapsomanikis (2015), who also stressed the need for political support in this regard.

The landscape of agriculture in the Czech Republic, as assessed from 2016 to 2022, illustrates significant trends and characteristics. During this period, both conventional and ecological farming enterprises experienced growth. However, ecological farms, while increasing their number slightly relative to conventional farms, remain predominantly small to medium-sized, contrasting with the larger sizes typical of conventional farms (Rigg et al., 2016). This aligns with ongoing global observations of smallholder persistence due to their adaptability and the socioeconomic dynamics surrounding their operations, as demonstrated by Lesiv et al. (2019). Rosero et al. (2023) discuss limited market access and customer interaction issues due to external factors such as the COVID-19 pandemic, while Jellason et al. (2024) call for better customer relationships. Such challenges underscore the importance of ensuring effective support and communication strategies tailored to organic farmers, which is crucial for the Czech ecological farming sector as it navigates a competitive landscape dominated by larger conventional farms.

The analysis of profit structures reveals an interesting dichotomy. While larger conventional farms dominate in absolute production output, small to medium farms, conventional or ecological, often demonstrate higher profitability per hectare once subsidies are considered (Ren et al., 2019; Dudek and Piewak, 2022). The heavy dependence on subsidies, especially for ecological farms (Cimpoieș and Coșalîc, 2024 or Redlichová et al., 2023), indicates a critical dependence on state support to maintain financial viability. This suggests the need for policies that enhance independent profitability through market expansion and value-added production (Tudor et al., 2022 or Chmelíková and Redlichová, 2013). The broad trends highlight the increasing importance of subsidies in sustaining ecological agriculture but also pose questions about long-term sustainability and autonomy for these farms. Investment in technology, training, access to finance (Chmelíková and Redlichová, 2020) and market access could help transition these farms to more self-sufficient business models (Brătulescu et al., 2019). Simultaneously, improving consumer awareness and demand for organic products can catalyse growth and support a stable market for ecological products.

Conclusion

From the analyses, the results of which are presented in this paper, the research questions can be answered as follows.

1) Are there differences in the size structure of organic and conventional farms?

The number of farms that are farming in both conventional and organic systems has increased during the period under review. The number of organic farms is slightly less than 10% compared to the number of conventional farms. In the case of organic farms, the size structure tends to favor smaller farms, while conventional farms are larger. This conclusion is consistent with the nature of the production method, where organic will tend more towards family farms.

The summary of the analysis results suggests that the size structure of organic and conventional enterprises differs significantly, with organic enterprises being smaller and more diversified. This finding may have important implications for the development of policies supporting different types of enterprises.

2) What are the differences in the level and evolution of profit for farms of different sizes and different farming systems?

From the point of view of profit, due to the system of state subsidy interventions, which aim, among other things, to support ecological systems, it is necessary to define not only the profit itself, but also its structure, or the structure of the income side of the achieved economic result. The latter can be divided, with a certain degree of generalisation, into a 'production' and a 'subsidy' part.

The production per hectare (expressed in euros) of organic farms is half to a quarter of that of conventional farms. However, after considering the subsidy policy, profitability (profit/cost) is the same for both types of farms. Logically, therefore, the profit after deduction of subsidies is more strongly influenced by organic enterprises than by conventional enterprises. In both systems, small and medium companies have higher profit. Small conventional enterprises have a positive economic result even after deducting operating subsidies. Other groups of companies would make a loss without subsidy support.

3) What are the differences in the level and evolution of efficiency for farms of different sizes and different farming systems?

The efficiency does not show a significant trend during the period under review. In the case of cost profitability (including subsidies), the results for conventional and organic companies are de facto comparable. In both groups, small and medium enterprises have higher efficiency. After deduction of subsidies, there is a more pronounced decline for organic enterprises, especially SMEs, where subsidies account for a higher share of total revenues.

The number of workers per hectare is higher for conventional farms. However, due to their higher production, they still achieve higher labour productivity (labour efficiency) than organic enterprises. Again, no significant trend can be observed.

From these results, it can be concluded that organic farms have a higher share of subsidies. Subsidies make up a significant part of their income, and once they are received, profitability is brought back to the level of conventional enterprises. In the size structure of organic farms, there is a higher proportion of small and medium-sized enterprises compared to conventional farms

The Czech agricultural sector is defined by a growing but still limited ecological agriculture sector that needs strategic support to overcome inherent productivity challenges and to leverage its environmental and societal benefits. As observed globally, fostering innovation is one of the ways to increase productivity. Together with robust policy support, innovations are essential to maintain agricultural diversity and economic resilience in line with ecological priorities.

The findings of the paper can serve as a basis for agricultural policy decision making regarding production efficiency and food self-sufficiency.

Acknowledgements

The article was written as a partial result of the project IGA24-FRRMS-013 "Impacts of public support for science and research on the development of regional innovation systems".

Corresponding author:
Radka Redlichová
Faculty of Regional Development and International Studies
Mendel University in Brno, Zemědělská 1, 613 00 Brno,
Czech Republic
E-mail: radka.redlichova@mendelu.cz

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Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

Does Biological Assets´ Tangibility Matter from the Profitability and Cost of Debt Perspective for Agricultural Firms?

Zdeněk Toušek[1], Jana Hinke[1], Barbora Gregor[2], Martin Prokop[1]

[1] Department of Trade and Finance, Faculty of Economics and Management, Czech University of Life Sciences Prague, Czech Republic

[2] Institute of Economic Studies, Faculty of Social Sciences, Charles University in Prague, Czech Republic

Abstract

The research aim is to identify specific production factors (biological assets) and target potential profitability and cost of external debt dependency on these biological assets (as an anticipated essential driving forces) due to relative scarcity of this topic coverage. Underlying unbalanced data set consist of 229 agricultural firms managing their business operations from 2011 till 2019 in the Czech Republic. The paper is innovative based on its combination of several different factors including incorporation of biological assets' variables influencing firm's profitability and by assessing determinants concerning cost of external debt using a panel regression analysis with fixed effects. Biological assets tangibility is relatively low with declining trend. Contrary to it land tangibility experienced exactly opposite development caused by "skyrocket" land price appreciation. It has been proven that cost of debt is depending only on the short/long-term leverage levels, thus primarily the total indebtedness is essential and relevant driving force.

Keywords

Cost of debt, leverage, return on assets, tangibility, variables.

Toušek, Z., Hinke, J., Gregor, B. and Prokop, M. (2025) "Does Biological Assets´ Tangibility Matter from the Profitability and Cost of Debt Perspective For Agricultural Firms?", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 95-106. ISSN 1804-1930. DOI 10.7160/aol.2025.170207.

Introduction

Since profitability is in the epicentrum of the interest from alternative stakeholders' point of view with respect to the effective capital allocation, understanding its determinants is desirable. Understanding of non/essential production factors behaviours (accessibility, availability etc.), as initial inputs for transformation production process, can be viewed in general as an essential part of profitability generation, which is dictated by the efficiency and productivity of their used and has been extensively covered by literature (Setianto et al., 2022). Special attention shall be also paid to the essential production factors, more precisely specific ones that are crucial and possess irreplaceable character (with very limited substation possibility) in production process (agricultural land in crop production etc.). Contrary to it, inadequate and/or inefficient handling of these production factors can detrimentally affect profitability generation and can also lead to higher financial cost (higher risk premium on external debt charged by lenders). Thus, managing these production factors effectively shall lead to profitability as well as cost of external debt enhancement.

The agriculture sector can serve as a good example of industry that is employing and significantly depending on specific production factors possessing unique features due to its natural origin (biological assets) (Mukaila, 2022). The goal of this paper was to identified specific factors of biological character on selected sample of agricultural firms. Consequently, statistical models targeting potential profitability and cost of external debt dependency on biological assets (specific factors) as an anticipated essential driving force were introduced. Apart of these specific production factors also other factors in different effect categories: effects specific to individual firms and macroeconomic effects were utilized.

The authors believe that the paper is innovative in cumulating several factors, namely both types of biological assets (fixed and current assets) and land determining the profitability and cost of senior debt of selected sample of agricultural firms, thus overlapping relative scarcity of this topic coverage (at least in the context of the Czech Republic). In addition, the underlying dataset comprises predominantly from unlisted firms (mostly SMEs), which typically face information asymmetry resulting in severe resources limitation (excess to external financing etc.), but at the same time represent majority of agricultural entities (family farms). Therefore, this research provides relevant beneficial contribution to academic literature and the results can also serve as guideline for policy makers with respect to agricultural policy, especially public aid policies (subsidies adjustments etc.).

The paper is organized as follows: Section 2 provides an overview of related literature including empirical findings concerning bioassets as potential profitability driver, dataset its adjustments and subsequent descriptive analyses are detailed in Section 3, proposed methodology is explained in Section 4, the results including robustness checks are elaborated in Section 5 and concluding remarks are provided in Section 6.

Literary research

Primary agricultural production contrary to the most other sectors of national economy is employing specific production factors, i.e., assets of biological character that poses unique features due to its natural origin (Du and Li, 2018). The efficient use of assets and the degree of debt financing together with labor productivity create comparative strengths of the agribusinesses in individual countries (Beyer and Hinke, 2020; Bielik et al., 2013; Yakubu et al., 2022). Asset size and leverage as determinants of profitability have been confirmed by many researches conducted in the agricultural sector - for example Mijic and Jaksic (2017) in Eastern Europe, Korneta (2017) in Poland or Pokharel et al. (2019) in the United States. Therefore, the aim of this paper is to test, whether biological assets and their tangibility (as an irreplaceable production factor) play any crucial role in agricultural firms' profitability determination and at the same time influence the cost of external debt (higher biological fixed assets tangibility representing higher level of tangibility that can be used as a collateral). This focus of the article makes it unique, as the authors are not aware of any similar study. A bright spot is only the study of Chinese authors Xie, Wang and Wang (2019). Their paper examines the effect of biological assets, an agricultural characteristic asset on cost of debt capital for Chinese listed agricultural firms over the period 2007 similar to 2016. They find that biological assets have significant positive effect on cost of debt capital.

The Czech financial accounting regulations are distinguishing long-term biological assets (part of fixed assets) and agricultural production (part of current assets) in the form of animals or living plants (Čermáková, 2013). For the purpose of this study, biological assets (excluding land) are considered as items having natural origin and are divided into two group based on their lifetime expectancy (accounting principal), more precisely long-term biological assets (fixed biological assets) and short-term biological assets (current biological assets). Fixed biological assets are formed by breeding livestock and perennials. Current biological assets (agricultural production) are consisting of young animals (Sedláček, 2010).

Biological assets are subject of biological transformation, i.e., process of growth, degeneration, production, and procreation causing qualitative and quantitative changes in living being and generated new assets in the form of agricultural products or additional biological assets of the same type (Bohušová and Svoboda, 2017).

Also, agricultural land can be viewed as a special type of biological production factor due to its natural nature (Simtion, 2020). Therefore, the land is considered as special fixed biological asset playing increasing role at least from the tangibility point of view due to its increasing monetary expression (land prices were in general rather steadily increasing over the period of time and similar path is anticipated in the future) (Zdenek et al., 2019). The land more precisely area of agricultural land may play also important role with the respect to the overall public aid support transfers to farmers (certain subsidies' payments may be in/directly linked to the cultivated farmland area) (Takac et al., 2020).

In order to achieve the above-defined aim, the following hypotheses were defined and will be verified in this study:

H1: Biological assets tangibility positively and significantly influences agricultural firm's profitability.

H2: Profitability of bigger firm tends to have higher dependency on biological assets tangibility (under the assumption that bigger firms tend to have the higher volume and share of biological assets on its balance sheet).

H3: There is a negative relationship between cost of debt and bio assets tangibility.

Materials and methods

Underlying unbalanced data set consist of 229 agricultural firms managing their business operations from 2011 till 2019 in the Czech Republic, thus representing 2.018 observations. Financial figures are derived primarily from publicly accessible resources. Final financial statement (where applicable audited) was used. Following adjustments were imposed on raw data like Bena and Ondko (2012) and Vithessonthi and Tongurai (2015) firms with relatively high indebtedness (short/long term debt to total assets ratio greater than one) and/or firms with negative net worth. No limitation applied from performance (Turnover) point of view to ensure full complexity of the Czech agricultural sector.

To capture profitability and cost of debt determinants (including potential effects of biological assets) following variables were defined and used. Please see Table 1 for comprehensive overview.

Prior to quantitative analysis examination underlying data set was inspected for potential inconsistencies and statistical properties were analysed. Please see Table 2. for descriptive statistics.

The minimum value (equal to zero) of biological assets (both fixed and/or current) represents firms that either farm without own biological assets (crop farming without breeding animals etc.) or are renting them (long term lease of perennials etc.). Also, minimal values equal to zero in the case of land tangibility stands for firms having no own land. Zero debt (without any external debt) firms amount short and/or long-term leverage ratios to zero. Consequently, applied interest rate (in the case of zero debt firms) counts also for zero.

Profitability itself is defined as Return on Assets (ROA). To overcome potential discrepancies resulting from alternative depreciation and amortization scheme earnings before tax and depreciation (EBIT) is employed. The motivation is to capture potential market distortions caused by public policies leading to "non-market" behaviours under the necessity of the subsidy’s conditions alignment from producer point of view. To understand, whether the agricultural production is sustainable under the free-market conditions or is in the phase of perilous dependency on public transfers. Since different types of subsidies are relatively common in primarily agricultural production (cash transfers in the favour of firms’ cash flow), alternative profitability (ROA_2) is calculated by including also other operating income (OOI), where majority subsidies are booked. From the description, it is obvious that achieved profitability magnitudes differ between ROA and ROA_2 (effect of OOI caused by subsidies). ROA figures are smaller compared to ROA_2 values and even attack negative area (both median and mean values) leading to the conclusion that overall profitability is significantly driven by subsidies.

Interestingly, the observed trend of profitability (both ROA and ROA_2) is decreasing, experiencing relatively significant reduction by -48.1 % and -22.9 % (total average values) for ROA_2 and ROA, respectively. This could lead to assumption (OOI is used as a proxy

	Variables	Abr.	Description
Endogenous variables	Return on Assets	ROA	(EBIT - Other operating income)/Total Assets
	Return on Assets_2	ROA_2	EBIT/Total Assets
	Interest rate (in % p.a.)	IR	Interest expenses/Total bank debt
Exogenous variables	Fixed Bio Assets intensity	Bio.Fix_TA	Fixed Biological Assets/Total Assets
	Current Bio Assets intensity	Bio.Ca_TA	Current Biological Assets/Total Assets
	Land intensity	Land_TA	Land/Total Assets
	Fixed Assets intensity	NCALB_TA	Fixed Assets (excluding Bio Fix Assets & Land)/Total Assets
	Long term leverage	LTBL_TA	Long term financing /Total Assets
	Short term leverage	STBL_TA	Working capital financing/Total Assets
Macroeconomic variables	Inflation (in % p.a.)	CPI	Customer price index
	Price of money (in % p.a.)	3MPRIBOR	3M Pribor at the end of the fiscal year
	GDP growth (in % p.a.)	GDP	Annual GDP growth

Source: own processing

Table 1: The list of used variables.

AgroSector	Mean	Std.De	Min	Median	Max	MAD	IQR	CV
Bio.Ca.TA	0.057	0.040	0.000	0.049	0.435	0.028	0.041	0.695
Bio.Fix.TA	0.030	0.017	0.000	0.028	0.141	0.015	0.021	0.566
CPI	0.017	0.010	0.003	0.019	0.033	0.014	0.018	0.596
GDP	0.025	0.019	-0.008	0.025	0.054	0.010	0.014	0.769
IR	0.048	0.069	0.000	0.040	2.190	0.015	0.020	1.429
LAND_TA	0.118	0.096	0.000	0.095	0.649	0.082	0.115	0.820
LTBL_TA	0.182	0.128	0.000	0.155	0.692	0.118	0.172	0.704
NCALB_TA	0.493	0.136	0.045	0.506	0.830	0.129	0.177	0.275
ROA	-0.103	0.083	-0.561	-0.091	0.263	0.066	0.090	-0.810
ROA2	0.042	0.043	-0.184	0.038	0.353	0.036	0.049	1.042
STBL_TA	0.047	0.056	0.000	0.034	0.469	0.051	0.069	1.175
X3MPRIBOR	0.009	0.007	0.003	0.005	0.022	0.003	0.008	0.800

Source: own processing

Table 2: Statistical properties of used variables.

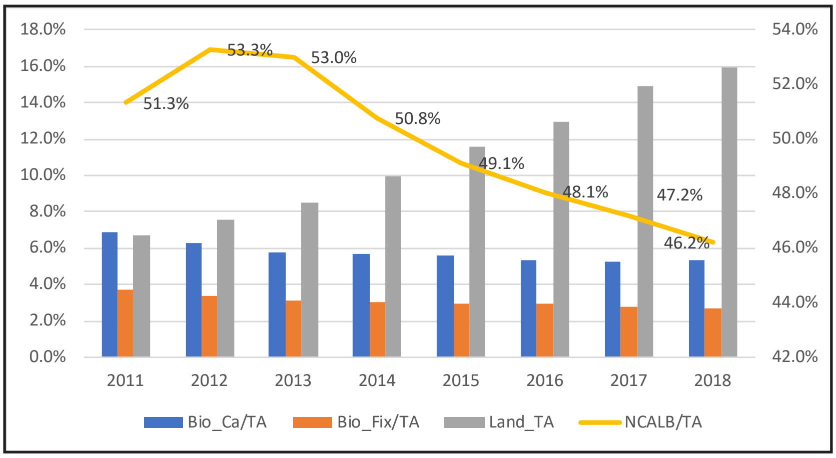
for public transfers level) that slightly less than half of profitability drop is driven by unfavourable market conditions such as uneven margin distribution within the agro-food supply chain (for further detail please see Toušek et al., 2021) and remaining part counts for public aid support level decrease. Regardless of similar trend development, there are differences in magnitudes between selected sub-segments. Where lower subsegment (L) is achieving lower profitability (both ROA and ROA_2) compared to upper subsegment (U), which is higher app. by +28.4 % (average value) for ROA. By comparing development of profitability variables across subsegments it seems that ROA gap (L subsegment lower by app. 46.6 % in average) is narrowed when considering ROA_2 characteristic suggesting higher level of subsidies favouring lower subsegment firms.

