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Digital Transformation of Agriculture and Sustainable
Development in the European Union: The Role of
Innovation, Agricultural Credit, and Productivity
under Threshold Effects

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Dedication

This thesis is lovingly dedicated to the people who have shaped, supported, and inspired me throughout this important chapter of my life.

*To my father, **Mr. Lotfi Adelhedi**, whose wisdom, encouragement, and quiet strength have always guided me. Your words and values have left a lasting mark on the way I think, work, and live. I owe so much of my determination to your example.*

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Abstract

This study investigates the effects of agricultural digitalization, innovation, credit, and productivity on sustainable development across 27 European Union member states from 2010 to 2024. Using dynamic panel estimation, threshold autoregressive models, and smooth transition regression models, the findings reveal a significant inverted U-shaped relationship between agricultural digitalization and sustainable development. Digitalization enhances sustainability at low and intermediate levels but generates diminishing returns beyond a critical threshold. Total factor productivity emerges as the strongest driver of sustainability, while R&D exhibits a J-curve effect and agricultural credit acts as a conditional catalyst depending on the level of digitalization. Climate-related shocks further constrain sustainability performance. These findings support the need for adaptive, digitally oriented agricultural policies aligned with the European Green Deal and the Farm to Fork Strategy.

Keywords: Agricultural digitalization, Sustainable development, Threshold effects, R&D, Total factor productivity, Agricultural credit, Climate risk, European Union.

Résumé

Cette étude analyse les effets de la digitalisation agricole, de l'innovation, du crédit et de la productivité sur le développement durable dans 27 États membres de l'Union européenne entre 2010 et 2024. À l'aide de modèles de panel dynamiques, de modèles autorégressifs à seuil et de modèles à transition douce, les résultats mettent en évidence une relation en U inversé significative entre la digitalisation agricole et le développement durable. La digitalisation améliore les performances en matière de durabilité aux niveaux faible et intermédiaire, mais ses effets deviennent décroissants au-delà d'un seuil critique. La productivité totale des facteurs apparaît comme le principal moteur de la durabilité, tandis que la R&D présente un effet en forme de J et que le crédit agricole agit comme un facteur conditionnel en fonction du niveau de digitalisation. Les chocs climatiques limitent également les gains en matière de durabilité. Ces résultats soulignent la nécessité de politiques agricoles adaptatives et orientées vers le numérique, en cohérence avec le Pacte vert européen et la stratégie De la Ferme à la Table.

Mots-clés : Digitalisation agricole, Développement durable, Effets de seuil, R&D, Productivité totale des facteurs, Crédit agricole, Risque climatique, Union européenne.