To gain further inside into the biological capital tangibility with respect to agricultural firms' size, underlying data set was divided into two subgroups (Lower and Upper) based on the actual firms' performance in the last year of observation (2019). Where median value of turnover adjusted by other operating income (added) was used as a criterion. Thus Upper (U) subsegment represents firms with performance over the median value and Lower (L) stands for remaining part of firms.

Analytic evidence is showing that agricultural firms predominantly prefer long-term financing to short-term financing (in average appr. 3x higher long-term than short-term leverage), regardless relative dramatic increase of working capital leverage (appr. +63.2 % but starting from the significantly lower base) to slightly modest expansion of long-term leverage (app. +5.5 %). With respect to the subsegments' indebtedness ratios (average values) followed similar path of increase namely short-term leverage expanded by app. +53.9 % and appr. +77.8 % for lower and upper subsegment respectively. In the case of long-term leverage diverse trends can be tracked, lower subsegment experienced increase app. +11.9 % contrary to upper subsegment facing slight reduction app. by -0.6 %.

As can be seen from the Figure 1, fixed assets components' tangibility experienced different development. Average share of fixed biological assets as well as other fixed assets are similarly diminishing over the time achieving reduction by -28.5 % and -11.3 % respectively. Contrary to it land tangibility has performed dramatic increase by +157.6 % causing the total fixed assets tangibility reinforcement regardless other fixed asset types opposite development.

Both fixed and current biological assets make up relatively small share of balance sheet (mean as well as median values correspond to the single digit value) contrary to other fixed assets tangibility (NCABL_TA) (excluding biological fixed assets and land to avoid double counting). The other fixed assets significantly outcompeted (by twentyfold times) biological fixed assets on the firms' balance sheet (+89.3 % in average over the respective period, whole sample). Also, from the biological assets (as a whole) perspective, firms' capital is predominantly tied up in biological current assets, which is in average (over the respective period) higher roughly by 89.2 %, thus counting for majority of the whole biological capital. Regarding trend development, biological assets



Source: Authors' own elaboration

Figure 1: Asset tangibility comparison (average annual values).

tangibility is decreasing with more progressive decline in the case of fixed biological assets (-28 %) and biological current assets follow similar path with milder magnitude (-23 %). The analyses revealed that smaller firms (subsegment L) tend to face higher biological assets tangibility compared to bigger ones (subsegment U), in average (over the respective period) both biological fixed and current assets tangibility are higher by appr. 24.2 % and appr. 19.9 % respectively. Also, in the case of land tangibility smaller firms outperformed bigger ones on average by +9.8 %. Opposite situation is in the other fixed capital tangibility (NCABL_TA), where smaller agricultural firms (subsegment L) are achieving lower tangibility ratio in average (over the respective period) by appr. -6.8 % regardless similar trend development. Both subsegments are experiencing comparable dynamics in biological asset tangibility decline (over the respective period), but different in its magnitude. Fixed bio assets tangibility is jointly reduced more significantly by appr. -30.5 % and appr. -25.9 % for lower and upper subsegment respectively compared to the current biological assets, where same trend, but of milder reduction occurred by appr. – 24 % and appr. -22 % for lower and upper subsegment respectively. Opposite dynamics is observed for land, where the land tangibility for smaller firms increased significantly by + 138.6 % and for bigger ones by + 181 %.

The standard panel data analysis was used to explore effect of bio assets on company’s balance sheet on its performance as well as cost of external financing. For the former, the following model was estimated:

$$\begin{aligned} ROA_{it} &= Bio\_Fix\_TA_{it} + Bio\_Ca\_TA_{it} + \\ &+ LAND\_TA_{it} + NCABL\_TA_{it} + STBL\_TA_{it} + \\ &+ LTBL\_TA_{it} + GDP_t + CPI_t + 3MPRIBOR_t + \\ &+ \upsilon_i + \varepsilon_{it} \end{aligned} \quad (1)$$

where *ROA* refers to return on assets, B*io_Fix_TA* refers to share of fixed bio assets on total assets, *Bio_Ca_Ta* represents share of current bio assets (namely animals) on total assets, *LAND_TA* represents share of land on total assets and *NCABL_TA* represents other than total fixed assets tangibility approximated by share of non-current assets on total balance sheet (excluding biological fixed assets and land). Also leverage-related variables (namely short-term bank loans to assets and long-term bank loans to assets) were included which were found to have negative impact on company’s performance (Toušek et al., 2021). Multiple macroeconomic controls variables were also included such as GDP growth (*GDP*), inflation (*CPI*) and 3-month Prague interbank offered rate (*PRIBOR*). The error term includes a company-specific (υ) and a disturbance term (ε).

Due to specifics of agro sector in relation to public subsidies two alternatives of the dependent variable (*ROA*) were inspected. Under Czech accounting regulations, public subsidies which usually represent an instrumental part of profits in agro sector, are booked as other operating income. On one hand, subsidies tend to distort operating efficiency measures, but on the other they form essential source of cash reflected in bank assessments, etc. Therefore, the ROA’s nominator as EBIT excluding and including other operating income as *ROA* and *ROA_2* was defined, respectively.

Further, the relationship between share of bio assets on company's balance sheet and cost of its debt were explored. Thus, the following model was estimated:

$$IR_{it} = Bio\_Fix\_TA_{it} + Bio\_Ca\_TA_{it} + LAND\_TA_{it} + NCABL\_TA_{it} + ROAit + STBL\_TA_{it} + LTBL\_TA_{it} + GDP_t + CPI_t + 3MPRIBOR_t + \upsilon_i + \varepsilon_{it} \quad (2)$$

where *IR* refers to cost of debt in terms of interest rate calculated as interest expense over total bank loans on balance sheet. Remaining variables have the same meaning as in the previous model. Also here, the effect of performance measured by return on assets in two modifications – including and excluding other operating income (represented mainly by subsidies) was inspected.

The standard procedures for selection of the appropriate estimation method based on panel dataset were performed. In our dataset the evidence of presence of fixed individual effects as F-test based on results of pooled ordinary least squares and fixed effects estimation yields p-value lower than 0.001 was found. Further, the consistency of random effects and fixed effects estimation using Hausman test was inspected. As zero hypothesis was rejected at p-value < 0.001, random effects estimation might generate inconsistent estimates and thus the individual fixed effects ordinary least squares were employed. In general, fixed effects models account for individual-specific characteristics by introducing a fixed effect (dummy variable) for each cross-sectional unit in the dataset, such as companies in Agro sector in our case. These fixed effects capture time-invariant heterogeneity, allowing to control for unobserved individual differences, making them useful for addressing endogeneity and omitted variable bias. However, fixed effects models alone do not explicitly address for example cross-sectional dependence, arising from correlations or interdependencies between these individual units over time. In panel data, especially when dealing with a small time dimension and a large cross-sectional dimension (which is our case), the error terms may exhibit correlation within individual units or clusters (cross-sectional dependence) and non-constant variance over time, which was also detected in our analysis (based on Pesaran CD test for cross-sectional dependance). As panel-corrected standard errors (PCSE) introduced by Beck and Katz (1995) provides a way to adjust the standard errors to accommodate these issues, we apply these in our final analysis (in all cases).

Finally, the potential multicollinearity among variables was tested using variation inflation factor (VIF) test on the pooled model. In the case of all variables VIF values remained safely below 3 being considered in the literature to be a conservative rule-of-thumb threshold implying no strong correlation among explanatory variables (maximum VIF value 1.82).

Results and discussion

This section sets forth estimation results of the models specified above using R statistical software. First, the attention was focused on determinants of agricultural firm's performance taking into consideration impacts of public subsidies often transforming operating loss to profit. Also a closer look was taken on how the situation changes if the distinction on the smaller and the larger companies in the sample was considered. Second, the hypothesis that cost of debt of agricultural companies might be impacted by bio assets tangibility (i.e., share of biological assets on company's balance sheet) was explored. This section concludes with final discussion of robustness of the results and potential limitations.

Effect of biological assets tangibility on agricultural firm´s profitability

Table 3 summarizes determinants of return on assets excluding other operating income largely represented by subsidies in agricultural sector. In entire sample was found significantly (with at least 95 % confidence) that fixed biological assets (i.e., mainly breeding livestock and perennials) tangibility has a negative impact on company's operating performance caused by overall total fixed assets tangibility increase similar to empirical finding of Boadi, Antwi and Lartey (2013), Pratheepan (2014) and Vintila and Nenu (2015), etc. Other tangibility-related variables remain silent in case of full sample as observed alternatively also by other authors, such as Kotsina and Hazak (2012), Okwo et al. (2012), and Derbali (2014). Interestingly, was found significantly positive impact of long-term leverage on agricultural companies operating performance. Finally, macro control variables indicate that companies in data sample exhibit rather countercyclical patterns in their return on assets. It seems that applied public aid policies behaved as a "safety net" in the form of economic transfers independent on the national economy development. Alternatively, profitability measures of agricultural production (essential food production) are not primarily driven by general economic development (GDP), but rather other forces such as agro-food supply chain organization (internal margin redistribution) and inflationary pressure (captured by CPI) etc. Since leverage ratios are (both short/long-term) increasing over the time than associated financial burden (interest paid) out of which essential part is price of money (3M PRIBOR) lead to negative sign.

Determinants	All	Lower	Upper
Bio.Fix.TA	**-0.429 ***	**-0.405 °**	-0.235
	(0.191)	(0.245)	(0.371)
Bio.Ca.TA	-0.054	-0.127	**0.429 ***
	(0.110)	(0.146)	(0.186)
LAND_TA	-0.052	0.037	**-0.173 ****
	(0.044)	(0.065)	(0.056)
NCALB_TA	0.001	0.050	**-0.097 ***
	(0.034)	(0.050)	(0.044)
STBL_TA	-0.014	-0.031	0.057
	(0.045)	(0.071)	(0.052)
LTBL_TA	**0.079 ****	0.059	**0.139 *****
	(0.025)	(0.039)	(0.034)
GDP	**-0.360 *****	**-0.399 *****	-0.265 **
	(0.070)	(0.115)	(0.083)
CPI	**0.299 ***	-0.066	**0.671 *****
	(0.127)	(0.199)	(0.152)
X3MPRIBOR	**-0.358 °**	-0.281	-0.311
	(0.188)	(0.305)	(0.214)
Adjusted R2	68.6 %	68.1 %	55.4 %

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ° $p < 0.1$
Source: Authors' own elaboration

Table 3: Determinants of return on assets (excluding other operating income).

Looking closer at the smaller 50% of the sample, can be observed slightly weaker evidence of negative impact of fixed biological assets tangibility on ROA. Apart from strongly negative impact of GDP control variable, the remaining explanatory variables remain silent with respect to their significance. As expected, more is revealed in case of larger companies. Contrary to all sample and lower sub-sample result, was found significantly positive impact of young animals' tangibility on operating performance in case of larger companies and on the other hand no significance of the fixed biological assets tangibility. However, negative effect of fixed assets tangibility in general was detected. Unsurprisingly, stronger positive impact of long-term leverage was found as compared to the all-sample result suggesting that despite very similar long-term leverage in both subsamples, larger companies probably use the leverage for more value-accretive investments. The assumption of non-linear (e.g., the inverse "U" shape form) relationship between operating performance and leverage observed by Vithessonthi and Tongurai (2015) and Coricelli et al. (2012) etc. was not confirmed in the underlying sample. Therefore, other forces such as public state support in the form of interest rate subsidies (compensation of interest paid on granted senior bank lending to buy selected non-biological assets) could play the key role is the forming of this relationship. As far as macroeconomic variables are concerned, the results in case of larger companies are similar to all-sample results except for consumer prices inflation where larger companies are more successful in reflecting inflation to output prices and at the same time limiting these impacts on cost side.

Further, intention was to demonstrate how the inclusion of other operating income distorts return on assets as a measure of company's operating efficiency. As subsidies in agricultural sector are partly related to biological assets deployed on firm's business, a potential reverse causality issue was mitigated by including lagged variables related to biological assets tangibility. Estimation results are set forth in Table 4.

Determinants	All	Lower	Upper
Bio.Fix.TA	0.055	0.109	-0.134
	(0.132)	(0.178)	(0.228)
Bio.Ca.TA	-0.101	-0.098	-0.012
	(0.073)	(0.101)	(0.116)
LAND_TA	**-0.060 °**	-0.043	**-0.107 ****
	(0.032)	(0.049)	(0.037)
NCALB_TA	**-0.124 *****	**-0.128 *****	**-0.115 *****
	(0.023)	(0.037)	(0.027)
STBL_TA	**-0.085 ***	**-0.117 ***	-0.028
	(0.034)	(0.054)	(0.036)
LTBL_TA	-0.009	0.023	**-0.043 °**
	(0.019)	(0.030)	(0.022)
GDP	**-0.372 *****	**-0.533 *****	**-0.204 *****
	(0.058)	(0.102)	(0.053)
CPI	**-0.231 ***	**-0.444 ****	-0.007
	(0.096)	(0.154)	(0.110)
X3MPRIBOR	**-0.427 ***	-0.318	*-0.459 **
	(0.184)	(0.305)	(0.201)
Adjusted R2	34.8 %	32.7 %	40.7 %

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ° $p < 0.1$
Source: Authors' own elaboration

Table 4: Determinants of return on assets (including other operating income).

It was detected that both variables related to biological asset tangibility are insignificant for operating performance once other operating income to the returns was included, which is in line with nature of these subsidies. Consistently across all subsamples negative impact of general fixed assets tangibility was found which is also not surprising as these do not have an immediate compensating element in other operating income as in the case of biological assets. In contrast to the former analysis excluding subsidies from ROA, negative impact of short-term leverage for all and lower subsample and of long-term leverage in case of larger companies was found. Again, negative impact of GDP growth was confirmed. However, in case of inflation a negative impact of CPI in case of all sample and smaller companies' subsample was detected. This could be attributable to non-indexed nature of subsidies and lower market strength of smaller companies to translate general price increases to their output prices. This is also in line with the fact that CPI was detected insignificant in case of larger companies which are supposedly more successful in passing on the inflation to their customers as suggested by results of the former analysis (see Table 3).

As a robustness check lagged variables were included also in the case for the model explaining ROA excluding other operating income. The results for all sample are summarized in Table 5.

Determinants	All	Excluding OOI	Including OOI
Bio.Fix.TA	0.055	-0.336 °	0.055
	(0.132)	(0.177)	(0.132)
Bio.Ca.TA	-0.101	0.171 °	-0.101
	(0.073)	(0.098)	(0.073)
LAND_TA	**-0.060 °**	0.115 **	**-0.060 °**
	(0.032)	(0.042)	(0.032)
NCALB_TA	**-0.124 *****	**0.032**	**-0.124 *****
	(0.023)	(0.030)	(0.023)
STBL_TA	**-0.085 ***	**0.038**	-0.085 *
	(0.034)	(0.045)	(0.034)
LTBL_TA	-0.009	0.105 ***	**-0.009**
	(0.019)	(0.026)	(0.019)
GDP	**-0.372 *****	**-0.366 *****	**-0.372 *****
	(0.058)	(0.069)	(0.058)
CPI	**-0.231 ***	**0.408 ****	-0.231 *
	(0.096)	(0.129)	(0.096)
X3MPRIBOR	**-0.427 ***	-1.016 ***	*-0.427 **
	(0.184)	(0.217)	(0.184)
Adjusted R2	34.8 %	71.3 %	34.8 %

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ° $p < 0.1$
Source: Authors' own elaboration

Table 5. Determinants of return on assets in relation to subsidies.

The findings still hold (except for significance level of biological fixed assets tangibility decreasing to 90%) even with lagged variables employed suggesting that the reverse causality issue persists in case of ROA including subsidies only. Finally, it can be pointed out that goodness of fit in terms of adjusted R2 is dramatically lower as compared to the former analysis illustrating the necessity of controlling for subsidies when examining ROA as operating performance measure of agricultural companies.

Since majority of authors with respect to the biological assets focused their attention to the reporting techniques (differences caused by alternative accounting standards applications) and the related impact of disclosure of this information, there is rather limited source of literature regarding biological assets tangibility implication on agricultural firms' profitability. As showed the biological assets tangibility level (both fixed and current assets) influence the profitability in mixed way and is relatively small in its magnitudes. This may be caused by their relatively small share on the total balance sheet on agricultural firms (low tangibility). Which is even reduced by diminishing trend (in average app. -27.03% and -23.19% over period for fixed and current biological assets, respectively).

Alternatively, the insufficient differentiation of agricultural activities by Czech accounting legislation may result in the omission of critical aspects of biological transformation. Consequently, this may hinder the accurate reflection of associated economic benefits in the financial statements of agricultural entities (Hinke and Stárová, 2014).

Surprisingly biological assets (both fixed and current) as irreplaceable production factors play insignificant role in profitability formation under scenario with subsidies paid out. Contrary to it under alternative scenario (no subsidies considered) biological asset tangibility become significant profitability driver (but relatively low significance). With negative relationship to the profitability in the case of fixed biological assets tangibility suggesting that relatively high associated costs/investments and relatively long depreciation period ties up significant level of firms' own capital. It is assumed that possibility of external debts financing (such as bank loans) is rather limited due to its natural character (meaning higher vulnerability and inconvenience as a stable collateral). A limited positive relationship to profitability is observed for current biological assets tangibility (only for upper sub-segment). Therefore, proposed hypothesis 1 shall be rejected.

As empirical evidence revealed, the biological assets tangibility (both fixed and current assets) is higher rather for smaller firms (lower sub-segment) than for bigger ones (upper sub-segment). Please see text above. Also, based on the calculations there are no clear records proving that bigger firms' profitability (upper sub-segment) is more significantly driven by biological assets tangibility than smaller ones (lower sub-segment). Only one parameter (current biological assets tangibility) seems to be significant for bigger firms under scenario without subsidies paid out. Therefore, the hypothesis 2 shall be also rejected.