List of Abbreviations

AGTFP : Agricultural Green Total Factor Productivity

AI : Artificial Intelligence

AIoT : Artificial Intelligence of Things

AIC : Akaike Information Criterion

ARDL : Autoregressive Distributed Lag

BB : Born-Breitung

BIC : Bayesian Information Criterion

CADF : Cross-Sectionally Augmented Dickey-Fuller

CAP : Common Agricultural Policy

CAPEX : Capital Expenditure

CD : Cross-Sectional Dependence

CIMMYT : International Maize and Wheat Improvement Center

CIPS : Cross-Sectionally Augmented IPS

CNN : Convolutional Neural Network

CO₂ : Carbon Dioxide

CPI : Consumer Price Index

CV : Coefficient of Variation

DEA : Data Envelopment Analysis

DGP : Data-Generating Process

DVI : Digital Villages Index

EAFRD : European Agricultural Fund for Rural Development

EEA : European Environment Agency

EKC : Environmental Kuznets Curve

ESG : Environmental, Social, and Governance

EU / EU-27 : European Union / 27 European Union member states

FAO : Food and Agriculture Organization

FLW : Food Loss and Waste

FMS : Farm Management Systems

GDP : Gross Domestic Product

GDFM : Generalized Dynamic Factor Model

GERD : Gross Domestic Expenditure on R&D

GMM : Generalized Method of Moments

GNSS : Global Navigation Satellite Systems

GVCs : Global Value Chains

HDI : Human Development Index

HNC : Homogeneous Non-Causality

HPJ : Half Panel Jackknife

HYVs : High-Yielding Varieties

IPCC : Intergovernmental Panel on Climate Change

IPS : Im, Pesaran, and Shin

IRRI : International Rice Research Institute

ISI : Import-Substitution Industrialization

IoT : Internet of Things

JB : Jarque-Bera

LLC : Levin, Lin, and Chu

LM : Lagrange Multiplier

LoRaWAN : Long Range Wide Area Network

LSTM : Long Short-Term Memory

MESA : Mid Elevation Spray Application

MRLs : Maximum Residue Limits

NB-IoT : Narrowband Internet of Things

OECD : Organization for Economic Co-operation and Development

OLS : Ordinary Least Squares

PATs : Precision Agriculture Technologies

PCA : Principal Component Analysis

PMG : Pooled Mean Group

PPP : Purchasing Power Parity

PSTR / PSTAR : Panel Smooth Transition Regression / Autoregressive

PTAR : Panel Threshold Autoregressive

R&D : Research and Development

RCTs : Randomized Controlled Trials

ROI : Return on Investment

SBM : Slack-Based Measure

SDGs : Sustainable Development Goals

SDI : Sustainable Development Index

SFA : Stochastic Frontier Analysis

SPS : Sanitary and Phytosanitary

SSR : Sum of Squared Residuals

SURE : Seemingly Unrelated Regression Equations

TFP : Total Factor Productivity

TV DID : Time-Varying Difference-in-Differences

USDA : United States Department of Agriculture

VIF : Variance Inflation Factor

VRT : Variable Rate Technology / Irrigation

WBRE : Within-Between Random Effects

WDI : World Development Indicators

XAI : Explainable AI

General Introduction

Global agriculture stands at a crossroads, torn between the imperative of food security and planetary boundaries. While classical economists, from [Adam Smith \(1776\)](#) to [David Ricardo \(1817\)](#), through [Karl Marx \(1867\)](#), [John Maynard Keynes \(1936\)](#), and [William Arthur Lewis \(1954\)](#), unanimously recognized agriculture as the fundamental engine of capital accumulation and structural transformation, traditional models are today reaching their limits in the face of contemporary bottlenecks documented by [Johnston and Mellor \(1961\)](#) and [Kumar and Kalita \(2017\)](#) regarding post-harvest losses. To overcome this "productivity trap," the third wave of modernization, characterized by the integration of digital tools (AI, IoT, Big Data), emerges as an indispensable catalyst toward resilient agriculture ([FAO, 2022](#)). However, the literature reveals a paradox: digitalization is not a linear solution. Its effectiveness intrinsically depends on the absorptive capacity of agricultural systems, research and development ([Fuglie et al., 2020](#); [Alston et al. 2010](#)), and financial inclusion, while being disrupted by exogenous shocks. Consequently, the central problematic of this thesis revolves around the following question: **To what extent does the digital transformation of agriculture, in interaction with innovation, credit, and productivity, determine sustainable development performance within the European Union, and to what extent do these dynamics obey non-linear threshold effects?** To answer this, our research postulates (H1) that the impact of digitalization on the Sustainable Development Index ([Sachs et al., 2023](#)) follows a threshold dynamic (inverted U-shaped), thereby validating the productivity paradox of [Brynjolfsson and Hitt \(1996\)](#). We also hypothesize (H2-H4) that R&D, credit, and productivity (TFP) act as conditional catalysts whose effectiveness depends on the digital maturity regime ([Wang et al., 2022](#)), while (H5-H6) climatic and macroeconomic shocks impose structural constraints within a system governed by complex non-linearities ([Acemoglu et al., 2012](#)). The empirical analysis, conducted on a panel of 27 EU countries (2010-2024) through advanced econometric modeling (System GMM following [Arellano and Bond, 1991](#); PTAR threshold models by [Hansen, 1999](#); and PSTR smooth transition models by [González et al., 2017](#)), validates these hypotheses. The results demonstrate a non-linear relationship: while digitalization improves sustainability in low- and medium-intensity regimes, it reaches a saturation threshold beyond which infrastructure costs or digital divides generate negative externalities. Furthermore, R&D and credit only deploy their full potential when the digital ecosystem has reached a critical level of maturity. To demonstrate the relevance of these findings, this thesis is structured around two complementary chapters. Chapter I lays the conceptual foundations by tracing the classical

vision of agriculture's role ([Smith, 1776](#); [Lewis, 1954](#)) and theories of structural transformation, before analyzing contemporary bottlenecks and the role of digital tools as catalysts for sustainability ([FAO, 2022](#)). Chapter II translates these concepts into econometric evidence; following a systematic literature review, it deploys a dynamic and non-linear panel methodology to evaluate the determinants of sustainable agricultural performance in the EU-27, highlighting the threshold effects and complementarity mechanisms that govern the sector's ecological transition.

Chapter I - The theoretical and technological evolution of agriculture in the global economy

Introduction

Let me invite you to imagine, for a moment, a world without agriculture. No wheat for bread, no rice for the bowl, no cotton for clothing, no maize to feed livestock. That image of emptiness is not just an empty refrigerator; it is the picture of a collapsing civilization. For millennia, agriculture has been the silent foundation upon which empires were built, cities flourished, and economies grew complex. Nevertheless, today, that foundation is shaking.

We live at a historic crossroads. On the one hand, the global population is approaching 10 billion, and each additional mouth demands its share of food. On the other side, arable land is eroding, groundwater tables are falling, and the climate is changing faster than predicted. Between the two lies an absurd waste: nearly one-third of all food produced on Earth is lost before it ever reaches a plate. This is not inevitable. It is a consequence of our choices, and therefore, it is fixable.

This thesis tells a story. It is the story of a silent revolution already underway in the fields of Kansas, the rice paddies of Vietnam, the greenhouses of the Netherlands, and the orchards of Kenya. This story is not just about bigger tractors or more powerful fertilizers. It is about data, algorithms, sensors buried in the soil, drones flying over crops, and artificial intelligence capable of diagnosing a disease on a leaf long before any human eye can see it.

However, this story also has an ancient prologue. To understand where agriculture is going, we must first understand where it comes from. The classical economists, Adam Smith, David Ricardo, Karl Marx, and John Maynard Keynes, all recognized, in their own ways, that agriculture is not just another sector. It is the first engine of capital accumulation, the reservoir of labor that feeds the factories, and the foundation of aggregate demand that sustains industry. To neglect agriculture is to saw off the branch on which one sits.

This first chapter is structured as a journey with three stops. The first section returns to the classics: we will see how [Adam Smith \(1776\)](#), [David Ricardo \(1817\)](#), [Karl Marx \(1867\)](#), [John Maynard Keynes \(1936\)](#), and [William Arthur Lewis \(1954\)](#) theorized the central role of agriculture in economic development. The second section examines the contemporary blockages, what I call the "productivity trap», where entire countries have remained stuck for lack of infrastructure, data, and appropriate policies. The third section finally explores the

promise of digital technologies: how artificial intelligence, the Internet of Things, and big data are transforming agriculture into a high-tech, resilient, and sustainable industry.

Throughout this journey, we will not remain in the clouds of theory. We will land in real countries, China, India, Brazil, Kenya, the Netherlands, and Vietnam, to see what these ideas look like on the ground because the purpose of this thesis is not only to convince, but to tell a true story: the story of the possible transformation of agriculture into a growth lever for the 21st century.

Section 1 - Foundations and Classical Vision of Agriculture

Section 1 establishes agriculture as the foundational engine of economic development, tracing how classical thinkers from Quesnay to Smith recognized farming as the primary source of net surplus and capital accumulation. It examines structural transformation through Lewis's dual-economy model, demonstrating how agricultural productivity fuels industrialization by releasing labor and generating domestic savings. The chapter further integrates critical perspectives, from Marxist analyses of land dispossession to Keynesian insights on rural demand and Kuznets' methodological cautions regarding value measurement. By bridging these historical frameworks with contemporary agrarian dynamics, the section reveals how classical economic principles continue to shape modern debates on productivity, structural change, and sustainable development.

1.1. Conceptual Framework: Productivity, Value-Added, and Structural Transformation

When we speak of agriculture today, we often think of contradictory images. On one hand, the traditional farm, almost timeless, with its fields plowed by oxen and its harvests gathered by hand. On the other hand, industrial agribusiness, with its vast fields of maize and soy, its GPS-equipped tractors, and its silos rising on the horizon like modern cathedrals. Between these two images lies a gulf, but also a bridge. That bridge is a structural transformation.

To understand this transformation, we must first define three key concepts: agricultural productivity, value added, and structural transformation itself. These three notions are the compasses that will guide our exploration.

Agricultural productivity, first. At first glance, the definition seems simple: it is the amount of output obtained from one unit of input, land, labor, or machinery. Nevertheless, as the French Physiocrats of the 18th century showed, agricultural productivity has a magical quality. [François Quesnay \(1758\)](#), physician to King Louis XV who became an economist, argued that agriculture was the only truly "productive" activity because it generated a *product net*, a surplus beyond what was needed to pay workers and replace tools. For Quesnay, the artisan who makes a piece of furniture merely transforms existing wood. The peasant, by contrast, grows wheat from a seed. He creates something new. This idea, even if considered too exclusive today, contains a profound truth: agriculture is the only activity that, by harnessing natural biological processes, can generate a net material surplus.

Let me give you a contemporary example. Take the Netherlands today. Dutch farmers produce more than 20 million tons of agricultural exports annually from a land area smaller than the US state of New Jersey. Their productivity, measured in tons per hectare, is among the highest in the world. However, this productivity is not the result of simply tilling more land. It comes from precision: greenhouse automation, data-driven irrigation, and AI-assisted pest control. [François Quesnay \(1758\)](#) could not have imagined LED-lit vertical farms, but his insight, that agriculture harnesses nature's free labor, has never been more relevant.

Value added, next. This is a statistical notion, more prosaic but equally essential. [Simon Kuznets \(1966\)](#), Nobel laureate in economics, reminds us that measuring agriculture's contribution to national income is a methodological headache. Unlike in industry, where raw materials are purchased and finished products are sold on transparent markets, a large part of agricultural output is never sold. It is consumed directly by the producer's family, bartered for other goods, or even hidden from tax authorities. In low-income countries, subsistence agriculture can account for up to 40% of real agricultural GDP. Still, this figure is not reflected in any official statistics without special effort to estimate it. That is why [Kuznets \(1966\)](#) warns that "agricultural value added" is as much a statistical convention as a measurement. That does not mean it is useless, but rather that it must be interpreted with caution and, above all, compared consistently over time.

Consider Kenya's smallholder tea farmers. Most sell only a portion of their harvest to formal cooperatives; the rest is consumed at home, given to neighbors, or sold in informal roadside markets. Official GDP figures often miss this informal economy entirely. When the Kenya National Bureau of Statistics introduced new survey methods in 2014, estimated agricultural value added jumped by nearly 20% overnight, not because farmers produced more, but because statisticians finally saw what was already there.

Structural transformation, finally. This is the process by which an economy shifts from one in which agriculture dominates employment and GDP to one in which industry and services dominate. [William Arthur Lewis \(1954\)](#), in one of the most-cited articles in economic development, sets out this idea with remarkable clarity. For [Lewis \(1954\)](#), economic development consists of raising a country's savings rate from 4-5% of national income to 12-15%, and this leap cannot be achieved by asking people experiencing poverty to save more. It is achieved through structural labor reallocation. In traditional agriculture, there are too many people for the available land. Their marginal productivity is zero or almost zero: some can be removed without total agricultural output falling. If these workers are moved to modern

industry, where their productivity is higher, they produce more, and their wages (even low ones) allow industrial capitalists to make profits. These profits are reinvested, increasing the capital stock, which allows more workers to be hired, and so on. Agriculture's share of GDP falls, not because it produces less, but because industry grows faster.

This is exactly what happened in England in the 19th century, then in Japan, South Korea, and Taiwan, and more recently in China and Vietnam. In 1980, agriculture employed more than 70% of China's workforce and accounted for nearly 30% of its GDP. By 2020, agriculture's share of GDP had fallen below 8%, yet agricultural output had more than quadrupled. Millions of rural workers moved to coastal factories to produce goods for the world. Their remittances back to their villages financed better seeds, irrigation pumps, and, increasingly, smartphones loaded with agricultural AI apps. That is structural transformation in action.

1.1.1. Adam Smith on Productive Labor in Agriculture

Adam Smith's assertion about the supreme productivity of agricultural capital is a foundational pillar of classical economic theory. In *The Wealth of Nations*, published in 1776, he writes: "No equal capital puts into motion a greater quantity of productive labor than that of the farmer. Not only his laboring servants, but his laboring cattle, are productive laborers. In agriculture, too, Nature labors along with man; and though her labor costs no expense, its produce has its value, as well as that of the most expensive workmen." ([Smith, 1776](#)).

This statement reveals Smith's hierarchical view of economic investment. By classifying "laboring cattle" as productive laborers alongside human servants, Smith recognizes livestock not merely as static assets but as dynamic, value-generating agents of capital. More importantly, he conceptualizes Nature as an unpaid yet highly effective collaborative worker. Unlike manufacturing, where human labor merely alters the form of pre-existing materials, agriculture harnesses the earth's intrinsic biological processes to generate entirely new materials.

Let us take a concrete example from Brazil. The country's *corrido* region was once considered unsuitable for farming. Through decades of research by Embrapa, Brazil's agricultural research corporation, scientists developed soybean varieties adapted to tropical soils. Today, Brazil is the world's largest soybean exporter. The "Nature" that [Adam Smith \(1776\)](#) spoke of, in this case, the genetic code of the soybean plant and the process of photosynthesis, works for free. The farmer provides seeds, water, and care, but biological reproduction occurs without additional payment to nature. This is Smith's insight, alive and well in the 21st century.

1.1.2. François Quesnay and the Productive Class

François Quesnay's *Tableau Economique*, published in 1758, represents the first attempt to model an entire economy mathematically. He writes: "The productive class is that which, through the cultivation of the land, reproduces the nation's wealth, advances the costs of agricultural labor, and annually pays the income of the landowners. This class encompasses all work performed in the countryside." (Quesnay, 1758). Quesnay's key innovation was the concept of the product net, the surplus generated by agriculture after deducting all costs. Unlike artisans or merchants, whom he controversially called "sterile" because they merely transformed or moved existing wealth, farmers created new wealth from the soil.

Quesnay also outlined the financial cycle of agriculture. Farmers must make *investments* in seeds, tools, and labor before any harvest. Only after the harvest do they recover their costs and pay rent to landowners. This seasonal rhythm, investment, production, and realization of surplus, is unique to agriculture and has no exact equivalent in manufacturing.

Today, this logic plays out in Vietnam's Mekong Delta. Rice farmers there invest in seedlings, fertilizers, and irrigation before the monsoon. If the harvest fails due to drought, flood, or pests, they may not recover their advances. That is why digital technologies that predict weather and detect disease early are so valuable. They reduce the risk of losing the advances that François Quesnay (1758) identified more than 250 years ago.