Effect of biological assets tangibility on agricultural firm´s cost of debt

Also, the issue whether biological assets tangibility do have any impact on company's cost of debt was explored. Interestingly, there is no evidence of biological nor fixed assets in general tangibility having an effect on cost of debt. Unsurprisingly, negative impacts of both short- and long-term leverage with comparable effects in term of size and significance across all (sub)samples were observed.

Determinants	All	Lower	Upper
Bio.Fix.TA	0.158	0.059	-0.352
	(0.192)	(0.150)	(0.433)
Bio.Ca.TA	-0.022	0.028	-0.064
	(0.099)	(0.090)	(0.235)
LAND_TA	0.030	-0.003	0.053
	(0.041)	(0.039)	(0.059)
NCALB_TA	0.018	0.038	**0.095 °**
	(0.034)	(0.031)	(0.053)
ROA	-0.026	-0.041	0.043
	(0.031)	(0.027)	(0.055)
STBL_TA	**-0.246 *****	**-0.228 *****	**-0.264 *****
	(0.044)	(0.044)	(0.068)
LTBL_TA	**-0.171 *****	**-0.185 *****	**-0.190 *****
	(0.025)	(0.024)	(0.043)
GDP	**-0.184 °**	**-0.332 *****	-0.099
	(0.095)	(0.063)	(0.122)
CPI	0.122	-0.023	-0.039
	(0.149)	(0.135)	(0.138)
X3MPRIBOR	**-0.581 ***	-0.106	-0.634
	(0.262)	(0.172)	(0.430)
Adjusted R2	37.5 %	40.2 %	41.4 %

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ° $p < 0.1$
Source: Authors' own elaboration

Table 6. Determinants of cost of debt (controlling for ROA excluding other operating income).

As mentioned above, the biological assets tangibility has no significant influence on the cost of debt. Suggesting that external debt providers (typically banks) do not consider biological assets (especially fixed biological assets) as relevant tangible assets for loan collateralization, thus promoting lower applied interest rates and potentially increase in leverage itself. Also, other fixed assets type tangibility seems not to influence cost of debt (exception of NCALB_TA in upper sub-segment). Our finding does not support the conclusions of other authors, such as Lyandres and Palazzo (2016), who posited that firms with relatively high asset tangibility generally tend to have lower external financing costs. Conversely, firms with relatively fewer tangible assets are more likely to face difficulties in raising external capital and may be financially constrained, thereby missing investment opportunities (Almeida and Campello, 2007).

Simultaneously, it seems that both profitability measures (ROA and ROA_2) are not influencing the overall cost of debt significantly. Alternative scenario for ROA_2 (with exception of whole data set) shows no significance as well as. It is leading to conclusion that public aid policies have rather limit (if any) direct impact on the cost of debt (with exception of direct interest rate subsidies program). Interestingly, both leverages are having negative sign (caused by interest rate decline over the respective period with exception of two last years). In contrast to other authors, such as Kiyotaki (2011) and Bernanke, Gertler and Gilchrist (1999), who demonstrated that an increase in corporate leverage results in higher costs of external financing due to elevated default probabilities, which can ultimately result in a significant economic slowdown. Short-term leverage had stronger impact (expressed in the parameter magnitude) contrary to the long-term leverage probably due to the associated interest rate subsidies (public compensation scheme for paid interest margin associated with selected non-biological assets' purchases) and relatively low mortgage rates associated with agricultural land purchase (applied mortgage interest rates are typically significantly lower compared to "conventional" long-term loans' rates). Therefore, the hypothesis 3 must be rejected.

Conclusion

The aim of this paper was to elaborate on potential importance of biological assets tangibility (both fixed and current) including land from profitability and the cost of debt generation point of view due to relative scarcity of this topic coverage. The analysis revealed that biological assets tangibility is relatively low with declining trend for both sub-segments and almost twentyfold compared to NCABL_TA regardless their irreplaceable character in production process. Contrary to it land tangibility experienced exactly opposite development caused by "skyrocket" land price appreciation. Nevertheless, it showed that biological assets (including land) tangibility regardless their development influence profitability in the mixed way from sub-segments as well as their lifetime expectancy point of view.

Alternative models for different profitability distinguishing existence of public policies in the form of subsidies are suggesting market distortion leading to "non-market" behaviours under the necessity of the subsidy's conditions alignment from producer point of view (ROA negative and ROA_2 positive average figures). Thus, commonly expected economic rules (under the free market assumptions) are not in the place. Obtained findings are suggesting that public aid policies served rather as a "safety net" for agricultural firms to compensate insufficient profitability generation (in the most cases) than promoter of unbiased free market behaviours.

It seems that cost of debt is depending only on the short/long-term leverage levels, thus primarily the total indebtedness is essential and relevant driving force. Which may be also influenced either by public aid (interest margin paid compensation) and type of debt instruments employed (mortgage loan typically having lower interest rate compared to "conventional" long-term loans). Surprisingly profitability (ROA) itself is not significant variable (contrary to other sectors) suggesting that subsidies level (OOI) is other driving force. Interestingly, fixed assets tangibility both non/biological ones do not contribute to the cost of debt level (not significant parameters) as potential instruments of collateralization promoting lower applied interest rates (due to higher security level for external debt provider).

Regional scope limited to the Czech Republic caused by the necessity of the completeness and the consistency of underlying data may be viewed as a limitation. Also, certain level and structure of public aid policies (subsidies) uniqueness on the national level shall be distinguished and acknowledged. Nevertheless, obtained findings can be applicable to other countries in broader sense.

Acknowledgments

We would like to thank to Česká spořitelna, a.s. for its support and making the sample of its internal client database available for this research. This paper and conclusions present solely authors´ opinions and they do not present any official statement of Česká spořitelna, a.s.

Corresponding author:
Doc. Ing. Jana Hinke, Ph.D.
Department of Trade and Finance, Faculty of Economics and Management
Czech University of Life Sciences Prague, Kamýcká 129, 165 00 Praha – Suchdol, Czech Republic
Phone: +420 737 160 037, E-mail: hinke@pef.czu.cz

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Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

Economic Analysis of Grain Product Metrics

Valentin Uteulin[1], Gulnar Lukhmanova[2], Olessya Lemechshenko[2], Kulzhamal Bleutayeva[2], Baglan Murzabekova[3]

[1] Akhmet Baitursynuly Kostanay Regional University, Republic of Kazakhstan

[2] Zhetysu University named after I. Zhansugurov, Taldykorgan, Republic of Kazakhstan

[3] Almaty Technological University, Republic of Kazakhstan

Abstract

The study aims to analyse the key factors affecting grain production in Kazakhstan to develop recommendations for improving the efficiency and sustainability of the agricultural sector. Statistical methods and econometric modelling techniques were used, including the least squares method with heteroscedasticity and autocorrelation robust errors and autoregression with external factors for time series analysis. These methods were used to estimate the impact of various internal and external factors on the gross grain harvest. The analysis demonstrated that grain yields depend on a variety of factors, such as innovations in agricultural technology, climatic conditions and economic policy. The identified factors were grouped with measurable indicators for each, which became the basis for building models. The study determined that the autoregressive model is more suitable for describing the impact on the dependent variable – grain harvest. The most influential indicators are yields and research and development costs. The results of the study can be used to adjust agricultural policy and strategies for agricultural development in Kazakhstan. Proposals for optimising land use and integrating modern agricultural technologies will increase productivity and reduce the impact of negative factors.

Keywords

Yield, sown area, gross harvest, fertiliser, multiple regression model, food security.

Uteulin, V., Lukhmanova, G., Lemechshenko, O., Bleutayeva, K. and Murzabekova, B. (2025) "Economic Analysis of Grain Product Metrics", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 109-123. ISSN 1804-1930. DOI 10.7160/aol.2025.170208.

Introduction

In recent years, the issues of food security and sustainability in the agricultural sector have gained increased significance at both national and global levels, particularly in emerging economies where agriculture plays a critical role in economic and social development. This is especially true for the Republic of Kazakhstan, which possesses substantial potential for increasing the production and export of grain crops, thereby strengthening its economy and enhancing its position in the global market. However, a noticeable knowledge gap exists regarding the specific economic indicators and factors influencing grain production efficiency within the country (Marmul et al., 2020; Serhiienko et al., 2023). As global climate change continues to pose challenges, there is an urgent need to develop adaptive agricultural strategies that mitigate risks and minimize yield losses, particularly concerning grain production. Furthermore, global economic trends, such as food price volatility and changing trade regulations, necessitate that Kazakhstan adopt flexible and innovative approaches to agricultural production (Lukhmanova et al., 2019a). Despite existing resources, the grain sector faces numerous challenges, including yield fluctuations and technological inadequacies (Kalenska, 2022).

Baidybekova et al. (2022) examined the economic development of Kazakhstan's agricultural sector, asserting that food security is achieved through self-sufficiency in domestic food production, complemented by imports. Their analysis for 2017-2021 underscored the necessity of measures to enhance agricultural sector efficiency and sustainability. While Kazakhstan is a major supplier in the global grain market (Lukhmanova et al., 2019b), the industry encounters various challenges that necessitate comprehensive analysis and strategic solutions. Wang et al. (2021a) emphasized the role of grain exports in maintaining the global food balance and national food security, discussing the impacts of global factors, including

COVID-19, on food prices and Kazakhstani grain export potential.

The exploration of economic aspects related to grain production in Kazakhstan is particularly pertinent amidst the globalization of food markets and the climatic changes affecting agriculture. Although Kazakhstani agriculture is a fundamental element of the national economy, providing food security and significant export opportunities, it still faces challenges like yield variability and the necessity for technological advancement. Zhanaltay (2023) identified pressing issues within the agricultural sector through an analysis of national key indicators, noting significant progress but also unresolved challenges, such as low investment levels and outdated agricultural technologies. Furthermore, Namazova and Wei (2020) highlighted Kazakhstan's status as a producer and exporter of high-quality wheat, investigating the causes of issues such as low productivity and the adverse effects of weather on grain yields. Their findings stressed the need for reforms, investment attraction, and the application of advanced technologies to bolster productivity and competitiveness in the global grain market. Yuksel et al. (2023) evaluated the economic efficiency of Kazakhstan's agro-industrial complex using econometric tools to assess the industry's impact on economic development and public investment in agriculture.

The research seeks to address the current state of grain production in Kazakhstan by identifying key factors influencing its efficiency and proposing strategies to enhance competitiveness. It is crucial to understand the interplay of internal and external factors affecting crop production and distribution, as well as to explore innovative solutions that can be implemented to improve the situation. While existing studies on the economics of grain production in various countries cover a range of topics, including sustainability and global economic impacts, Kazakhstan's unique natural and economic conditions necessitate a targeted analysis that incorporates both local specifics and broader challenges. This study aims to fill that gap by providing a comprehensive analysis of the key factors affecting grain production in Kazakhstan.

Materials and methods

In this study, two econometric models were employed to analyze grain production indicators in Kazakhstan. The selection of the Least Squares Regression (LSR) and Autoregressive Moving Average with Exogenous Variables (ARMAX) models was driven by their suitability for analyzing grain production trends. LSR provides a straightforward assessment of relationships between variables, while ARMAX accounts for time dependencies and external influences, making it more robust for forecasting. Key variables were chosen based on their relevance to grain production: gross grain harvest, yields, R&D expenditures, precipitation, fertilizer consumption, and pesticide use. These indicators capture economic, environmental, and technological factors affecting agriculture. Limitations include LSR's assumption of linearity and independence, which may not fully reflect real-world complexities, and ARMAX's requirement for stationarity, necessitating data transformations. Additionally, data constraints and the exclusion of some relevant factors, such as soil quality and extreme weather events, may impact results. Alternative approaches could include panel data models to account for regional variations or machine learning techniques to capture nonlinear interactions. Structural equation modeling might offer insights into causal relationships, while Bayesian methods could provide probabilistic forecasts. These approaches could enhance the robustness of future agricultural analyses.

Data for this analysis were collected from various reputable sources, including national agricultural statistics, government reports, and research publications. The dataset covered the period from 2004 to 2022, providing a comprehensive view of grain production trends in Kazakhstan. Key variables included the amount of arable land, grain yields, research and development costs, and environmental factors such as average annual precipitation and fertilizer consumption. Prior to analysis, the data underwent preprocessing to ensure quality and consistency. This involved handling missing values, normalizing data ranges, and conducting preliminary statistical tests to assess the suitability of the dataset for the chosen econometric models. The preprocessing steps were essential to eliminate noise and enhance the reliability of the model outcomes, thus allowing for a more accurate interpretation of the factors affecting grain production in the Republic of Kazakhstan.

The modelling used indicators reflecting the dynamics of environmental indicators of environmental monitoring and assessment, statistics on agriculture, forestry, hunting and fishing for 2004-2022. according to the Bureau of National

Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a; 2024b):

- gross harvest of cereals, including rice, and legumes (in weight after cultivation);
- yields of cereals, including rice, and pulses;
- internal expenditures on research and development (R&D) by industry (agricultural sciences);
- average annual rainfall;
- volume of mineral fertiliser consumption per unit of sown area of agricultural land;
- consumption of organic fertilisers per unit of sown area of agricultural land;
- pesticide consumption per unit area of agricultural land.

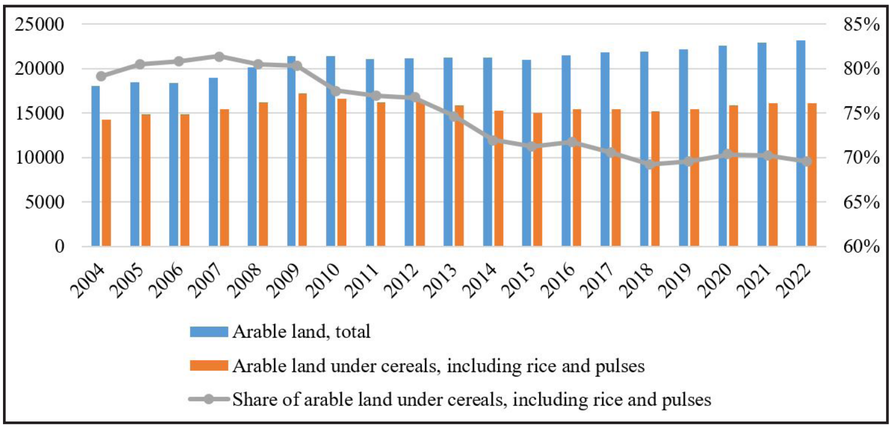
The limitation of the empirical data used for the modelling to 2022 is due to the lack of publicly available information on the values of environmental indicators of environmental monitoring and assessment. The complex methods employed in the study were used to form a sequence of actions necessary for the economic analysis of grain production indicators and to justify the expediency of choosing a model to explain the observed changes and forecasting.

Results and discussion

Assessment of individual indicators and grouping of factors affecting grain production in the Republic of Kazakhstan

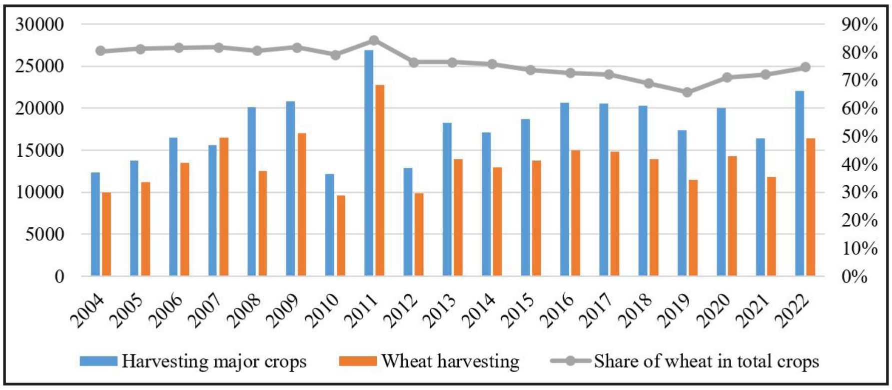
The economic analysis of grain production indicators involves the assessment of key indicators related to the amount of arable land, including both the total amount and the share of land under grain crops, which is important for studying the potential for grain production. The results of the analysis for 2004-2022 are shown in Figure 1.

The data shown in Figure 1 demonstrates that during 2004-2022, the share of arable land for grain in the total volume of grain production decreased by 9.59%. Figure 2 shows the growth rates of the harvest of major crops, including wheat, for 2004-2022, which was used to assess



Source: compiled by the authors based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a)

Figure 1: Ratio of arable land under grain to total arable land in the Republic of Kazakhstan.



Source: compiled by the authors based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a)

Figure 2: The ratio of wheat harvested to total crops harvested in the Republic of Kazakhstan.

the dynamics and efficiency of the agricultural sector of the Republic of Kazakhstan in the context of changing internal and external conditions.

According to the data presented, the share of wheat in the total crop harvest in the period from 2004 to 2022 ranged from 65.71% (in 2019) to 84.32% (in 2011). The information provided will form the basis for further analysis, where the interrelationships between the identified factors and grain production results will be assessed using modelling. This will not only determine the current state of the industry but also formulate reasonable proposals for optimisation and development. Table 1 shows the growth rates of indicators reflecting changes in the amount of arable land, harvested volume of major crops and wheat.