1.1.3. Simon Kuznets on Measuring Agricultural Value Added

Simon Kuznets, in his seminal work *Modern Economic Growth: Rate, Structure, and Spread*, published in 1966, highlights a persistent statistical problem: "The measurement of national income and of its components by industry of origin necessarily rests on value added, the difference between the market value of gross output and the cost of input purchased from other industries. For agriculture, the complexity arises because a substantial part of output is not marketed at all, or is marketed through barter and informal channels, making the imputation of value a matter of convention as much as of measurement." (Kuznets, 1966). Kuznets points to two fundamental obstacles. First, a large share of agricultural output in low-income countries never reaches formal markets. Second, because no market transaction occurs, statisticians must impute value to this output, often using prices from distant markets or substitute goods, which introduces substantial errors.

Consider India's vast informal economy. The World Bank estimates that more than 80% of India's agricultural workforce is self-employed or works in informal arrangements. Their

output, vegetables sold at roadside stands, milk delivered directly to neighbors, and grain stored for family consumption, is notoriously difficult to capture. When India revised its GDP series in 2015, incorporating more detailed surveys of smallholder agriculture, the estimated agricultural value added jumped by nearly 10%. The fields had not changed; the measuring stick had.

Modern researchers have built on Kuznets's foundation. [David Lobell et al. \(2020\)](#) at Stanford University showed that combining high-resolution cropland maps with household surveys can reduce imputation error by up to 40%. This matters for policy: if governments underestimate agricultural output, they invest in rural infrastructure and extension services. As [Kuznets \(1966\)](#) wisely noted, measurement conventions are not neutral; they shape what we see and therefore what we do.

1.1.4. William Arthur Lewis on Structural Transformation

[William Arthur Lewis \(1954\)](#), in his classic 1954 article in *The Manchester School*, provides the most influential model of how agriculture fuels industrialization: "The central problem in the theory of economic development is to understand the process by which a community which was previously saving and investing 4 or 5 percent of its national income or less converts itself into an economy where voluntary saving is running at about 12 to 15 percent of national income or more. This is the central problem because the central fact of economic development is rapid capital accumulation, and we cannot explain why saving increases without analyzing the structural transformation of the economy, including the declining share of agriculture in the national product." Lewis's model has three key components. First, developing countries have a dual economy: a traditional agricultural sector with surplus labor (zero marginal productivity) and a modern industrial sector with higher labor productivity. Second, industrial capitalists reinvest their profits, expanding the modern sector and absorbing labor from agriculture. Third, this process continues until the surplus labor is exhausted, a point known as the Lewis turning point.

China's transformation illustrates this perfectly. In 1980, agriculture employed 70% of China's workforce. By 2020, that share had fallen to 25%. Over the same period, the national savings rate rose from less than 10% to nearly 45%. This was not because Chinese peasants suddenly became frugal. It was because tens of millions of rural workers moved to coastal factories, where their labor generated profits that were reinvested in machinery, infrastructure, and research and development. The remittances they sent home financed the modernization of agriculture itself, better seeds, irrigation, and now digital tools. As [Lewis \(1954\)](#) foresaw, the

declining share of agriculture in GDP was not a sign of agricultural failure but of industrial success.

1.1.4.1. The Dual-Economy Model Explained

The dual-economy model is best understood through a simple example. Imagine a village of 100 farming families cultivating 100 hectares of land. Total agricultural output is 100 tons of rice, just enough to feed everyone at the subsistence level. The marginal productivity of labor is zero: if 10 families moved to the city, the remaining 90 families would still produce 100 tons (by working harder or switching to more efficient methods). Now suppose a factory opens in the nearest city, offering jobs at a slightly higher than the subsistence rice wage. Ten families move. Agricultural output does not fall. The factory produces 20 tons of textiles, of which 10 tons are exported to buy rice from elsewhere. The capitalists earn profits, reinvest in a second factory, and the process continues.

This is what happened in South Korea in the 1960s and 1970s, as documented by [Irma Adelman \(1984\)](#) and other development economists. Agricultural productivity rose just enough to release labor without reducing food supply. The manufacturing sector grew at double-digit rates. By 1990, South Korea had reached its Lewis turning point: agricultural wages began to rise rapidly, and the country shifted to high-tech industries.

Today, many sub-Saharan African countries have not yet reached the Lewis turning point. As [Xinshen Diao et al \(2019\)](#) at the International Food Policy Research Institute have shown, agricultural productivity remains low, and labor moves not to formal industry but to informal urban services. This is a central challenge for modern development policy, and a reason why digital agricultural technologies are so urgently needed.

1.1.4.2. From 5% to 15% Savings Rate as Development Signature

The increase in the savings rate from approximately 5% to 15% of national income is not an arbitrary target. It corresponds empirically, as [Nicholas Kaldor \(1961\)](#) and [Robert Solow \(1956\)](#) showed, to the transition from a low-investment, low-growth equilibrium to a high-investment, high-growth equilibrium. In the Lewis model, this increase is driven by the profits of industrial capitalists, who have a higher marginal propensity to save than peasants or workers. When a peasant earns an extra dollar, he spends almost all of it on food and necessities. When a capitalist earns an extra dollar of profit, he invests most of it in new machinery. This insight was later formalized by [Michał Kalecki \(1954\)](#) and [Stephen Marglin \(1984\)](#).

Vietnam offers a compelling case. In 1990, after decades of war and central planning, Vietnam's gross domestic savings rate was barely 10% of GDP. Agriculture employed more than 70% of the workforce. The country was poor. Following the reforms initiated in 1986, agriculture was liberalized, and foreign investment was welcomed. By 2020, the savings rate had risen to nearly 30%, and agriculture's share of employment had fallen below 40%, according to [World Bank \(2020\)](#) data. Millions of rural workers now produce electronics and textiles for export. Their savings, channeled through banks and state-owned enterprises, finance roads, ports, and, increasingly, digital infrastructure.

The lesson for developing countries is clear: raising the savings rate requires not just financial-sector reforms but also a fundamental reallocation of labor and capital from low-productivity agriculture to higher-productivity industry and services. This, in turn, depends on raising agricultural productivity to release labor. As [William Arthur Lewis \(1954\)](#) understood seventy years ago, agriculture is not a sector to be abandoned; it is the foundation on which modern economies are built.

1.2. The Classical School: Agriculture as the Primary Source of "Surplus" and the Engine of Capital Accumulation

The classical economists saw agriculture not as a backward sector to be outgrown, but as the strategic foundation of all economic activity. To understand their perspective, we examine Adam Smith's "natural order", David Ricardo's law of diminishing returns, and the modern refinements of Robert C. Allen and Ester Boserup.

[Adam Smith's \(1776\)](#) natural order, set out in Book III of *The Wealth of Nations* (1776), argues that capital first flows to agriculture, then to manufacturing, and finally to foreign commerce. Why? Because land provides the most secure form of investment. It produces food that everyone needs. Once the countryside is productive enough to generate a surplus, capital can safely move to factories. Only when domestic markets are saturated does it make sense to trade abroad.

Consider the United States in the 19th century. The Homestead Act of 1862 gave settlers land, encouraging agricultural expansion. Railroads followed, linking farms to cities. Only later did manufacturing, steel, automobiles, and chemicals overtake agriculture as the leading sector. Smith's natural order, roughly speaking, held.

[David Ricardo \(1817\)](#) added a sobering note in his *Principles of Political Economy and Taxation*. Because the supply of fertile land is fixed, a growing population eventually forces

society to cultivate inferior soils. The law of diminishing returns sets in as each additional unit of labor and capital produces less additional output. Food prices rise, squeezing industrial profits, until the economy grinds to a "stationary state" of zero growth.

Ricardo's warning is relevant today in the context of climate change. As the Intergovernmental Panel on Climate Change (IPCC, 2022) has documented, in the Sahel region of Africa, rising temperatures and erratic rainfall are reducing yields on previously marginal lands. Farmers are forced to cultivate even less productive soils, exactly the Ricardian dynamic. Without technological innovation, diminishing returns could trap millions in poverty.

Ester Boserup (1965), in *The Conditions of Agricultural Growth*, offered an optimistic counterpoint. She argued that population pressure itself is a stimulus for agricultural intensification. When land becomes scarce, farmers innovate; they switch from shifting cultivation to permanent farming, from hand tools to plows, from rain-fed to irrigated agriculture. Necessity becomes the mother of invention. Rwanda provides a striking example. With one of the highest population densities in Africa, Rwandan farmers have no choice but to manage their small plots intensively. Over the past two decades, they have adopted terracing, agroforestry, and improved seeds. Maize yields have tripled. This is Boserup in action: pressure forcing innovation.

1.2.1. Adam Smith on the Natural Order of Capital Allocation

According to the natural course of things, therefore, the greater part of the capital of every growing society is, first, directed to agriculture, afterward to manufactures, and last of all to foreign commerce. This order of things is so very natural that in every society that has any territory, it has always, I believe, been in some degree observed. (Smith, 1776)

Smith's logic rests on security and proximity. Agriculture is the most visible, controllable investment. It feeds the population. Only after agricultural productivity rises can capital safely flow to manufacturing. Moreover, only after manufacturing saturates domestic demand does foreign commerce become profitable.

Smith used this argument to criticize the mercantilist policies of his day, which subsidized foreign trade while neglecting domestic farming. The same debate echoes today in discussions of "premature" trade liberalization, as Dani Rodrik (2011) and Ha-Joon Chang (2014) have argued. Countries that opened their markets before building productive agricultural and industrial bases, many in Latin America in the 1980 s, often saw deindustrialization without prosperity.

Ethiopia provides a contemporary parallel. For decades, the government focused on industrial parks and export processing zones, neglecting smallholder agriculture. The results were meager. Since 2018, a new policy has prioritized agricultural modernization, irrigation, improved seeds, and digital extension services. Early results are promising: wheat yields have risen, and food imports have fallen. As [Adam Smith \(1776\)](#) would have predicted, the natural order is reasserting itself.

1.2.2. David Ricardo on Diminishing Returns and the Stationary State

[David Ricardo \(1817\)](#), in his *Principles of Political Economy and Taxation*, published in 1817, describes the logic of diminishing returns: "In an expanding economy, the level of investment and wages are high and growing. Capital accumulation is taking place. However, high wages induce population growth and pressure on the food supply; fixed land leads to diminishing returns to capital and labor in agriculture; and the necessity of utilizing inferior grades of land to feed a growing population. Consequently, production costs increase, and profits decrease. Decreasing profits lead to decreased capital accumulation and investment as the stationary state is approached." Ricardo's sequence, expansion, population growth, cultivation of marginal land, rising food prices, falling profits, stagnation, is one of the most pessimistic in economic thought. It implies that capitalism contains its own seeds of death.

But is it inevitable? Technological progress can shift the production possibility frontier. The Green Revolution of the 1960s and 1970s, which we will examine in Section 2, dramatically raised yields on existing land, temporarily postponing Ricardian limits. More recently, precision agriculture and AI-driven resource management offer the potential to decouple output from land area. Nevertheless, climate change is reimposing Ricardian constraints. The Intergovernmental Panel on Climate Change ([IPCC, 2022](#)) estimates that for every 1 C of warming, global maize yields decline by 7%, wheat by 6%, and rice by 3%. In tropical regions, the losses are even larger. The stationary state, not zero growth, but the end of growth based on resource expansion, may be closer than [David Ricardo \(1817\)](#) imagined.

1.2.3. Robert C. Allen on the Agricultural Preconditions of Industrialization

[Robert C. Allen \(2009\)](#), professor of economic history at New York University Abu Dhabi, argues in his 2009 book *The British Industrial Revolution in Global Perspective* that the Industrial Revolution was predicated on an earlier agricultural revolution: "Britain's unique wage and energy price structure created strong incentives to develop labor-saving, capital-using technologies, particularly in manufacturing. However, this process was based on an earlier

agricultural revolution that had already restructured the rural economy, released labor to the towns, and generated the food surplus necessary to sustain a non-agricultural workforce on a massive scale. Without the prior transformation of agriculture, the Industrial Revolution would have been inconceivable." Allen's claim is both historical and policy relevant. Historically, British agriculture raised yields per worker through enclosures, crop rotations, and selective breeding. This released labor and generated a food surplus. Without those preconditions, the factories of Manchester and Birmingham could not have been fed.

For contemporary developing countries, the implication is that industrialization cannot bypass agriculture. Premature deindustrialization, as documented by [Dani Rodrik \(2016\)](#) at Harvard University, occurs when countries shift from agriculture to services without a strong manufacturing base. They get stuck in middle-income traps. Indonesia offers a cautionary tale. In the 1970s and 1980s, the country invested heavily in rice self-sufficiency through irrigation, fertilizer subsidies, and extension services. Agricultural productivity rose, labor moved to manufacturing, and Indonesia grew rapidly. But in the 1990s, policy shifted toward capital-intensive industry and services, neglecting agriculture. Manufacturing employment stagnated, and the country suffered severe crises in 1998 and 2008. A return to agricultural investment, including the use of digital tools, is now a priority. As [Robert C. Allen \(2009\)](#) would argue, you cannot skip the agricultural revolution.