The dynamics of changes in the indicators characterising the volume of arable land compared to the base year 2004 shows an increase of 28.42% and 12.86% (for all arable land and arable land under grain, respectively). Every year during 2004-2022, the growth was positive compared to the base. At the same time, the total amount of arable land decreased in 2006, 2011, 2014 and 2015 (provided that the previous year was used as a comparison base), while for arable land metrics for grain, these years were 2006, 2010-2011, 2013-2015 and 2018. Thus, it is possible to draw an interim conclusion that the increase in arable land for grain, with the total growth from 14278 million hectares to 16114.4 million hectares, was 12.86%, which is significantly less than the change in arable land – 28.42%. Assessing the growth rates of the metrics reflecting the harvest of the main types of agricultural products and wheat harvest, significant fluctuations were noted. At the same time, in 2014, there was a decrease in metrics characterising both the size of arable land and the volume of harvested crops, which may indicate the presence of a correlation between the aforementioned indicators. The most significant changes in the growth rates of indicators characterising harvesting in general for the main types of agricultural products and for wheat were in 2008, 2010 and 2012. The absence of significant changes in the volume of cultivated land in these years suggests the need to address factors that have influenced the deterioration in overall performance. The economic analysis of grain product indicators was used to identify factors that affect the gross grain harvest, yields

Year	Growth rate of total arable land		The growth rate of arable land under cereals, including rice and pulses		Growth rate of harvest of major crops		Growth rate of wheat harvest	
	The chain method	Baseline method (2004 base)	The chain method	Baseline method (2004 base)	The chain method	Baseline method (2004 base)	The chain method	Baseline method (2004 base)
2005	102.27	102.27	103.95	103.95	111.37	111.37	112.69	112.69
2006	99.59	101.84	99.99	103.93	119.81	133.43	120.20	135.46
2007	103.19	105.09	103.96	108.05	121.96	162.74	122.33	165.71
2008	106.14	111.55	104.94	113.39	77.36	125.89	76.14	126.18
2009	106.49	118.79	106.28	120.51	133.72	168.34	136	171.60
2010	100.06	118.86	96.58	116.40	58.50	98.47	56.52	97
2011	98.34	116.89	97.59	113.60	221.26	217.88	235.85	228.76
2012	100.51	117.49	100.23	113.86	47.72	103.96	43.29	99.03
2013	100.38	117.93	97.67	111.20	141.71	147.33	141.66	140.29
2014	99.88	117.79	96.31	107.10	94.14	138.69	93.23	130.79
2015	98.96	116.56	97.98	104.93	108.80	150.90	105.77	138.34
2016	102.14	119.06	102.81	107.88	110.51	166.75	109.01	150.80
2017	101.71	121.09	100.01	107.90	99.76	166.35	98.78	148.97
2018	100.27	121.42	98.34	106.11	98.49	163.84	94.20	140.33
2019	101.08	122.73	101.63	107.83	85.97	140.85	82.13	115.24
2020	102.02	125.2	103.13	111.21	115.13	162.15	124.51	143.48
2021	101.52	127.11	101.45	112.82	81.61	132.34	82.86	118.89
2022	101.03	128.42	100.04	112.86	134.53	178.04	138.85	165.08

Source: compiled by the authors based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a)

Table 1: Results of the analysis of indicators reflecting changes in the amount of arable land, harvested volume of major crops and wheat, %.

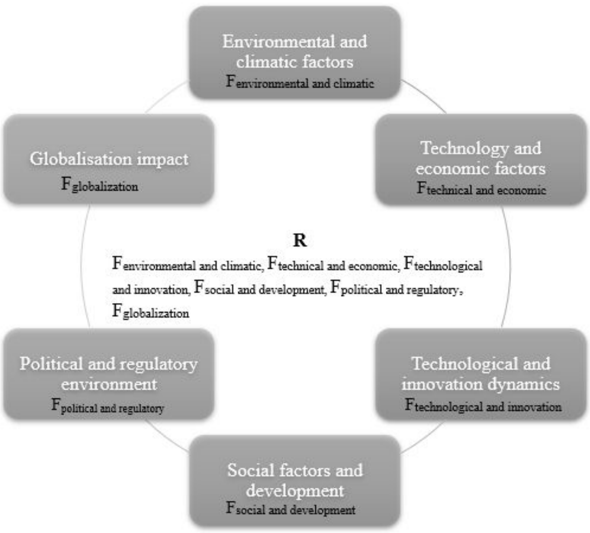
and other metrics. Table 2 summarises the groups of factors that are most relevant in the analysis of grain product performance. Notably, the list of factors and indicators can be expanded depending on the research objectives, but the presented grouping of factors provided a comprehensive image of the need to address a wide range of indicators for the parameter being assessed.

Table 2 provides a clearer picture of the measurable indicators associated with each factor, facilitating a more accurate quantitative analysis of their impact on grain production in Kazakhstan. It can be used as a basis for the development of econometric models that will allow for analysis, forecasting results and justification of policy decisions by including specific measurable variables. The interrelation of factors affecting grain production in Kazakhstan is shown in Figure 3,

Group of factors	Factor	Indicator	Unit of measurement
Environmental and climatic factors	Temperature fluctuations	Average annual temperature change	°C
	Precipitation	Average annual precipitation	mm
	Extreme weather events	Frequency of extreme weather events	Quantity/year
	Soil quality	Organic matter content	%
		Soil pH level	pH
		Degree of erosion	1000 ha
Technology and economic factors	Resource costs	Average cost of mineral fertilisers per hectare	Tenge/ha
		Average cost of organic fertilisers per hectare	Tenge/ha
	R&D investments	Domestic R&D expenses in the agricultural sciences	million tenge
Technological and innovation dynamics	New technologies	Percentage of land used for precision farming	%
	Innovations	Share of use of GM seeds	%
Social factors and development	Access to resources	Share of the population with access to education and healthcare services	%
Political and regulatory environment	Government support and subsidies	Amount of subsidies in the agricultural sector	million tenge
Globalisation impact	Global market trends	World grain/cereal price index	Index
	Currency fluctuations	National currency exchange rate against USD	Tenge/USD

Source: compiled by the authors

Table 2: Grouping of factors influencing the grain market of Kazakhstan.



Note: R – resultant indicator reflecting the dependence of grain production on a set of factors.
Source: compiled by the authors

Figure 3: Modelling logic of the external factor dependence of grain production.

including the dependence of the resulting indicator R for each of the groups shown in Table 2.

Following the objectives of the study, the identification of key productivity drivers and the development of recommendations for improving the efficiency of grain production in the Republic of Kazakhstan necessitates the construction of a model that, based on indicators reflecting the impact of previously identified factors, will allow to assess each of the parameters included in the model.

Modelling as a tool for analysing grain product performance

In the process of studying the indicators of grain products of the Republic of Kazakhstan, modelling allows not only to analyse current data and time series but also to predict future changes and assess the impact of various factors on economic efficiency. In the context of grain production, the models identify key drivers affecting gross yields, analyse profitability and formulate strategies for sustainable development. Two models were built in this study:

1. LSR-error-based HAC, which addresses distortions in the data caused by heteroscedasticity and autocorrelation. This regression model provides a more accurate assessment of the impact of various variables on the dependent variable, gross grain harvest (Gross_harvest).
2. The ARMAX model, integrating both autoregressive and external variables, is a powerful tool for analysing time series in grain production. The use of this model is appropriate when analysing relationships in data where time dependencies and external influences have a significant impact on the resulting indicator.

The LSR model was built in Gretlusing observations for 2004-2022. (T=19) (Tables 3 and 4).

	Coefficient	Statistical error	z	p-value
const	-4823.19	10532.8	-0.4579	0.647
Productivity_of_grains	1683.42	39.4184	42.71	<0.0001***
Internal_R_D_costs_by_industry	0.0645573	0.0278887	2.315	0.0206**
Average_annual_precipitation	-0.400898	2.60307	-0.154	0.8776
Volume_of_consumption_of_mineral_fertilizers	37.7981	93.8673	0.4027	0.6872
Consumption_of_organic_fertilizers	-36.4074	41.6326	-0.8745	0.3818
Consumption_of_pesticides	-161.773	1429.04	-0.1132	0.9099
Combined_water_and_wind_erosion	14.8686	54.2984	0.2738	0.7842

Source: compiled by the authors using the Gretltoolkit based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a; 2024b)

Table 3: Results of the LSR regression model for the analysis of grain harvest in the Republic of Kazakhstan.

Indicator	Value
Average dependant Variable	18035.98
Square sum Remainder	8345247
R-square	0.967149
F (7.11)	438.2468
Log Plausibility	-150.3911
Crit. of Schwartz	324.3377
Parameter rho	0.55927
Statistical Deviation of Dependent Variable	3756.712
Statistical Model Error	871.0102
Correction R-square	0.946244
P-value (F)	1.46e-12
Crit. Akaike	316.7822
Crit. Hannan-Quinn	318.0609
Statistical Durbin-Watson	0.866984

Source: compiled by the authors using the Gretltoolkit based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a; 2024b)

Table 4: Statistical indicators and quality assessments of the LSR model.

According to Table 3, the constant is statistically insignificant (p>0.05), which indicates that when all independent variables are zero, the predicted value of the dependent variable Gross_harvest is not statistically different from zero. The variable Productivity_of_grains is statistically significant and has a positive effect on the variable Gross_harvest. Its increase by one unit will result in an increase in Gross_harvest by 1683.42 units. Research and development costs (Internal_R_D_costs_by_industry) also have a statistically significant positive impact on Gross_harvest. The remaining variables (Average_annual_precipitation, Volume_of_consumption_of_mineral_fertilisers, Consumption_of_organic_fertilisers, Consumption_of_pesticides, Combined_water_and_wind_erosion) are not statistically significant (p>0.05), which indicates that they have no statistically significant effect on Gross_harvest in this model. To conclude on the quality of the model, the next step is to conduct a heteroscedasticity assessment. The results of White's test for heteroscedasticity assessed whether the model has an uneven scatter of residuals depending on the values of the independent variables (Table 5). For this purpose, the squares of the residuals u2 are used as the dependent variable.

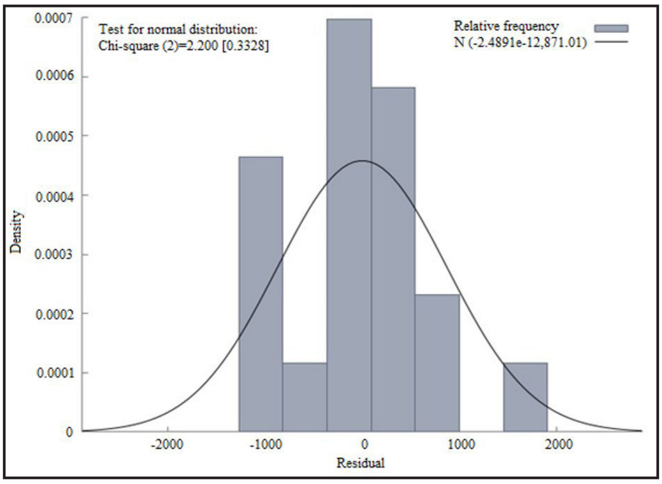
The test results show that the coefficients of all variables (initial and their squares) are not statistically significant (p>0.05). This indicates that there is no systematic change in the variance of the residuals depending on the values of these variables. The test statistic TR2 is 13.191, with a p-value of 0.511526 using a Chi-square distribution with 14 degrees of freedom. This p-value indicates that there is no reason to reject the null hypothesis of homoscedasticity (absence of heteroscedasticity). According to the results of the White test, it is possible to conclude that there is no significant evidence of heteroscedasticity in the model residuals. This is a good sign since heteroscedasticity can cause inefficient estimates of standard errors and, as a result, to incorrect conclusions about the statistical significance of the coefficients. Thus, it is possible to assume that the model adequately describes the data in terms of the stability of the variance of the residuals. The results of the assessment of the normality of the residual distribution are shown in Figure 4.

According to the data obtained, the average balance is close to 0 (-2.48914e-12), which is a positive characteristic of the model. The standard deviation is 871.01, which indicates the dispersion of the residuals relative to their mean. Most of the residuals are in the range of -360.14 to 546.16, with the main concentration around -133.57 to 319.59. This demonstrates that most residuals do not deviate significantly from the mean. The test of the normality of the residuals (using the Chi-square test) shows that the p-value is 0.33279, which is higher than the standard threshold

	Coefficient	Statistical error	t-statistics	p-value
const	-2.22167e+09	3.43572e+09	-0.6466	0.5531
Productivityofgr~	-2.37046e+06	3.40050e+06	-0.6971	0.5241
InternalR_Dcosts~	1028.27	1548.44	0.6641	0.543
Averageannualpre~	89965.5	65251.2	1.379	0.2401
Volumeofconsumpt~	-301346	1.00917e+06	-0.2986	0.7801
Consumptionoforg~	-64806.9	678707	-0.09549	0.9285
Consumptionofpes~	4.54158e+06	1.53192e+07	0.2965	0.7816
Combinedwaterand~	2.29489e+07	3.54306e+07	0.6477	0.5525
sq_Productivityo~	93488	136562	0.6846	0.5312
sq_InternalR_Dco~	-0.0490078	0.0712331	-0.6880	0.5293
sq_Averageannual~	-120.26	92.445	-1.301	0.2632
sq_Volumeofconsu~	38470.2	95190.2	0.4041	0.7068
sq_Consumptionof~	-559.956	23250.5	-0.02408	0.9819
sq_Consumptionof~	-2.74128e+06	1.34873e+07	-0.2032	0.8489
sq_Combinedwater~	-59316.7	90874.5	-0.6527	0.5495
Uncorrected R-squared = 0.694274				
Test statistics: TR^2 = 13.191209				
p-value = P (Chi-square (14) > 13.191209) = 0.511526				

Source: compiled by the authors using the Gretltoolkit

Table 5. Results of White's test for heteroscedasticity for the LSR model (dependent variable: u^2).



Source: compiled by the authors using the Gretltoolkit

Figure 4: Estimation of normality of residuals distribution in the LSR model.

	Coefficient	Statistical error	t-statistics	p-value
const	17743.2	8997.68	1.972	0.0769
Productivityofgr~	12.9488	72.5999	0.1784	0.862
InternalR_Dcosts~	-0.00368316	0.0657731	-0.056	0.9564
Averageannualpre~	6.48583	4.1302	1.57	0.1474
Volumeofconsumpt~	81.9098	187.659	0.4365	0.6718
Consumptionoforg~	-13.5675	62.1881	-0.2182	0.8317
Consumptionofpes~	2024.36	1859.95	1.088	0.302
Combinedwaterand~	-105.411	49.2402	-2.141	0.058
uhat_1	1.01001	0.280529	3.6	0.0048
Uncorrected R-squared = 0.564511				
Test statistics: LMF = 12.962714				
p-value = P (F(1.1) > 12.9627) = 0.00484				
Alternative statistics: TR^2 = 10.725717				
p-value = P (Chi-squared (1) > 10.7257) = 0.00106				
Ljung-Box Q' = 6.92461				
p-value = P (Chi-square (1) > 6.92461) = 0.0085				

Source: compiled by the authors using the Gretltoolkit

Table 6: Results of the Breusch-Godfrey test for first-order autocorrelation for the LSR model, using observations from 2004-2022 (T=19).

of 0.05. This means that there is no reason to reject the null hypothesis that the residuals are normally distributed. Consequently, it can be assumed that the residuals are normally distributed, which is an important prerequisite for statistical tests and confidence in the intervals in linear regression. To further analyse the quality of the model, the presence of autocorrelation was assessed since its presence can lead to a bias in the estimates of the standard errors of the coefficients, making statistical conclusions about them unreliable (Table 6 above). To detect the presence of autocorrelation in the model residuals, the Broich-Godfrey test was applied.

The analysis of the autocorrelation of the residuals using the Broich-Godfrey test was used to conclude that there is autocorrelation in the model residuals. This can be the result of dynamic dependencies not accounted for by the model or the presence of trends, seasonality or other time dependencies in the data. The presence of autocorrelation requires model adjustment, possibly by adding lags to the dependent variable or by using models specifically designed for time series. Moreover, the tests for heteroscedasticity and normality of the residuals showed that these problems were not present, which simplifies the process of modifying the model to account for autocorrelation only. Thus, the LSR model for analysing grain harvest shows that the main factors affecting the resulting indicator (Gross_harvest) are grain yields and research and development costs. To correct the shortcomings in the previous model (LSR with HAC errors) associated with the autocorrelation of the residuals, an ARMAX model was built in Gretlfor which observations from 2004-2022 were used. (T=19), the dependent variable is Gross_harvest, and the standard errors are calculated via Hessian (Tables 7-9).

The interpretation of the results suggests that the constant is not statistically significant (Tables 7 and 8). The autoregressive parameter (phi_1) shows that previous values of the variable have a positive impact on the current ones, albeit on the verge of statistical significance; the moving average parameter (theta_1) is a significant coefficient, indicating a strong influence of errors of the previous period on the current one. The Productivity_of_grains metric has a significant and positive coefficient, indicating that grain yields have a strong influence on Gross_harvest. Consumption_of_pesticides has a statistically significant coefficient, indicating a positive effect of pesticide consumption on Gross_ harvest. Model characteristics: the R-squared value indicates that the model explains almost 99% of the variability in the dependent variable, which is a good result. The corrected R-squared (0.980826) is also high, given the number of parameters in the model. The log plausibility ratio, and information content criteria (Akaike, Schwartz, Hannan-Quinn) help assess the quality of the model concerning the number of parameters;

	Coefficient	Statistical error	z	p-value
const	2191.68	7517.58	0.2915	0.7706
phi_1	0.410903	0.221361	1.856	0.0634
theta_1	1	0.162993	6.135	<0.0001
Productivity_of_grains	1700.14	35.4587	47.95	<0.0001
Internal_R_D_costs_by_industry	0.0322136	0.0700613	0.4598	0.6457
Average_annual_precipitation	2.41336	2.0585	1.172	0.241
Volume_of_consumption_of mineral_fertilizers	-19.409	76.2072	-0.2547	0.799
Consumption_of_organic_fertilizers	-38.6374	55.3344	-0.6983	0.485
Consumption_of_pesticides	2306.04	928.42	2.484	0.013
Combined_water_and_wind_erosion	-28.4238	38.4502	-0.7392	0.4598

Source: compiled by the authors using the Gretltoolkit based on Environmental Indicators of environmental monitoring and assessment (2024) and Statistics of agriculture, forestry, hunting and fishing (2024)

Table 7: ARMAX model results for analysing grain harvest in the Republic of Kazakhstan.