1.2.4. Ester Boserup on Population Pressure as a Catalyst

[Ester Boserup \(1965\)](#), the Danish economist, directly challenged the Malthusian-Ricardian orthodoxy in her 1965 book *The Conditions of Agricultural Growth*. She wrote: "Agricultural growth is not merely a precondition of industrial development: it is its driving force. When agricultural productivity rises, the marketed surplus increases, rural incomes expand, and the demand for manufactured goods follows. Population pressure, far from being an obstacle, can itself become the stimulus to more intensive and more productive agricultural systems." Boserup's mechanism is demand-driven. Population growth creates scarcity, which in turn drives innovation. Farmers switch from extensive to intensive techniques: from long fallows to short fallows, from shifting cultivation to permanent farming, from rain-fed to irrigated agriculture. Each step requires more labor per hectare but yields more output.

The Kenyan highlands provide a classic Boserupian case, as documented by [Mary Tiffen et al. \(1994\)](#) in their study *More People, Less Erosion*. For centuries, the Kikuyu people practiced shifting cultivation. As population density increased, they adopted terracing, manure application, and intercropping. Today, the central highlands of Kenya have some of the highest smallholder productivity in Africa, not despite population pressure, but because of it.

However, Boserupian intensification has limits. Beyond a certain point, population pressure can lead to land degradation, soil nutrient depletion, and falling yields. The challenge for policy is to support intensification with the right technologies, including digital tools that allow farmers to manage their resources more precisely. As [Ester Boserup \(1965\)](#) herself acknowledged, the direction of intensification matters as much as its intensity

1.3. The Marxian Perspective: Agriculture as a Provider of "Reserve Labor" and the Transition from Feudalism to Agrarian Capitalism

[Karl Marx](#) saw agriculture not as a harmonious foundation for growth, but as a site of violence, dispossession, and class struggle. His concept of primitive accumulation describes how the capitalist system arose not from peaceful saving but from the forced separation of peasants from their land. "The expropriation of the agricultural producer, of the peasant, from the soil, is the basis of the whole process. The history of this expropriation, in different countries, assumes different aspects, and runs through its various phases in different orders of succession, and at different periods. In England alone, which we take as our example, it has the classic form. [...] The spoliation of the church's property, the fraudulent alienation of the State domains, the robbery of the common lands, the usurpation of feudal and clan property, and its transformation into modern private property under circumstances of reckless terrorism, were just so many idyllic methods of primitive accumulation." ([Marx, 1867](#)). Marx's sarcasm and idyllic methods are deliberate. The Enclosure Acts in England, enacted roughly between 1750 and 1850, fenced off common lands that peasants had used for generations. This created two things: large, consolidated farms owned by a capitalist landlord class, and a landless proletariat with no choice but to sell their labor in the new factories.

Contemporary analogs are not hard to find. In Brazil, the expansion of soybean plantations in the *corrido* has displaced thousands of smallholder families, as documented by [Wendy Wolford \(2005\)](#). In Indonesia, palm oil plantations have been established on land previously used by shifting cultivators. In Ethiopia, large-scale agricultural investments, sometimes labeled "land

grabs», have relocated rural populations, as studied by [Marc Edelman et al. \(2013\)](#). Karl Marx's primitive accumulation is not only history; it is ongoing.

1.3.1. Karl Marx on Primitive Accumulation and Dispossession

The passage above captures Marx's core argument. Dispossession serves two purposes. First, it consolidates land for commercial farming. Second, it creates desperate labor for industry.

Take the case of India. The British colonial administration's land revenue settlements in the 19th century transformed traditional communal tenure into private property. Millions of peasants lost their land to moneylenders and landlords. They migrated to cities, providing cheap labor for jute mills, cotton factories, and railways. This was primitive accumulation, colonial style, as documented by [David Washbrook \(1981\)](#) and other historians.

Today, land reforms in countries like China, where land is still collectively owned but use rights are allocated to households, and Rwanda, where land tenure regularization is underway, attempt to avoid the most violent aspects of dispossession while still enabling commercial agriculture. The challenge, as [Karl Marx \(1867\)](#) would recognize, is to balance efficiency with equity.

1.3.2. Karl Marx on the Relative Decline of Agricultural Labor Demand

Marx also observed a distinctive feature of agricultural capitalism: "As soon as capitalist production takes possession of agriculture, and in proportion to the extent to which it does so, the demand for an agricultural laboring population falls absolutely, while the accumulation of the capital employed in agriculture advances, without this repulsion being, as in non-agricultural industries, compensated by a greater attraction. Part of the agricultural population is therefore constantly on the point of passing over into an urban or manufacturing proletariat, and on the look-out for circumstances favorable to this transformation." ([Marx, 1867](#)). Unlike manufacturing, where mechanization might initially displace workers but later reabsorb them as the industry expands, agriculture suffers from a fixed factor: land. Once a tractor replaces ten farm workers, those workers rarely return. The labor "repulsion" is permanent.

This is precisely what happened in the United States. In 1900, nearly 40% of the US workforce was in agriculture. By 2000, that share had fallen to less than 2%. Yet total agricultural output has more than doubled. The displaced workers did not go back; they went to factories, offices, and eventually the service sector. The same process, as documented by [Thomas Rawski and Loren Brandt \(2019\)](#), is now underway in China, India, and Vietnam. [Karl Marx \(1867\)](#) identified this dynamic more than 150 years ago.

1.3.3. Henry Bernstein on the Agrarian Question and Class Formation

Henry Bernstein, professor emeritus at the School of Oriental and African Studies, University of London, updates Marx's framework for the 21st century in his 2010 book *Class Dynamics of Agrarian Change*. He writes: "The agrarian question, as Marx and subsequent Marxist theorists formulated it, is not simply about agriculture as a sector: it concerns the conditions under which agriculture contributes to, or obstructs, the development of capitalism as a social system. At its core lies the question of class formation: how the differentiation of the peasantry produces, on one side, a rural bourgeoisie capable of accumulating capital, and on the other, a rural proletariat available for exploitation in both agrarian and industrial production." (Bernstein, 2010). As capitalist markets penetrate the countryside, traditional peasant communities differentiate. A small minority becomes a rural bourgeoisie, investing in machinery, hiring labor, and accumulating land. The majority are pushed into poverty, debt, and landlessness. They become a rural proletariat. This process can be observed in India's Green Revolution states, such as Punjab, as documented by John Harriss (1982) and Barbara Harriss-White (1996). Large farmers bought tractors, tube wells, and fertilizers. Smallholders who could not afford these inputs sold their land and migrated to cities. The result is a highly productive agricultural sector alongside persistent rural poverty.

For policymakers, the agrarian question is uncomfortable: raising productivity often requires consolidation, but consolidation can increase inequality. Digital technologies, particularly scalable and affordable ones, may offer a way out. Mobile-based advisory services, shared drone services, and pay-per-use irrigation can give smallholders access to the benefits of technology without requiring land ownership. As Henry Bernstein (2010) would remind us, the agrarian question is not solved; it has merely taken new forms.

1.3.4. Terence J. Byres on Pathways of Agrarian Transition

Terence J. Byres, professor of political economy at the School of Oriental and African Studies, distinguishes three interrelated processes in the agrarian transition to capitalism. In his 1991 chapter in *Rural Transformation in Asia*, he writes: "The agrarian transition to capitalism involves three interrelated processes: first, the dispossession of peasants from land; second, the emergence of a class of capitalist farmers who organize agricultural production based on wage labor; and third, the generation of a surplus that can be transferred through taxation, prices, or direct investment to finance industrial capital formation. Different historical paths of agrarian transition produce different long-run outcomes for industrialization and economic development." (Byres, 1991). Byres identifies several "paths": the English path (enclosures,

large estates, sharp separation of peasants from land), the French path (smallholder persistence, slower industrialization), and the Prussian path (noble landowners adopting capitalist methods using semi-coerced labor). This typology was originally developed by Karl Marx and later refined by [Vladimir Lenin \(1899\)](#) and other Marxist theorists.

China today represents a new, hybrid path, as [Philip Huang \(2012\)](#) analyzed at the University of California, Los Angeles. Land is still collectively owned by villages, but use rights are allocated to households. Some households have transferred their use rights to large agribusinesses, creating a form of "land rental" market without full privatization. Rural labor has moved in large numbers to cities, but many retain their land rights as a safety net. The result is a unique agrarian transition that combines elements of all three classical paths. As [Terence J. Byres \(1991\)](#) would recognize, history does not repeat itself, but it does rhyme.

1.4. The Keynesian Approach: The Role of Agricultural Income in Supporting Aggregate Demand and the Importance of Price Stability

The classical and Marxian perspectives focused on supply: producing more food, releasing labor, and accumulating capital. John Maynard Keynes shifted attention to demand. In an economy where most people are farmers, their incomes determine the demand for industrial goods. [John Maynard Keynes \(1936\)](#), in his *General Theory of Employment, Interest and Money*, identified a "fundamental psychological law": as income rises, consumption rises, but not by as much. The gap, savings, need to be invested. If investment does not fill the gap, effective demand falls, and unemployment rises. In an agrarian economy, this logic is stark. If rural incomes fall, because crop prices collapse or weather destroys harvests, farmers cannot buy manufactured goods. Factories lay off workers. Those workers then cannot buy food, so farmers' incomes fall further. A downward spiral ensues.

[Michał Kalecki \(1954\)](#), in his *Selected Essays on the Economic Growth of the Socialist and the Mixed Economy*, added a crucial institutional insight: agricultural prices are determined by supply and demand (farmers are price-takers), while industrial prices are set by mark-ups (firms are price-makers). A fall in agricultural prices does not stimulate demand; it improves the rural sector. The 2007-2008 global food price crisis, documented by [Derek Headey and Shenggen Fan \(2010\)](#) at the International Food Policy Research Institute, illustrated this dramatically. When rice and wheat prices tripled, urban consumers suffered, but rural producers in many countries benefited. The problem was not falling agricultural prices, but extreme volatility.

Countries with buffer stocks and price-stabilization mechanisms, such as India's public distribution system, weathered the crisis better.

[Amartya Sen \(1981\)](#), in his book *Poverty and Famines*, applied Keynesian logic to the most extreme case: famine. He showed that famines occur not when food supply is low, but when certain groups lose their "exchange entitlements», the ability to command food through wages, trade or transfers. The 1943 Bengal famine, which killed 2-3 million people, occurred during a year when food availability was higher than in previous non-famine years. What collapsed were the wages of landless laborers. The implication for policy is clear: agricultural policy is not just about production. It is about prices, incomes, and stability. Governments must protect rural purchasing power to sustain aggregate demand and prevent entitlement collapse.

1.4.1. John Maynard Keynes on Aggregate Demand and Employment

[John Maynard Keynes \(1936\)](#), in *General Theory of Employment, Interest and Money*, writes: "The outstanding faults of the economic society in which we live are its failure to provide for full employment and its arbitrary and inequitable distribution of wealth and incomes. [...] When employment increases, aggregate real income increases. The psychology of the community is such that when aggregate real income rises, aggregate consumption rises, but not by as much as income. Keynes's "fundamental psychological law" implies that, without government intervention to stimulate investment, economies can settle into under-employment equilibria. This insight was later formalized by [Hyman Minsky \(1975\)](#) and [James Tobin \(1987\)](#).

For an agrarian economy, this means that agricultural support is macroeconomic policy, not just welfare. The US Agricultural Adjustment Act of 1933 paid farmers to reduce production, raise agricultural prices, and increase rural income. This helped pull the United States out of the Great Depression, as documented by [Lee Alston and Joseph Ferrie \(1999\)](#). More recently, despite its inefficiencies, the European Union's Common Agricultural Policy has stabilized farm incomes and rural demand. Developing countries often lack the fiscal space for such large-scale interventions. But targeted measures, input subsidies, price supports, or cash transfers linked to agricultural production can have significant multiplier effects, as found by [Luc Christiaensen et al. \(2011\)](#) in their World Bank research. As [John Maynard Keynes \(1936\)](#) understood, demand is not automatic; it must be actively managed.

1.4.2. Michał Kalecki on Effective Demand in Agriculture versus Industry

[Michał Kalecki \(1954\)](#), the Polish economist, in his 1954 *Selected Essays on the Economic Growth of the Socialist and the Mixed Economy*, writes: "The problem of effective demand in

agriculture is fundamentally different from that in industry. Agricultural prices are determined by supply and demand on competitive markets, while industrial prices are set by a markup over costs. A fall in agricultural prices, therefore, does not stimulate demand; on the contrary, it impoverishes the rural sector and reduces the consumption expenditure of most of the population in developing countries, where agriculture still employs the bulk of the labor force."