Indicator	Value
Average dependant Variable	18035.98
Square sum Remainder	8345247
R-square	0.967149
F (7.11)	438.2468
Log Plausibility	-150.3911
Crit. of Schwartz	324.3377
Parameter rho	0.55927
Statistical Deviation of Dependent Variable	3756.712
Statistical Model Error	871.0102
Correction R-square	0.946244
P-value (F)	1.46e-12
Crit. Akaike	316.7822
Crit. Hannan-Quinn	318.0609
Statistical Durbin-Watson	0.866984

Source: compiled by the authors using the Gretltoolkit based on Environmental Indicators of environmental monitoring and assessment (2024) and Statistics of agriculture, forestry, hunting and fishing (2024)

Table 8: Statistical indicators and quality assessments of the ARMAX model.

the lower the value, the better the model in terms of the balance between complexity and quality. Thus, the ARMAX model proved to be effective in explaining the change in Gross_harvest, with high R-squared values and significant coefficients for the key predictors. The analysis of the normality of the ARMAX model's error distribution shows that the P-value (0.852673) is significantly higher than 0.05, indicating that there are no grounds to reject the null hypothesis that the errors are normally distributed (Figure 5). This is an indication that the model residuals do not deviate from the normality assumption, which is important for the credibility of the results of statistical tests conducted on the model coefficients.

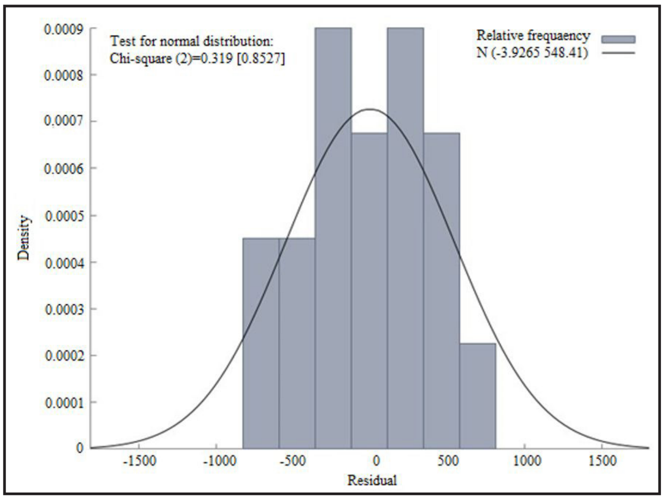
The distribution of the residuals shows a fairly symmetrical distribution around the mean value (-3.92649), with a relatively even distribution of frequencies across the intervals from the central part to the extreme values. Thus, the mean of the residuals is close to zero, which is typical for well-specified models. The standard deviation of the residuals (548.414) is moderate, indicating that the residuals are not significantly scattered around the mean. The shape of the distribution based on frequency analysis further confirms the conclusions of the normality test. An ARMAX model that is adequately specified in terms of the distribution of balances. The normal distribution of the residuals confirms that the model assumptions about the normality of the errors are met, which is relevant for estimating confidence intervals and performing other statistical tests. This suggests that the model can be used for reliable statistical inference and forecasting. The next step was to test for autocorrelation up to the order of 3 (Table 9).

Indicator	Value
Test statistics (Ljung-Box Q')	0.923505
Degrees of freedom	1
p-value	0.3366

Source: compiled by the authors using the Gretltoolkit

Table 9: Results of the Leung-Box test for the presence of autocorrelation of residuals.

The analysis of the results of the Leung-Box test indicates that there is no statistically significant autocorrelation of the residuals up to order 3, as the p-value (0.3366) is significantly higher than the threshold level (0.05). This indicates that the model residuals are time-independent at the lags considered, which is a desirable property in a regression model, especially if the goal is to make predictions. The autocorrelation test of the residuals shows that there is no significant autocorrelation in the ARMAX model residuals up to the third order, which in turn indicates that the model adequately accounts for the time dependence between observations and the assumptions of independence of the residuals are met. This increases confidence in the accuracy and reliability of statistical conclusions drawn from this model. As a result of the study, it is possible to conclude that the model of LSR with HAC errors is characterised by simplicity in application and interpretation and allows taking into account heteroscedasticity through the use of standard errors. At the same time, the identified problems with the autocorrelation of the residuals can lead to a bias in the estimates



Source: compiled by the authors using the Gretltoolkit

Figure 5: Estimation of normality of residuals distribution in ARMAX model.

and standard errors. Moreover, the LSR model does not address potential temporal dependencies between consecutive observations.

The ARMAX model addresses both autocorrelation and exogenous inputs, rendering it more flexible and adaptive to the data. The high R-squared and corrected R-squared values indicate that the model explains the variability of the data well. The ARMAX model demonstrated the absence of significant autocorrelation of the residuals, which indicates the correct specification of time dependencies. The residuals are normally distributed, which confirms the adequacy of the model assumptions and the possibility of applying traditional statistical methods. Each of the models used for the analysis has strengths and weaknesses. The choice between these models should be based on the specific goals of the analysis and the specifics of the data. However, for a more in-depth analysis that addresses time dependencies and ensures high accuracy and reliability of the results, the ARMAX model is preferable. This model is better suited for time series, where time dependencies play a key role. The two models together provide a comprehensive analytical toolkit that allows not only the estimation of past Analyses of the results of the Lewng-Box test indicate that there is no statistically significant autocorrelation of residuals up to order 3, as the p-value (0.3366) is significantly higher than the threshold level (0.05). This indicates that the model residuals are time-independent at the lags considered, which is a desirable property in a regression model, especially if the goal is to make predictions.

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The analysis of the econometric models revealed important insights into the factors influencing grain production in Kazakhstan. In the LSR model, the coefficient for grain yields demonstrated a statistically significant positive effect on the gross grain harvest, indicating that an increase in productivity directly contributes to higher overall production. Specifically, the results suggested that for each unit increase in grain yield, there was an associated increase of approximately 1,683.42 units in the gross grain harvest. This underscores the critical importance of enhancing agricultural practices and investing in research and development to boost yield, thereby improving the country's grain output. In contrast, the ARMAX model provided a more nuanced understanding of the dynamics at play. The autoregressive parameter showed that past values of grain production positively influence current outputs, highlighting the relevance of historical performance in shaping present-day agricultural success. Additionally, the moving average component of the model indicated that previous errors significantly impact current results, emphasizing the need for continuous monitoring and adjustment of agricultural strategies. The ARMAX model's superior ability to incorporate both autoregressive elements and external influences makes it a preferred choice for analyzing grain production in this context. It effectively captures the complexities of time series data and allows for a more robust interpretation of how various factors interact over time.

Relevant examples from Kazakhstan provide deeper insights into the practical implications of the identified factors. For instance, in recent years, the adoption of modern agricultural technologies, such as precision farming and improved seed varieties, has led to notable increases in wheat yields. Regions like North Kazakhstan have successfully implemented these innovations, resulting in higher grain outputs and contributing significantly to the overall national harvest. Additionally, adverse climatic events, such as droughts, have been documented to impact grain production adversely, particularly in years when rainfall was significantly below average. These case studies highlight the importance of integrating technological advancements and adaptive strategies in agricultural practices to mitigate the effects of external challenges and enhance grain production sustainability in Kazakhstan.

The results of this study provide valuable insights into the dynamics of grain production in Kazakhstan, contributing to both the understanding of agricultural productivity and the development of strategies to enhance the sector's sustainability. As the analysis shows, factors such as grain yields and research and development investments significantly impact the overall production, while climatic conditions and agricultural practices also play key roles. The autoregressive and ARMAX models used in the study revealed that past yields have a considerable influence on present grain production. This finding aligns with previous research, such as Z. Zhanaltay's (2023) analysis of agricultural transformation in Kazakhstan, which highlighted the importance of long-term planning and policy adjustments to improve agricultural productivity. The observed challenges—low levels of investment and technological development —persist as major barriers to enhancing the efficiency of grain production. Our study confirms that without significant investment in modern technologies and R&D, the grain sector may struggle to fully capitalize on its export potential and adapt to changing climatic conditions.

Additionally, the analysis confirms that Kazakhstan's grain production faces external challenges such as fluctuating climatic conditions, poor infrastructure, and inefficient policies, consistent with the findings of Tokenova et al. (2019) and Razakova (2013). For example, Tokenova et al. pointed out that logistical issues in storage, transportation, and export are key limiting factors. In our study, the inclusion of variables such as average precipitation and soil erosion indicators further underscores the vulnerability of grain yields to environmental conditions. The ARMAX model, which accounts for these external variables, proved particularly useful in predicting grain harvest trends, confirming that climate factors like precipitation play a critical role. One of the key findings is the significant positive impact of R&D investments on grain production. This result supports the assertions by Mistry et al. (2017) and Wang et al. (2021b) that innovation and technological adoption are essential to maintaining competitive agricultural output. However, despite some government initiatives to support innovation, Kazakhstan still lags behind other countries in the adoption of advanced agricultural technologies. The findings suggest that a more focused approach to promoting technological innovation could yield substantial improvements in both grain yields and overall agricultural sustainability. Moreover, studies by Gaba et al. (2020) and Peltoniemi et al. (2021) suggest that biodiversity and sustainable land management practices are critical to long-term agricultural productivity. The fluctuations in yields observed in this study indicate that greater attention needs to be paid to sustainable farming methods, such as the use of organic fertilizers and biodiversity conservation strategies. Incorporating these practices could mitigate some of the risks associated with climate change and improve the resilience of the agricultural sector.

A comparative analysis of grain production in Kazakhstan and other major grain-producing countries, including Canada, the United States, Ukraine, Australia, and Argentina, reveals significant differences in agricultural strategies, climate conditions, and policy frameworks. Canada and the United States benefit from advanced technological innovations, including precision farming, genetically modified crops, and large-scale mechanization. These factors contribute to high yields despite challenging climatic conditions. In both countries, extensive government subsidies and insurance programs mitigate risks related to weather variability and global market fluctuations. Additionally, well-developed transportation infrastructure ensures efficient grain distribution domestically and internationally. Ukraine, with its fertile black soil and relatively favorable climate, maintains a strong position as a major grain exporter. However, logistical inefficiencies and political instability pose challenges to stable production and export capacities. Despite these limitations, Ukraine's agricultural sector has increasingly focused on technological modernization, including the adoption of high-yield seed varieties and digital farming practices. Australia presents a unique case due to its dry climate and dependence on water-efficient farming techniques. The country's grain industry has adapted through extensive research into drought-resistant crops and conservation agriculture, which maximizes productivity while minimizing water use. Government policies promoting sustainability and climate resilience have played a key role in supporting agricultural stability. Argentina, another leading grain producer, benefits from a combination of fertile land and a strong tradition of commercial farming. However, fluctuating economic policies, export restrictions, and inflation pose challenges to long-term agricultural growth. The country has invested heavily in biotechnology, particularly in soybean and wheat production, to maintain competitive yields and profitability. Kazakhstan, in comparison, faces unique constraints related to extreme climate variability, water shortages, and less-developed agricultural infrastructure. While the country has made strides in adopting sustainable farming practices and increasing investment in research and development, challenges remain in mechanization, irrigation efficiency, and supply chain logistics. Strengthening trade partnerships, improving transportation networks, and fostering innovation in climate adaptation strategies will be critical for enhancing Kazakhstan's competitiveness in the global grain market.

The findings also highlight the strategic importance of cereal exports, as pointed out by Wang et al. (2021a), particularly in the context of global food security. Kazakhstan's position as one of the largest grain exporters, coupled with the challenges posed by climate change and shifting international markets, requires a comprehensive export strategy that aligns with global demand while ensuring domestic food security (Jia & Zhen, 2021; Jumabayev et al., 2023; Zhenskhan et al., 2022). In conclusion, the results of this study underscore the need for a multi-faceted approach to improving grain production in Kazakhstan. Addressing both internal factors, such as investment in R&D and agricultural innovation, and external factors, such as climate resilience and infrastructure improvements, is essential for boosting productivity and ensuring the sector's sustainability. These findings provide a foundation for future policy recommendations aimed at increasing the competitiveness of Kazakhstan's grain sector while addressing the broader challenges posed by climate change and market fluctuations (Orazov et al., 2021; Zhupankhan et al., 2022; Karatayev et al., 2022; Barrett et al., 2017).

This research is relevant for determining how risk factors and the international economy affect the agricultural sector in Kazakhstan and should be addressed when developing strategies to improve agricultural productivity and sustainability, which is directly related to the modelling and data analysis conducted in the study. Thus, the studies emphasise the complexity and multidimensionality of the problems associated with grain production in the Republic of Kazakhstan, including the impact of climate change, water shortages, changes in the global food balance, and the introduction of innovations. The results obtained in this paper contribute to a deeper understanding of the processes that shape the current dynamics in agricultural production and emphasise the importance of integrating scientific approaches into the practice of agricultural management.

The findings have significant practical applications for policymakers and stakeholders in the agricultural sector. Recommendations include optimizing land use, integrating modern agricultural technologies, and improving sustainability practices to enhance productivity and mitigate negative externalities. These insights can inform agricultural policies aimed at ensuring long-term food security and economic resilience.

Conclusion

An economic analysis of the Kazakhstani agricultural sector has revealed significant changes in the volume and structure of arable land and the dynamics of grain yields in 2004-2022. The observed decline in the share of arable land under grain crops and changes in wheat harvest volumes point to the importance of a detailed analysis of internal and external factors affecting the country's agricultural sector.

The results of the study show that despite the overall decline in the share of arable land under grain, there are still significant fluctuations in the share of wheat in the total crop harvest. The paper proves that these fluctuations are related to various factors, a grouping of which and the presentation of measurable indicators for each group was used to study the mechanisms of their influence on grain production and provide a database for building econometric models. The study presents a logical model that illustrates the relationship between groups of factors (environmental and climatic; technical and economic; technological and innovation dynamics; social factors and development; political and regulatory environment; impact of globalisation) and their impact on grain production.

The study of grain products in Kazakhstan demonstrated how modelling serves as a tool for analysing the impact of various factors on the agro-industrial complex. Two key models, the LSR-error HAC and ARMAX, were used to estimate the impact of environmental, economic and technological factors on grain harvest.

The LSR model with HAC errors addressed the heteroscedasticity and autocorrelation of the data, which helped to improve the accuracy of the estimates. Yields and R&D expenditures were the main factors with a significant impact on gross grain harvest, highlighting the importance of innovation and improved agricultural technologies to increase efficiency. The ARMAX model, including autoregressive components and external variables, is more suitable for time series analysis, considering time dependencies and external influences on grain production. This determined the dynamics and main trends in grain production in detail. Thus, the use of the LSR and ARMAX models was used not only to analyse the current state of the grain industry but also to formulate sound strategic recommendations for improving the sustainability and development of grain production in Kazakhstan.

Corresponding author:
Gulnar Lukhmanova
Zhetysu University named after I. Zhansugurov
040009, 187A Zhansugurov Str., Taldykorgan, Republic of Kazakhstan
E-mail: gulnar.lukhmanova@gmail.com

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Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

The Impact of Information and Communication Technology (ICT) and Bank Credit on Agricultural Performance in Uzbekistan: An Econometric Analysis

Fozil Xolmurotov[1], Xolilla Xolmuratov[2]

[1] Department of Economics, Mamun University, Khiva, Uzbekistan

[2] Electrical Engineering and Power Engineering Department, Technology Faculty Urgench state university, Uzbekistan

Abstract

This study examines the dynamic effects of information and communication technology (ICT) penetration and bank credit on agricultural performance in rural Uzbekistan using an autoregressive distributed lag (ARDL) model. Based on data from the World Bank and the State Statistics Committee of the Republic of Uzbekistan for the period 2000-2022, this study examines the important role of ICT and financial resources in improving agricultural productivity. Descriptive statistics show moderate variability in agricultural performance, with strong positive correlations between agricultural output and variables such as education, internet access, and mobile phone penetration. Unit root tests confirm the stationarity of all variables after first differencing, confirming the application of the ARDL model. The results of the paired test indicate a significant long-run equilibrium relationship between the variables under study. The short-run results of the ARDL model show that changes in bank credit have a significant impact on agricultural performance, with a robust adjustment mechanism to correct deviations from the long-run equilibrium. The long run results show that while ICT variables do not significantly affect agricultural performance, bank credit has a negative effect on it and education has a strong positive effect.

Keywords

Agricultural performance, ICT penetration, bank credit, ARDL model, rural development, agriculture.

Xolmurotov, F. and Xolmuratov, X. (2025) "The Impact of Information and Communication Technology (ICT) and Bank Credit on Agricultural Performance in Uzbekistan: An Econometric Analysis", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 125-134. ISSN 1804-1930. DOI 10.7160/aol.2025.170209.

Introduction

According to research, many countries pay great attention to the development of agriculture. In particular, in Uzbekistan, great attention is being paid to the development of agriculture, many new decisions are being made. In many studies, it is important to note that agriculture contributes to the development of the national economy, especially by providing employment and food security, freeing it from poverty and becoming the main source of livelihood of the population. Indicators of the agricultural sector of the economy in Uzbekistan continue to face serious problems due to the decrease in the contribution to the GDP compared to the industry and service sectors.

The role of information and communication technologies (ICT) in improving agriculture is particularly important in smallholder farming in developing countries (McNamara, 2009). ICT helps to overcome problems such as low education level and lack of motivation to use technology and plays an important role in solving the problems of increasing production and improving the living standards of small farmers (Beteng, 2020; Kassanuk and Phasinam, 2021). In addition, by providing timely and relevant agricultural information to the public, improved market access and increased efficiency can be achieved (Lubis, 2010). Potential applications of ICT in agriculture include e-commerce, production expansion and staff training activities and knowledge transfer (Allahyari et al., 2009). In general, the successful implementation of ICT in agriculture requires the establishment of communication networks in agriculture and the integration of knowledge and information needs of farmers in this direction (Ajani, 2014).

As a result of observations, it was found that the relationship between ICT and agricultural efficiency has been studied by many researchers. In general, the relationship between ICT and agricultural productivity is complex, and this has been determined in different contexts, especially given the research question. Some scholars have found a positive impact of ICT on agricultural productivity, but have also noted the gap between rich and poor countries (Lio and Liu, 2006). Chancellor (2023) and de Berquin Eyike Mbongo and Djoumessi (2024) support this positive relationship, while Chancellor justifies the importance of agriculture and access to the digital internet in particular, Mbongo justifies the indirect effects of ICT on education and access. However, Cardona and Onyeneke state that the productivity impact of ICT varies depending on the methodological approach and the specific type of ICT used (Cardona et al., 2013; Onyeneke et al., 2023). Otter and Goyal explore this complexity through the impact of ICT on different types of farms and the potential role of ICT in increasing market efficiency in specific areas, thereby making a significant contribution to the field (Goyal and GonzÃ¡lez-Velosa, 2013; Otter and Theuvsen, 2014).

It should be noted that many areas of agriculture in Uzbekistan today have low efficiency. In agriculture, the transition from traditional farming methods to modern farming methods requires continuous financing, but this is often lacking due to various circumstances and factors. Financial institutions are hesitant to invest in agriculture because of the sector's inherent risks (Ruete, 2016) and government policies aimed at modernization that often lead to economic dislocation (Haghayeghi, 1990).

Financial institutions are hesitant to invest in agriculture because of the sector's inherent risks (Ruete, 2016) and government policies aimed at modernization that often lead to economic dislocation (Haghayeghi, 1990). For example, studies show that despite efforts to improve agricultural financing in Nigeria, poor budget allocation and corruption have hindered progress (Eze et al., 2010). The effectiveness of state support for agriculture is affected by the choice of direction and mechanisms, as well as the amount of benefits provided (Polukhin et al., 2019). In Albania, the budgetary expenditure on agriculture is relatively low, which indicates the absence of state support (Thomaj, 2015). The financial and economic conditions of rural development in Ukraine are also problematic, there are significant gaps in budget financing (Dema et al., 2019). Despite these various challenges, the continued commitment of reformers is critical to the growth and competitiveness of the agricultural industry.

The importance of bank loans to the real economy in research can be seen from several previous studies that have identified the important role of commercial banks in private sector development and economic growth. At the same time, in many studies, we can make different conclusions, such as bank loans have a significant effect only in the long term, but do not have an effective effect in the short term. Empirical studies in countries as diverse as USA, Bangladesh, Nigeria and China substantiate the crucial role of bank credit in improving agricultural performance. Access to cheap credit boosts production in rural areas, which increases production and employment opportunities (Reyes et al., 2023). Studies in Bangladesh and Nigeria have shown a positive effect of bank credit on agricultural output, with the results showing a significant relationship between bank credit and agricultural performance in the long run (Islam et al., 2023; Patwary et al., 2023). In addition, studies in China show that the extent of agricultural credit significantly increases the green productivity of agriculture, which has an inverted U-shaped relationship, indicating the optimal effect of credit on performance (Wang and Du, 2023). Together, these results underline the importance of using agricultural credit to finance productive activities and ultimately contribute to increased agricultural performance and economic growth (Saribayevich et al., 2024).

Through this study, we tried to study the dynamic impact of the introduction of ICT and bank loans on agricultural indicators in Uzbekistan. Why is this topic relevant, because the agricultural sector in Uzbekistan plays an important role in the formation of the country's GDP. However, as a result of the study, it was found that there have been no studies on the impact of rural ICT and bank credit on agricultural indicators in Uzbekistan using econometric models. In addition, we distinguish the relationship between the above-mentioned variables in this study by using the ARDL model. This research can make an important contribution to the development of science and provide practical policy direction to improve agricultural productivity and improve the welfare of farmers (Xolmurotov et al., 2024).

The chosen topic of this research is an interesting issue for Uzbekistan, and attention is focused on finding answers to the following research questions. First, will the penetration of ICT in agriculture affect the agricultural performance in Uzbekistan in both the short and long term? Second, does bank credit affect agricultural performance in Uzbekistan in both the short and long term? The specific tasks of this research are to study the impact of ICT penetration in agriculture in the short and long term and to study the impact of bank credit on agricultural indicators in Uzbekistan in the short and long term. The remaining sections of this paper include materials and methods, results and discussion, and conclusions.

Materials and methods

In this study, we used open data of the World Bank and secondary data of the Statistical Office of the Republic of Uzbekistan. The data covers the years 2000-2022. The dependent variable of this study is the agricultural sector performance (lnAGR- Agriculture, Forestry and Fisheries, Value Added). The independent variables of this study are bank credit (lnCRED - Domestic Credit to the Private Sector) and rural ICT penetration. The penetration of ICT in villages is represented by the level of penetration of rural Internet (lnINT - Internet users) and mobile phones (lnMP - Mobile cellular subscriptions) in rural areas. Education (lnEdu - Compulsory education, duration) is considered as a control variable. There are various indicators that can be used to measure ICT penetration. However, in rural areas, this study only focuses on two ICT measures, namely mobile phone and internet access. This approach is explained by the fact that a large part of the rural population in Uzbekistan relies on mobile phones and the Internet as the main means of communication and information exchange. On the other hand, the use of other ICT tools such as landline telephones and radios has significantly decreased and is hardly used by the rural population. In addition, most of the ICT models implemented by local governments in rural development projects in Uzbekistan rely on the Internet and mobile phone communication. Therefore, it is important for policy makers to consider the limitations of each ICT tool and design models that suit the specific needs of their target communities. In Uzbekistan, education is considered as a control variable due to its important role in realizing the potential of technology, securing bank loans and improving agricultural efficiency (Nadirkhanov, 2023). Table 1 lists the names, symbols, measurements, units, and expected signs of the variables.

Model specification

The ARDL (Auto-Regressive Distributed Lag) model was used in the analysis because of its suitability for small sample sizes and the ability to simultaneously estimate short-run and long-run relationships (Narayan, 2004).

Mathematical representation

The ARDL model is specified as follows:

$$\Delta lnAGR_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \,\Delta lnAGR_{t-i} + $$
$$+ \sum_{j=0}^{q} \gamma_j \,\Delta X_{t-j} + \varphi EC_{t-1} + \varepsilon_t \qquad (1)$$

Where:

Δ - denotes the first difference operator.

$lnAGR_t$ - is the logarithm of agricultural sector performance.

X_t – represents the independent variables *lnINT, lnMP, lnCRED and lnEDU.*

EC_{t-1} – is the error correction term lagged one period, capturing the long-run equilibrium relationship.

α_0 – is constant term.

β_i, γ_j, φ - are the coefficients to be estimated.

ε_t – is the error term.

Variable name	Symbol	Measurment	Unit
Agricultural sector performance	*InAGR*	Agriculture, forestry, and fishing, value added	current US$
Rural internet penetration	*lnINT*	Individuals using the Internet	% of population
Rural mobile phone penetration	*lnMP*	Mobile cellular subscriptions	pcs
Bank credit	*LnCR*	Domestic credit to private sector	% of GDP
Education	*LnEDU*	Compulsory education, duration	years

Source: Authors

Table 1: Operational variables.

Results and discussion

Table 2 provides a complete overview of the time series data, presenting statistics such as mean, standard deviation, minimum and maximum values, and number of observations for each variable. All data were transformed to natural logarithms (ln) to increase accuracy, This process helps us to interpret and understand the statistical data more easily during the analysis process (Huntington-Klein, 2021).

By converting variable values to natural logarithms during analysis, relative magnitudes of variables can be compared more effectively and easily (LAWLESS, 1989). In addition, this method in research helps to significantly reduce the influence of values that can distort the results of statistical analysis (Galiahmetova et al., 2019).

Descriptive statistics provide an overview of the central tendency, spread, and shape of the distribution for each variable (Hui, 2018). Indicators for the agricultural sector and rural Internet penetration show moderate volatility and slight negative skewness. Mobile phone penetration in rural areas has significant negative skewness and moderate variability. Bank credit exhibits an almost symmetric distribution with moderate volatility. The duration of education shows minimal variability and is almost symmetrical, indicating the consistency of the duration of education over the observed period (Oluwatayo, 2012). These concepts help to understand the distribution and variability of key variables in a study.

Table 3 shows the correlation matrix, which we use to determine the direction and strength of correlation between variables and to determine whether there are multicollinearity problems. The correlation matrix shows the pairwise correlations between the variables involved in the study. Values range from -1 to 1, where values closer to 1 or -1 indicate stronger linear relationships and values closer to 0 indicate weaker linear relationships. However, the correlation coefficient has limitations, which is that it cannot determine cause-and-effect relationships between variables (Janse et al., 2021). Hence, it is essential to use inferential statistical methods such as econometric models to assess the causality of these variables. By using such methods, we can better understand the underlying relationships between variables, which can help us make decisions based on results.

The correlation matrix reveals a strong positive correlation between the agricultural sector indicators and each of the independent variables, namely education (0.91), internet access (0.88) and mobile phone penetration (0.86). These strong correlations suggest that improvements in education, internet access, and mobile phone penetration may be associated with improved agricultural performance. Furthermore, the positive correlation between the independent variables themselves, such as internet and mobile phone penetration (0.66), suggests that advances in one technological aspect can be matched by improvements in other areas and further support rural development.

Unit root tests such as augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used

Variable name	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis
InAGR	22.97	23.36	23.95	21.78	0.79	-0.28	1.4
lnINT	2.54	2.92	4.34	-0.72	1.61	-0.67	2.26
lnMP	15.61	16.85	17.39	10.88	2.11	-1.04	2.53
LnCRED	2.27	2.21	3.61	0.41	0.81	-0.11	3.01
LnEDU	2.44	2.48	2.48	2.39	0.04	-0.08	1.01

Source: Authors

Table 2: Descriptive statistics.

Variable name	*InAGR*	*lnINT*	*lnMP*	*LnCRED*	*LnEDU*
InAGR	1				
lnINT	0.88	1			
lnMP	0.86	0.66	1		
LnCRED	0.66	0.71	0.53	1	
LnEDU	0.91	0.63	0.73	0.71	1

Source: Authors

Table 3: Correlation matrix.

to test the stationarity of time series (Zuo, 2019). A stationary series has a constant mean, variance, and autocorrelation over time, making it suitable for regression analysis. The Augmented Dickey-Fuller test checks for unit roots in a time series, while the Phillips-Perron test is another way to test for unit roots that adjusts for any serial correlation and heteroskedasticity in the errors. The p-values associated with the test statistic are presented in parentheses (Table 4). A p-value less than 0.05 usually indicates a rejection of the null hypothesis of a unit root, indicating that the series is stationary. The results of the unit root test show that all variables (*InAGR, lnINT, lnMP, LnCRED, LnEDU*) are not stationary in their levels as suggested by the high p-values in the ADF and PP tests. However, after taking first differences, all variables remain stationary as both tests show significant p-values (less than 0.05). This shows that the variables are integrated of order I(1), meaning they are stationary after being differentiated once. This finding is very important for ARDL model applications that require variables to be either I(0) or I(1). The stationarity achieved after differentiation ensures the validity of the subsequent regression analysis.

The ARDL bounds testing approach is used to determine whether there is a long-run relationship between the variables in the model. The bounds test compares the calculated F-statistic with critical values (lower and upper bounds) at various significance levels (90%, 95%, and 99%). Table 5 shows the results of this test according to our analysis. According to him, the results of the marginal test confirm the existence of a long-term equilibrium relationship between the indicators of the agricultural sector, rural Internet penetration, rural mobile phone penetration, bank credit and education variables. The F-statistic equal to 5.26 is greater than the upper bound critical value at the 99% significance level, indicating that the variables act together in the long run, which justifies the use of the ARDL model for analysis (Table 5).

This conclusion is very important because it supports the hypothesis that technological penetration and financial factors have a significant impact on agricultural performance in rural Uzbekistan in the long run.

Significance level	Lower bound	Upper bound
90%	1.9	3.01
95%	2.26	3.9
99%	3.07	4.44
F-statistics = 5.26 (K = 4)		

Source: Authors

Table 5: Bound test results.

Table 6 shows the results of the ARDL (1,0,0,1,0) model in the short and long term. Short-Run Estimation Results: The coefficient of D(LNCRED) is -0.587004, with a t-statistic of -2.443176 and a p-value of 0.0265. This indicates a statistically significant negative short-run effect of bank credit on agricultural performance at the 5% significance level. The error correction term CointEq(−1) has a coefficient of -0.522339, which is highly significant (p-value 0.0000), indicating a strong correction mechanism toward the long-run equilibrium.

Variable	Coefficient	Std. Error	t-Statistic	Prob
Short-run				
D(lnCRED)	*-0.58*	*0.24*	*-2.44*	*0.02*
CointEq(-1)	*-0.52*	*0.09*	*-5.73*	*0.00*
Long-run				
lnINT	*0.21*	*0.25*	*0.81*	*0.03*
lnMP	*0.22*	*0.17*	*1.29*	*0.01*
lnCRED	*-0.51*	*0.23*	*-2.22*	*0.04*
lnEDU	*8.31*	*0.92*	*8.99*	*0.00*

Source: Authors

Table 6: Short-run and long-run estimation results

Long-Run Estimation Results: The coefficient of lnINT is 0.209379, with a t-statistic of 0.807316 and a p-value of 0.4313, indicating no significant long-run effect of internet penetration

Variable name	ADF test		PP test	
	at Level	first-difference	at Level	first-difference
InAGR	*1.11 (0.92)*	*-2.61 (0.01)*	*1.14 (0.92)*	*-2.61 (0.01)*
lnINT	*-0.36 (0.53)*	*-3.45 (0.00)*	*1.15 (0.93)*	*-1.61 (0.04)*
lnMP	*0.92 (0.89)*	*-2.34 (0.02)*	*1.87 (0.98)*	*-2.29 (0.02)*
LnCRED	*2.52 (0.99)*	*-2.61 (0.01)*	*2.01 (0.98)*	*-3.69 (0.00)*
LnEDU	*0.98 (0.91)*	*-4.47 (0.00)*	*1.01 (0.91)*	*-4.47 (0.00)*

Source: Authors

Table 4: Unit root test results (Include in test equation - None).

on agricultural performance. The coefficient of lnMP is 0.221642, with a t-statistic of 1.292094 and a p-value of 0.2147, indicating no significant long-run effect of mobile phone penetration. The coefficient of lnCRED is -0.517929, with a t-statistic of -2.225354 and a p-value of 0.0408, indicating a significant negative long-run effect of bank credit on agricultural performance. The coefficient of lnEDU is 8.306513, with a t-statistic of 8.992272 and a p-value of 0.0000, indicating a highly significant positive long-run effect of education on agricultural performance.

The results show that while internet and mobile phone penetration have no long-run effect on agricultural performance, bank credit has a negative effect and education has a robust positive effect in the long run. In the short term, changes in bank credit also have a significant impact on agricultural performance, and there is an important adjustment mechanism to correct deviations from long-term equilibrium.

Table 7 shows the results of the Ramsey RESET Test. The Ramsey RESET test evaluates whether the model is correctly specified. The high p-values for both the F-statistic (0.774) and the Chi-Square (0.723) indicate that we fail to reject the null hypothesis, suggesting no evidence of model misspecification. This implies that the functional form of the model is appropriate.

Table 8 shows the results of the Heteroskedasticity Test: Breusch-Pogan-Godfrey. According to him, the Breusch-Pagan-Godfrey test examines the presence of heteroskedasticity (non-constant variance of the error terms). The p-values for the F-statistic (0.12) and Chi-Square (0.133) are above the common significance levels, indicating that we fail to reject the null hypothesis of homoskedasticity. This suggests that the error variances are constant, supporting the assumption of homoskedasticity in the model.

Table 9 presents the results of the Breusch-Godfrey Serial Correlation LM Test. According to him, the Breusch-Godfrey test checks for serial correlation in the residuals (error terms) of the model. The p-values for the F-statistic (0.58) and Chi-Square (0.44) are high, indicating that we fail to reject the null hypothesis of no serial correlation. This suggests that the residuals are not autocorrelated and are independently distributed over time.

The diagnostic tests jointly confirm the robustness and validity of the regression model used in this study. The Ramsey RESET test shows that the model is correctly specified and has an appropriate functional form. The Breusch-Pagan-Godfrey test ensures that the error variances are constant, indicating the absence of heteroskedasticity. In addition, the Breusch-Godfrey serial correlation LM test confirms that the residuals are not serially correlated, supporting the assumption of independent error terms. These results confirm the reliability of the estimated coefficients and conclusions drawn from the model and justify the robustness of the research findings.

Test	Null hypothesis	F-statistic	Prob (F-statistic)	Obs*R-squared	Prob (Chi-Square)
Ramsey RESET Test	Model is correctly specified	*0.085*	*0.774*	*0.124*	*0.723*

Source: Authors

Table 7: Ramsey RESET Test result.

Test	Null hypothesis	F-statistic	Prob (F-statistic)	Obs*R-squared	Prob (Chi-Square)
Heteroskedasticity Test: Breusch-Pogan-Godfrey	Homoskedasticity	*2.01*	*0.12*	*9.81*	*0.133*

Source: Authors

Table 8: Heteroskedasticity Test: Breusch-Pogan-Godfrey.

Test	Null hypothesis	F-statistic	Prob (F-statistic)	Obs*R-squared	Prob (Chi-Square)
Breusch-Godfrey Serial Correlation LM Test	No serial correlation	*0.56*	*0.58*	*1.62*	*0.44*

Source: Authors

Table 9: Breusch-Godfrey Serial Correlation LM Test.

Conclusion

The study highlights the important role of ICT penetration and bank credit in improving agricultural productivity. Although ICT can significantly improve efficiency and market access, its impact varies according to contextual and methodological factors. Bank credit is essential for financial investment in modern agricultural practices and has a positive long-term impact on productivity. Conclusions from Uzbekistan are consistent with global trends and emphasize the importance of technological and financial support in rural development. Policymakers should focus on increasing ICT penetration, improving access to education, and increasing agricultural productivity and providing financial resources for rural development. Future research should continue to explore these dynamics, taking into account the evolving technological landscape and financial systems in developing countries.

In addition, our research has identified several key policies that can significantly impact agricultural development and improve the well-being of farmers in rural areas. First, the government should prioritize providing adequate internet infrastructure covering all rural areas of Uzbekistan. This will significantly increase agricultural sector performance by improving communications and facilitating economic activity, distribution, and marketing of products. In turn, this is expected to reduce the development gap between rural and urban areas, including between eastern and western regions of Uzbekistan. Second, it is important to ensure that farmers have easy access to financial services, such as bank loans. Inclusive bank credit is essential in financing agricultural activities, which can increase farmers' productivity and income. The government should intervene by reducing interest rates, which are high capital costs and a business burden for farmers. Third, training rural communities to adopt and use ICTs can significantly improve agricultural efficiency, financial management, and agricultural production. Therefore, the government should focus on providing education and knowledge related to the use of ICTs for these purposes.

In addition to our research findings, we have identified several key policies that can significantly impact agricultural development and improve the welfare of farmers in rural areas. First, the government should prioritize the creation of a comprehensive internet infrastructure covering all rural areas of Uzbekistan. Improved connectivity will facilitate economic activity, streamline product distribution and marketing, and significantly increase the performance of the agricultural sector. Such improved connectivity is expected to reduce the development gap between rural and urban areas, as well as between different regions of Uzbekistan.

Second, it is essential to ensure that farmers have easy access to financial services such as bank loans. Inclusive banking services are important for agricultural financing as they can boost farmers' productivity and income. The government should intervene by reducing interest rates, which is a huge capital cost and financial burden for farmers.

Third, training rural communities to adopt and use ICT can significantly improve agricultural efficiency, financial management, and agricultural production. Therefore, the government should focus on providing education and training related to the use of ICT for these purposes. In this way, farmers can better utilize technology to improve farming practices and overall productivity.

Corresponding author:
Fozil Xolmurotov
Department of Economics, Mamun University
220900, Qibla Tozabog, Khiva, Uzbekistan
Phone: +998-93-7536633, E-mail: fozil.econometrics@gmail.com

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Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

Innovation in Agriculture: Driving Economic Development through EU Knowledge-Based Economy

Tatia Zarkua, Wim Heijman, Irena Benešová

Department of Economics, Faculty of Economics and Management, Czech University of Life Sciences Prague, Czech Republic

Abstract

Innovation in agriculture is vital for enhancing sustainability, productivity, and economic development, especially in light of global challenges such as population growth, resource scarcity, and climate change. This study, adopting a quantitative cross-sectional approach, investigates the relationship between agricultural innovation and productivity within the EU. By employing multiple regression analysis with a log-log transformation, the study explores how R&D expenditure in agriculture and various control variables impact agricultural productivity across EU-27 countries from 2000 to 2019. To address potential endogeneity concerns, the Instrumental Variables (IV) approach was applied, using the Two-Stage Least Squares (2SLS) method, which reduced bias in the estimation. The results revealed that a 1 % increase in R&D spending in agriculture corresponds to an approximate 0.33% increase in total crop output, indicating a strong positive link between innovation and agricultural productivity. The model residuals confirm a satisfactory fit, highlighting the robustness of the findings. This study provides valuable insights into how agricultural innovation can drive productivity, offering important implications for policymakers and researchers aiming to optimise agricultural output through increased investment in innovation.

Keywords

Innovation, agriculture, R&D expenditure, KBE, economic development.

Zarkua, T., Heijman, W. and Benešová, I. (2025) "Innovation in Agriculture: Driving Economic Development through EU Knowledge-Based Economy", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 135-148. ISSN 1804-1930. DOI 10.7160/aol.2025.170210.

Introduction

The adoption of innovation in agriculture through a knowledge-based economy (KBE) has been increasingly emphasized in policy frameworks around the world (Evenson & Gollin, 2003; OECD, 2019; Wang et al., 2019). The European Union (EU) has highlighted the importance of knowledge-driven development and agricultural innovation in various strategic documents, such as the 'European Green Deal', 'Farm to fork strategy', 'Horizon Europe', and 'Horizon 2020' (Pound & Conroy, 2017; European Commission, 2021). These documents outline the role of innovation in enhancing agricultural productivity while ensuring sustainability and environmental protection. Additionally, these initiatives aim to foster a knowledge-based economy, where intellectual capabilities, technological advancements, and information are primary drivers of economic development (European Commission, 2021).

A KBE in agriculture involves integrating research, knowledge, and innovative approaches to enhance farming practices and increase productivity. This idea exceeds traditional farming by integrating advancements like biotechnology, precision agriculture, and digital technologies in agriculture (OECD, 1997; Qaim, 2009; Gebbers & Adamchuk, 2010; Wolfert et al., 2017). Embracing this approach may result in transformed agricultural output, greater environmental sustainability, and strengthened economic development (OECD, 2023).

A KBE is characterized by the reliance on intellectual capabilities, innovation, and information as key drivers of economic development. In the context of agriculture, this means leveraging scientific research, advanced technologies, and data analytics to improve agricultural outputs and sustainability. The EU's policies and funding priorities, which emphasise the integration of knowledge and innovation across various sectors, including agriculture, reflect its commitment to fostering a KBE (OECD, 1997).

In the context of a KBE, one of the key pillars driving agricultural innovation is research and development (R&D) in agriculture. R&D and expenditure in this field facilitate the discovery of new agricultural techniques, crop varieties, and environmental practices that align with sustainable development goals. Numerous studies (Piesse and Thirtle, 2010; Alston and Pardey, 2013) have demonstrated that agriculture R&D is a crucial determinant of agricultural productivity. This aligns with endogenous growth theory, introduced by Romer in 1990, that suggests that economic growth is driven by internal elements like technological innovation, human capital, and knowledge spillovers. This theory is especially important for grasping how agricultural innovation may stimulate economic development within the EU's KBE. Innovation in agriculture, a crucial aspect of endogenous growth theory, increases productivity and fosters sustainability (Sonnino et al., 2014; Lundvall, 2007; Johnson and Lundvall, 2013).

To operationalise innovation, agricultural innovation systems (AIS) play a crucial role (Riaz et al., 2014; Gildemacher and Wongtschowski, 2015; Barry and Czech, 2017). These systems consist of networks that include various actors, organisations, and individuals that cooperate in order to introduce existing or new products, processes, and organisational forms into social and economic contexts. The networks are organised into three primary categories: research and education; business and enterprises, which encompass farmers and their associations; and bridging institutions, including extension services, brokering agencies, and contractual arrangements. Another component includes the supporting policies and institutions, whether formal or informal, that influence the interactions, reflections, knowledge creation, sharing, and collaborative learning and adaptation to external changes among these actors, thereby shaping the "enabling environment" (Tropical Agriculture Platform, 2016).

Government policies and institutional structures are another significant factor that either encourage or hinder agricultural innovation. For instance, the EU's Common Agricultural Policy (CAP) offers direct subsidies to farmers, facilitates rural development projects, and finances innovative efforts (European Commission, 2020).

The Triple Helix model, developed by Etzkowitz and Leydesdorff, offers a framework for understanding the dynamic interactions between universities, industry, and government in fostering innovation and economic development (Etzkowitz and Leydesdorff, 1998). The model emphasises how these three spheres collaborate to create a knowledge-based society where innovation drives technological advancement and entrepreneurship. Universities, traditionally viewed as centres of knowledge generation, now play a more active role in innovation through research, commercialisation, and entrepreneurial activities. The industry that applies and markets new technologies benefits from collaboration with universities, gaining access to cutting-edge research and talent. Governments act as facilitators, providing policy frameworks and funding mechanisms to promote research and innovation. The interplay between these sectors creates a synergy that accelerates economic growth and technological progress, making the Triple Helix model a key theoretical approach in innovation studies (Fidanoski et al., 2022; Cai and Lattu, 2022). This collaborative model is particularly relevant in knowledge economies, where technological innovation is vital for maintaining competitiveness and fostering sustainable economic development.

Given the extensive array of agricultural innovations and economic advancements among the various EU member states, Germany, the Netherlands, and Denmark stand out as some of the most progressive nations in sustainable farming practices and advanced agricultural technology. Their success stems from a robust digital infrastructure, favourable policies, and substantial expenditures in research and development (OECD, 2023).

However, not all member states have achieved the same level of progress. Comparative studies suggest that countries with limited access to finance, inadequate infrastructure, and regulatory barriers face challenges in adopting new agricultural technologies. These barriers highlight the need for tailored policy interventions that address the specific needs and conditions of each country (Hall et al., 2005; European Parliament, 2019).

Upon examining agricultural innovation through a KBE and the crucial role of R&D in the agricultural sector, it's evident that despite notable advancements, there are still areas requiring additional investigation. This study aims to address some of the existing gaps in understanding how R&D expenditure in agriculture directly influences agricultural productivity, particularly in the context of varying economic and environmental conditions across different countries.

To address these gaps, this study aims to provide a comprehensive analysis of how agricultural innovation impacts economic development at the country level within the EU. By focussing on national-level impacts and integrating the concept of a knowledge-based economy, this research seeks to offer a nuanced understanding of the transformative potential of agricultural innovation. Addressing this research gap, the following questions emerge as central to our inquiry:

- How does innovation in agriculture contribute to economic development in EU countries?
- What are the key factors that enable or hinder the integration of agricultural innovation within a knowledge-based economy at the country level?

To structure this exploration, we propose the following hypotheses:

(H1): Innovation in agriculture positively influences agricultural productivity.

While prior research has explored the relationship between agricultural productivity and factors like technological advancements and policy interventions, the novelty of this study lies in its focus on R&D expenditure as a critical driver of innovation in agriculture. Unlike studies that primarily emphasise broader technological innovations or external factors, this research specifically examines how R&D expenditures directly translate into measurable improvements in productivity. Moreover, the potential interactions between R&D and economic variables, such as emissions and trade, remain underexplored in the existing literature.

Previous studies also tend to overlook the differentiated effects that R&D expenditure might have in various contexts, particularly in relation to real factor income and subsidies (Špička et al., 2009). By addressing these gaps, this study offers a novel combination of control variables that provide fresh insights into the broader implications of agricultural innovation (OECD, 2023). The application of a KBE framework, along with the evaluation of control variables such as population density and CO_2 emissions, further enhances the understanding of how agricultural innovation can be made more effective.

This approach not only contributes to academic research but also has important implications for policy discussions, filling a key gap in the literature on the role of R&D expenditure in boosting agricultural productivity.

This paper is structured as follows: The next section will outline the research design, data sources, and analytical techniques used in this study. The results and discussion section will then present the findings, comparing different EU countries and analysing the impact of agricultural innovation on economic development. Finally, the conclusion will summarise the key insights, discuss policy implications, and suggest areas for future research.

Materials and methods

This study employed a quantitative research design to investigate the relationship between agricultural innovation and economic development within the EU for the period 2000-2019. A cross-sectional analysis was conducted using secondary data from sources such as Eurostat, the World Bank, and the European Commission.

Data collection focused on gathering variables that reflect both agricultural innovation and economic development across EU member states (Table 1).

The dependent variable, agricultural productivity, is represented by total crops output (€/ha). R&D expenditure in agriculture is employed as a proxy for agricultural innovation, serving as the independent variable. To control for other factors influencing agricultural productivity, additional variables such as population density (inhabit/km²), trade balance per hectare, CO_2 emissions per hectare, real factor income in agriculture per annual work unit (chain-linked volumes), and subsidies per hectare will be included in the model. Selected variables in this study have been adjusted for inflation, allowing for accurate comparisons over time and reflecting real changes in productivity rather than nominal price fluctuations.

One of the analytical methods used in this study is multiple regression analysis in log-log form (Greene, 2003). We employed the Ordinary Least Squares (OLS) approach to ensure the accurate estimate of regression coefficients (Oksanen, 1991). This approach was chosen due to its ability to capture the elasticity between the dependent and independent variables, thereby providing insights into the percentage change in economic development resulting from a one-percent change in agricultural innovation. The model also includes control variables to account for other factors that

Variables	Variable Expected Effects	Source
	Dependent	
Total crops output (per ha)	We expect that total crops output (per ha) will serve as a key indicator of agricultural productivity, reflecting the combined influence of innovation, economic conditions, and external factors.	Farm accountancy data network-European Commission, 2024
	Independent	
R&D expenditure in agriculture (per ha)	As the main independent variable, we expect a positive relationship between R&D expenditure and total crops output. More investment in R&D should lead to better technologies, farming practices, and innovations that boost productivity.	Eurostat, 2024
	Control	
Population density (Ihab/km^2)	Higher population density might positively affect productivity through improved infrastructure, market access, and labour availability. However, it could also lead to negative effects if it results in land overuse or environmental degradation. Thus, we expect a neutral to moderate positive relationship depending on the context of the country.	The World Bank, 2024
Trade Balance (per ha)	A positive trade balance in agriculture might signal higher exports and competitiveness. This could reflect greater productivity. Therefore, we expect a positive relationship between trade balance per hectare and agricultural productivity.	Farm accountancy data network-European Commission, 2024
CO_2 Emissions (per ha)	This variable could have a negative effect on agricultural productivity if high emissions are associated with unsustainable farming practices. On the other hand, emissions might reflect the intensity of agricultural activities, which could be tied to high-output farming techniques. The expected relationship could be context-specific, but higher emissions could suggest lower productivity in sustainable contexts.	The World Bank, 2024
Real factor income in agriculture (per annual work)	Higher real factor income suggests that the agricultural sector is generating more value relative to labour input, which should correlate with higher productivity. We expect a positive relationship between income and agricultural productivity.	Eurostat, 2024
Subsidies (per ha)	Agricultural subsidies are often aimed at increasing productivity by supporting farmers with financial resources to invest in new technologies or inputs. Therefore, we expect a positive relationship between subsidies per hectare and productivity, though this could depend on the type and targeting of the subsidies.	Farm accountancy data network-European Commission, 2024

Source: Authors

Table 1: Variables and expected effects.

might influence economic development.

$$lny_i = \beta_0 + \sum_{j=1}^{n} \beta_j lnx_{ij} + \sum_{k=1}^{m} \gamma_k lnc_{ik} + \delta_i + \tau_i + \varepsilon_i \quad (1)$$

Where y_i – dependent variable (total crops output (€/ha)) for country i; x_{ij} – independent variables for country i with j indexing the different independent variables; c_{ik} - control variables country i with k indexing the different independent variables; β_0, β_i – regression coefficients; δ_i - entities fixed or random effects; n – number of independent variables; m – number of control variables; ε_i – error term.

This model specification allows for the interpretation of coefficients as elasticities, which is particularly useful in understanding the proportional impact of changes in agricultural innovation on economic development.

Prior to estimation, diagnostic tests were conducted to ensure the suitability of the model. These tests include checking for multicollinearity using Variance Inflation Factor (VIF) analysis (Sarabia and Ortiz, 2009).

By using both random effects (RE) and fixed effects (FE) models ("within"), we aimed to account for different potential sources of bias and test the consistency of our results (Clarke et al., 2013). Specifically, the RE model enabled the consideration of unobserved heterogeneity across entities that may correlate with explanatory variables, whereas the FE ('within') model addresses time-invariant qualities within each entity, thereby isolating the effects of variables that vary over time. This dual method allowed us to evaluate the robustness and consistency of our findings across various model assumptions. The choice of these models was further validated through the Hausman test (Hausman, 1978; Deutsch, 2012), which helped determine whether the random or fixed effects model is appropriate.

Additionally, to address potential endogeneity issues, instrumental variable (IV) techniques were considered. This approach involves estimating a two-stage least squares (2SLS) technique, a widely used IV estimation method. Therefore, as the first step in the 2SLS method, we regressed R&D expenditure in agriculture on four instrumental variables: population density, CO_2 emissions, real factor income, and subsidies. This approach allowed us to account for the influence of these external factors and mitigate potential endogeneity concerns, ensuring a more accurate assessment of the relationship between R&D expenditure and agricultural productivity. Based on these findings, we decided to exclude CO_2 emissions from the final list of instruments, as it was found to be insignificant in the first stage. By making this adjustment, we improve the accuracy and reliability of the model, ensuring that the remaining instruments offer a stronger and more robust explanation of the relationships between the selected variables.

$$lnx_1 = \theta_0 + \sum_{j=1}^{n} \theta_j lnz_j + \nu_i \quad (2)$$

$$lny_i = \beta_0 + \beta_1 \widehat{x_1} + \varepsilon_i \quad (3)$$

In equation (2), z_j – represents instrumental variables (population density, real factor income in agriculture, CO_2 emissions, and subsidies); θ_j – regression coefficients; v_i – error term. We believe that these instruments, backed by theoretical justification, contribute to the novelty of the instrumentalisation, offering a more reliable approach to addressing potential biases arising from omitted variables and measurement errors.

Equation (3) contains fitted values of the dependent variable from equation (2). In this model specification, independent variables from the study dataset can be used as instruments. The estimated value of the coefficient β_1 is used to test the hypothesis, evaluating whether (instrumented through z_j) has a substantial effect on y_i. Specifically, by estimating β_1, we test whether x_1 has a substantially affects on y_i . Significant results, indicated by the p-value, would confirm this relationship.

To strengthen our assumptions, we conducted diagnostic tests, including the weak instruments, Wu-Hausman and Sargan tests (Patrick, 2020), to assess the presence of endogeneity in regression models.

While this study aims to provide robust insights into the relationship between agricultural innovation and economic development in the EU, several limitations must be acknowledged. The cross-sectional structure of the data restricts the capacity to determine a causal relationship. Additionally, the availability and quality of data across different countries may vary, potentially affecting the reliability of the findings. Despite these limitations, the study employs rigorous methods and comprehensive data sources to ensure the validity of the results.

In summary, this study employs a rigorous quantitative methodology to investigate the impact of agricultural innovation on economic development within the EU. By utilising a log-log multiple regression model and robust statistical techniques, the study aims to provide empirical evidence supporting the hypothesis that higher agricultural innovation leads to greater economic development.

Results and discussion

The research begins by performing a multiple linear regression analysis presented in log-log form, as shown in Table 3, where the dependent variable is the total crops output (€/ha). The log-log transformation enabled us to understand the coefficients as elasticities, indicating the percentage change in the dependent variable resulting from a 1 % change in the independent variable.

However, it is important to note that after performing the multicollinearity analysis (Table 2), we observed that R&D spending in agriculture and population density exhibited significant multicollinearity, with VIF values above 30 and low tolerance values. The trade balance displayed moderate to high multicollinearity, shown by a VIF of around 19.65 and a tolerance at 0.05, suggesting potential complications within the model. We intended excluding trade balance from our models, as removing it reduced overall multicollinearity without impacting the

	R&D expenditure in agriculture (per ha)	Population density (inhab/km^2)	Trade balance (per ha)	CO_2 emissions (per ha)	Real factor income in agriculture (per annual work)	Subsidies (per ha)
Tolerance	0.03013273	0.02557199	0.05089327	0.23870413	0.28468222	0.50399519
VIF	33.186507	39.105289	19.648962	4.189287	3.512689	1.984146

Source: Autor's own calculation

Table 2: Multicollinearity statistics in log-log form.

	Estimate	Std. Error	t-value	Pr (> |t|)
(Intercept)	3.21141	0.74909	4.287	3.05e-05***
R&D expenditure in agriculture (per ha)	0.20083	0.05606	3.582	0.000447***
Population density (inhab/km^2)	0.60153	0.05460	11.016	<2e-16***
CO_2 emissions (per ha)	0.03499	0.08211	0.426	0.670615
Real factor income in agriculture (per annual work)	0.15437	0.05863	2.633	0.009255**
Subsidies (per ha)	-0.04523	0.01316	-3.437	0.000742***
Residual standard error	0.3715 on 167 degrees of freedom			
	(367 observations deleted due to missingness)			
Multiple R-squared	0.7688			
Adjusted R-squared	0.7619			
F-statistic	111.1 on 5 and 167 DF			
p-value	<2.2e-16			

Note: Autor's own calculation, Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 3. Multiple linear regression (OLS) model in log-log form. Dependent variable: Total crops output (per ha).

core relationships under examination, resulting in a more robust and accurate model while preserving the key variables of interest (R&D expenditure and population density).

Hence, from Table 3 above, we see that the R&D spending in agriculture showed a positive and statistically significant impact on total crops output. A 1 % increase in agricultural R&D spending is associated with a 0.20% increase in total crop output per hectare. This positive relationship emphasises the importance of investing in R&D to enhance agricultural output. R&D in agriculture contributes to technological advancements, improved agricultural practices, and increased crop output, directly benefiting overall output.

This model showed that population density had a highly substantial association with crop output, with a coefficient of 0.60153 (p <2e-16), indicating that a 1 % increase in population density corresponds with a 0.60 % increase in total crop output. This outcome indicates that increased population density may stimulate demand for agricultural production or enable more effective use of land resources, maybe owing to improved infrastructure or market accessibility. The substantial volume and importance of this coefficient underscore the vital role of population-driven agricultural practices and market access in affecting productivity.

The coefficient for CO_2 emissions per hectare is 0.03499; however, it is not statistically significant (p = 0.6706). This suggests that variations in CO_2 emissions do not significantly influence total crop output in this model. While CO_2 emissions may contribute to broader environmental and sustainability challenges, they seem to have no direct impact on productivity within the scope of this dataset (Ali et al., 2022). The absence of importance may indicate that other variables, such as agricultural methods or technology, ease the impact of emissions on production. This finding suggests more in-depth investigation. Future research might delve into the impact of other factors, like climate adaptation strategies, crop resilience, or the use of renewable energy, to gain a clearer understanding of how emissions and environmental elements affect agricultural productivity over time.

The coefficient for real factor income is statistically significant (p = 0.009255). An elevated factor income signifies enhanced productivity and profitability within the agricultural sector, which may result in more effective resource utilisation, investments in production, and augmented output. This finding highlights the necessity of maintaining strong agricultural income to improve productivity development.

The coefficient for subsidies per hectare is negative and statistically significant ($p = 0.000742$). This result, however odd, may suggest that ineffectively targeted subsidies might lead to inefficiencies or misallocation of resources. Subsidies may promote excessive utilisation of inputs that do not directly improve productivity or may discourage farmers from innovating or optimising output. This outcome necessitates a thorough analysis of subsidy programs and their efficacy in enhancing production rather than just providing financial assistance (Kumbhakar et al., 2023). The findings by Rizov et al. (2013) highlight the importance of subsidy design. When subsidies were tied directly to production, they had negative effects on productivity, primarily because they encouraged inefficient and unsustainable farming practices. However, once subsidies were decoupled from production, farmers became more efficient and responsive to market signals, resulting in increased productivity in many countries. To further investigate and demonstrate the positive relationship between subsidies and productivity, we will require more detailed data. This might include specific farm-level data on productivity measures before and after subsidy reforms, broken down by crop type, region, and farming methods.

As a next step, we employed both the RE (Table 4) and FE models ("within") (Table 5) to account for the unobserved heterogeneity across selected countries and to test the robustness of the relationships between our variables.

The RE model (Table 4) offered important insights into how the selected variables are related. Significant positive effects were noted for population density ($p<0.001$) and real factor income in agriculture, indicating that these elements contribute significantly to increases in total crop output. CO_2 emissions per hectare demonstrate a notable negative correlation ($p<0.01$), underscoring the possible negative effects of emissions on agricultural results. Other scholars have reported similar findings, observing the negative effect of CO_2 on productivity (Afjal, 2023; Otim et al., 2023). Nevertheless, R&D spending in agriculture and subsidies per hectare show no statistically significant effects, indicating a limited direct impact on the outcome variable given the current model specifications.

Before examining the results of the fixed effects "within" model, it is crucial to emphasise that by focusing on the variation within each entity over time, this model accounts for unobserved, time-invariant characteristics specific to each entity, thereby strengthening the reliability of the findings. Most importantly, the "within" transformation eliminates the constant term since each variable is centred around its specific average, which helps to highlight the effect of time-varying predictors on the dependent variable. Further, similar to the RE effects model, the FE model (Table 5) showed that CO_2 emissions have a negative impact. This negative relationship could indicate that increased CO_2 emissions per hectare are associated with detrimental effects in the agricultural sector, highlighting the possible environmental costs tied

	Estimate	Std.Error	z-value	Pr (> |z|)
(Intercept)	-0.2740252	0.9303198	-0.2945	0.768338
R&D expenditure in agriculture (per ha)	0.0870106	0.0614271	827277,00	0.156634
Population density (inhab/km^2)	0.6984273	0.1301219	648428,00	7.984e-08***
CO_2 emissions (per ha)	-0.4712783	0.1635570	-2.8814	0.003959**
Real factor income in agriculture (per annual work)	0.5081643	0.0656272	2020705,00	9.695e-15***
Subsidies (per/ha)	-0.0057691	0.0151033	-0.3820	0.702478
Total Sum of Squares	49.47			
Residual Sum of Squares	8.5266			
R-Squared	0.82796			
Adj. R-Squared	0.82281			
Chisq	118.603 on 5 DF			
p-value	<2.22e-16			

Note: Autor's own calculation, Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 4. Random Effects Model.

	Estimate	Std.Error	z-value	Pr (> |z|)
R&D expenditure in agriculture (per ha)	0.029200	0.061272	0.4766	0.6344
Population density (inhab/km^2)	0.463549	0.505541	0.9169	0.3606
CO_2 emissions (per ha)	-1.649152	0.304397	-5.4178	2.352e-07 ***
Real factor income in agriculture (per annual work)	0.650856	0.069295	740226,00	<2.2e-16***
Subsidies (per/ha)	0.010184	0.015273	0.6668	0.5059
Total Sum of Squares	10.664			
Residual Sum of Squares	187158,00			
R-Squared	0.41472			
Adj. R-Squared	0.32887			
Chisq	21.2571 on 5 and 150 DF			
p-value	4.9083e-16			

Note: Autor's own calculation, Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 5: Fixed Effects Model.

to intensive farming methods (Zafeiriou and Azam, 2017).

On the other hand, the real factor income in agriculture per annual work unit revealed a highly significant positive effect ($p < 0.001$), highlighting the strong relationship with the dependent variable. This finding underscored the important impact of income produced for each unit of agricultural labour on agricultural performance, possibly indicating advancements in productivity or efficiency.

Based on the results of both RE and FE models, it is reasonable to presume that increased CO_2 emissions could lead to a decline in agricultural productivity. This outcome indicates that rising environmental damage, especially due to CO_2 emissions, might negatively impact crop yields, potentially by worsening climate change, causing unfavourable weather patterns, or diminishing soil fertility. The finding corresponds with wider concerns regarding the harmful impacts of environmental stressors on sustainable farming practices (Ali et al., 2022; Otim et al., 2023). Nonetheless, the positive connection between real factor income in agriculture and total crop output underscores the significance of economic incentives and income growth in enhancing productivity in the agricultural sector. Furthermore, it highlights how financial backing and profitability are crucial for advancing agriculture, as improved income enables farmers to embrace innovative methods and invest in modern tools, resulting in increased productivity.

The findings additionally indicate that areas with higher population density could benefit from improved access to infrastructure, markets, and labour, potentially resulting in enhanced agricultural efficiency. High-density areas often exhibit more efficient transportation systems, improved access to farming resources, and greater opportunities for knowledge exchange and innovation, leading to better agricultural outcomes. This body of literature highlights the complex relationship between population density and agricultural productivity, emphasising that under the right conditions, higher population density can positively impact total crop output (Ricker-Gilbert et al., 2014; Komarek and Msangi, 2019).

In order to determine whether the model with RE or FE was more appropriate for analysing the relationship between selected variables, the Hausman test was employed. The Hausman test assessed the null hypothesis that the RE model yields consistent and efficient estimates, in contrast to the FE model, which addresses unobserved heterogeneity by emphasising within-group variance. The test revealed a chi-squared statistic of 17,903 with 5 degrees of freedom and a p-value of less than 2.2e-16. Due to the very low p-value, we reject the null hypothesis, asserting the consistency of the random effects model.

The null hypothesis rejection in the Hausman test strongly suggests that the random effects model is inconsistent and possibly biassed due to the probable correlation between individual effects and explanatory factors. Consequently, the fixed effects model is the more suitable option for this study.

In the next step of our analysis, we applied an IV 2SLS model (Table 7) to address potential endogeneity issues in our regression analysis. In the first stage of the IV 2SLS model, we used

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-10.36799	0.63113	-16.428	< 2e-16***
Trade Balance (per ha)	0.54782	0.06221	8.806	1.40e-15***
CO_2 emissions (per ha)	0.16994	0.11197	1.518	0.131
Real factor income in agriculture (per annual work)	0.43125	0.07212	5.980	1.27e-08***
Subsidies (per ha)	0.07470	0.01713	4.360	2.24e-05***
Residual standard error	0.5117 on 171 degrees of freedom			
	(364 observations deleted due to missingness)			
Multiple R-squared	0.7117			
Adjusted R-squared	0.705			
F-statistic	105.5 on 4 and 171 DF			
p-value:	< 2.2e-16			

Note: Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 6: First Stage Model in log-log form.

	Estimate	Std. Error	t-value	Pr(> |t|)
(Intercept)	5.60396	1.12245	4.993	1.89e-05***
R&D expenditure in agriculture (per ha)	0.32738	0.07341	4.460	8.98e-05***
Real factor income in agriculture (per annual work)	0.27185	0.09918	2.741	0.00981**
Diagnostic tests				
	df1	df2	statistic	p-value
Weak instruments	2	32	282.987	<2e-16***
Wu-Hausman	1	32	6.704	0.0144*
Sargan	1	NA	0.004	0.9504
Instruments	Population density, real factor income in agriculture and subsidies.			
Residual standard error	0.3303 on 33 degrees of freedom			
Multiple R-Squared	0.682			
Adjusted R-squared	0.6628			
Wald test 37.43 on 2 and 33 DF	p-value = 3.309e-06			
chisq = 28.192, df = 3, p-value = 3.309e-06				
alternative hypothesis: one model is inconsistent				

Note: Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 7: IV 2 Stage Least Square Model in log-log form.

specific instruments (population density, trade balance, CO_2 emissions, real factor income in agriculture per annual work, and subsidies) to explain our dependent variable R&D expenditure in agriculture (Table 6). Each instrumental variable, except CO_2 emissions, demonstrated significant coefficients. Furthermore, the F-statistic result (105.5) and a significant p-value <2.2e16 indicate that these variables are crucial in predicting R&D expenditure in agriculture. This strengthened the 2SLS approach, as robust instruments are essential for addressing the endogeneity in the second stage.

In the second stage, we incorporated R&D expenditure in agriculture, acknowledging the complexity of the agricultural system and economic development, as well as real factor income in agriculture as a control variable due to its direct relevance to agricultural productivity. We investigated various alternative model specifications by adding additional control variables. However, through examinations, we discovered that the model featuring R&D expenditure in agriculture and real factor income in agriculture as primary variables provided the most robust results.

Specifically, results demonstrated that R&D expenditure in agriculture is positive and statistically significant. A 1 % rise in R&D spending in agriculture correlates with an approximate 0.33% increase in total crops outputs. The residuals indicated a satisfactory fit of the model. Our finding aligns with the results of other scholars (Heisey and Fuglie, 2018; Guesmi and Gil, 2021). This highlights the essential role of R&D expenditure in enhancing agricultural productivity, supporting the broad consensus in the existing literature that innovation is a key factor in agricultural productivity development.

Real factor income in agriculture, on the other hand, has demonstrated a positive and statistically significant coefficient of 0.27185 (p-value 0.00981), confirming its influence on agricultural productivity. This is in line with studies such as those highlighting that higher income levels enable farmers to adopt innovations and increase efficiency, ultimately resulting in greater productivity ("Productivity Growth in Global Agriculture," 2013). Additionally, OECD reports have shown that as incomes in agriculture improve, farmers have more financial flexibility to implement advanced practices, purchase higher-quality inputs, and adopt precision farming techniques, all of which contribute to higher yields.

Furthermore, the Wald test and Weak instruments test reinforced the strength and reliability of the instruments, while the Sargan test validated our instrument selection with a p-value of 0.9504, suggesting no overidentification problem. The Wu-Hausman test revealed a p-value of 0.0144, which confirms the presence of endogeneity. Therefore, we rejected the null hypothesis. Hence, the OLS model lacks consistency, causing the implementation of IV to be an appropriate replacement for OLS.

The decision to exclude other variables stemmed from their statistical insignificance and the potential risk of overfitting. Thus, the final model in our study offers robust empirical evidence and serves as the most accurate representation of whether or not R&D expenditure in agriculture affects agricultural productivity. This relationship remains valid even when considering the impact of other significant factors, such as real factor income. The model validated its strength and reliability, indicating that R&D expenditure in agriculture ought to be a key focus for policymakers looking to boost agricultural productivity.

Conclusion

This study highlighted the significant role of innovation, particularly R&D expenditure in agriculture, in enhancing agricultural productivity across the EU-27 for the period 2000-2019.

By applying a quantitative cross-sectional approach using multiple regression analysis and addressing endogeneity concerns with the IV 2SLS method, the findings demonstrate that innovation positively influences total crops output. Therefore, this analysis revealed that our hypothesis is corroborated. Specifically, a 1 % increase in R&D spending is associated with a 0.33% rise in crops output, emphasising the direct impact of research and technological advancements on agricultural performance. Furthermore, real factor income in agriculture was found to contribute a 0.27% increase in crop output, indicating the critical role of income dynamics in driving productivity.

The inclusion of control variables such as population density, CO_2 emissions, and trade balance allowed for a more comprehensive understanding of the broader economic factors influencing productivity. These variables provide valuable insights into how external conditions shape agricultural performance and highlight the complex interplay between innovation and external influences. The robustness of the model, confirmed through residual analysis, reinforces the argument for prioritising R&D in agriculture as a strategic tool for enhancing sustainability, economic development, and resilience in the face of global challenges such as population growth, resource scarcity, and climate change.

Interestingly, subsidies consistently demonstrated a negative effect in each model, suggesting that government financial support may not always translate into increased productivity. This counterintuitive finding could reflect inefficiencies in subsidy distribution, misalignment between subsidy programs and innovation goals, or potential crowding-out effects, where subsidies reduce the incentive for private investment in innovation. Further investigation is needed to explore these dynamics and identify the conditions under which subsidies may contribute positively to agricultural productivity.

This study contributes to the growing body of literature on the impact of innovation in agriculture, providing empirical evidence that supports the knowledge-based economy framework. By demonstrating the direct relationship between R&D expenditure and agricultural output, the findings might have important policy implications. Policymakers might be encouraged to increase investments in agricultural innovation, particularly in R&D, as part of broader strategies aimed at improving agricultural sustainability, enhancing productivity, and fostering long-term economic growth in the agricultural sector.

The study has its limitations, as it focusses solely on internal factors and does not take into account any external factors that could have a significant impact on the productivity indicator. Furthermore, this study delivers opportunities for future research. While the current model provides a solid foundation for understanding the effects of R&D expenditure on agricultural productivity, further studies could investigate additional factors that may enhance model accuracy, such as technological adoption rates, farmer education, and the role of digital tools in precision agriculture. Understanding these elements could deepen the insights into how innovation and external factors interact to shape agricultural outcomes.

In conclusion, this study highlights the transformative potential of R&D investment in agriculture. As the world faces increasing environmental and economic challenges, promoting innovation-driven growth through strategic R&D initiatives will be essential for ensuring the future sustainability and productivity of the agricultural sector, particularly in the EU context.

Corresponding author:
Ing. Tatia Zarkua
Department of Economics, Faculty of Economics and Management, Czech University of Life Sciences Prague
Kamýcká 129, 165 00 Praha – Suchdol, Czech Republic
Phone: E-mail: zarkua@pef.czu.cz

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Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

Agris on-line Papers in Economics and Informatics

The international reviewed scientific journal issued by the Faculty of Economics and Management of the Czech University of Life Sciences Prague.

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ISSN 1804-1930