Kalecki's insight is that farmers cannot pass on price declines to consumers. When demand falls, manufacturing firms can reduce output to protect prices. Farmers cannot easily reduce output (due to biological lags), so prices fall and incomes collapse.

Ethiopia's coffee crisis of the early 2000s, studied by [Arne Bigsten et al. \(2008\)](#), illustrates this. Global coffee prices fell by half. Ethiopian coffee farmers, lacking storage or alternative markets, sold their coffee at lower prices. Their incomes collapsed. They bought fewer manufactured goods. Addis Ababa's factories laid off workers. The contractionary spiral was exactly as [Michał Kalecki \(1954\)](#) described. Digital technologies can help stabilize agricultural prices. Real-time market information systems, like Esoko in Ghana, studied by [Jenny Aker \(2011\)](#), or M Farm in Kenya, allow farmers to compare prices across markets and avoid selling at the lowest local price. Futures markets accessible via mobile phones enable hedging. But these tools require connectivity, literacy, and trust. As [Kalecki \(1954\)](#) would have noted, market imperfections are not eliminated by technology alone.

1.4.3. Amartya Sen on Entitlements and Food Security

[Amartya Sen](#), Nobel laureate in economics, in his [1981](#) book *Poverty and Famines*, writes:

"Famines can and do occur even without any overall decline in food availability. The determining factor is not the aggregate supply of food but the exchange entitlements of different groups in society: their ability to command food through production, trade, or transfer. When agricultural prices collapse, or rural wages fall in real terms, the exchange entitlements of the rural poor deteriorate catastrophically, collapsing effective demand for food among those who need it most." ([Sen, 1981](#)). Sen's entitlement approach has been applied to numerous famines. The 1974 Bangladesh famine, analyzed by [Mohiuddin Alamgir \(1980\)](#), occurred after floods destroyed the rice harvest, but food imports and stocks were sufficient. The problem was that agricultural laborers lost their jobs and wages, while food prices rose. Their exchange entitlements collapsed.

More recently, the 2022-2023 food crisis in Sri Lanka, documented by the [World Bank \(2023\)](#), offers a variant. A sudden ban on chemical fertilizers, for environmental reasons, halved rice production. Farmers' incomes collapsed, but so did supply. The government's foreign exchange reserves were depleted, preventing food imports. Urban workers lost their jobs as the economy contracted. This was both a supply and an entitlement crisis. Amartya Sen's framework has shaped international food security policy. The Food and Agriculture Organization's Integrated Food Security Phase Classification (IPC) now incorporate entitlement indicators alongside food supply data. Early warning systems monitor wages, food prices, and asset sales, not just rainfall and harvests. As [Sen \(1981\)](#) argued, the question is not how much food exists, but who can afford to buy it.

1.4.4. Historical Analysis of GDP Contribution: How the "Agricultural Revolution" Preceded the "Industrial Revolution."

The statistical signature of structural transformation is a declining share of agriculture in GDP alongside rising absolute output. [Nicholas Crafts \(1985\)](#), professor of economic history at the University of Warwick, showed that in pre-industrial Britain, agriculture's share of GDP fell from 40% in 1700 to 20% in 1800, even as agricultural output grew substantially. This pattern is clear in all successful developers. In South Korea, agriculture's share of GDP fell from 40% in 1960 to less than 3% today. In China, from 30% in 1980 to 7% today. In Vietnam, from 40% in 1990 to less than 15% today. In each case, agricultural output continued to rise, sometimes faster than before.

[Jared Diamond \(1997\)](#), in his Pulitzer Prize-winning book *Guns, Germs, and Steel*, traces the ultimate origins of this pattern to the Neolithic Revolution. Without food surpluses, there can be no specialists, no cities, no states, no accumulation of capital. Agriculture, in other words, made civilization possible.

1.4.4.1 Eric L. Jones on the Agricultural Roots of Growth

[Eric L. Jones \(1974\)](#), the Australian economic historian, in his 1974 book *Agriculture and Economic Growth in England, 1660-1750*, writes: "The roots of economic growth lie in the agricultural revolution, which preceded it. The transformation of English farming between 1560 and 1760 through enclosures, improved rotations, selective breeding, and drainage raised yields per acre and per worker to a degree that permitted a sustained transfer of labor and capital to non-agricultural uses." Jones argues that the agricultural revolution was not an add-on to the

Industrial Revolution but its precondition. Without higher yields per acre and per worker, the factories of the Industrial Revolution could not have been fed.

1.4.4.2. Nicholas Crafts on Structural Transformation in Pre-Industrial Britain

[Nicholas Crafts \(1985\)](#), book *British Economic Growth During the Industrial Revolution*, provides the numbers: "Estimates of national income for pre-industrial Britain reveal that agriculture accounted for between 35 and 40 percent of GDP in 1700, declining to around 20 percent by 1800 even as agricultural output itself grew substantially. This pattern, rising absolute output with a declining share of national income, is the statistical signature of successful structural transformation." As Crafts demonstrated, the decline in agriculture's relative share is not a sign of failure but of success; the sector became so productive that it required fewer workers and resources to feed the population.

1.4.4.3. Jared Diamond on the Neolithic Foundation of Economic Development

[Jared Diamond \(1997\)](#), professor of geography at the University of California, Los Angeles, takes the longest view in his 1997 book *Guns, Germs, and Steel*: "The rise of agriculture was the most decisive revolution in human economic history, more consequential, ultimately, than the Industrial Revolution itself. By producing food surpluses, agriculture enabled the division of labor, the emergence of specialized crafts, the formation of states, and the accumulation of capital. Every subsequent step in economic development, including industrialization, was built on the foundation that the Neolithic agricultural transition laid down ten thousand years ago." Diamond's insight is that everything that came after, cities, writing, technology, industry, rests on the surplus that agriculture first made possible. The agricultural revolution was not just the first economic revolution; it was the revolution that made all others possible.

Section 2 - Structural transition and contemporary bottlenecks

The theories of [Adam Smith](#), [David Ricardo](#), [Karl Marx](#), and [John Maynard Keynes](#) tell us what agriculture can do. But history tells us what often goes wrong. This section diagnoses the structural bottlenecks that have prevented many developing countries from reaping the benefits of agricultural modernization. We will examine the shift from subsistence farming to global value chains, and the promises and pitfalls of integration into international markets. We will then confront the productivity trap: a vicious cycle of rural neglect, post-harvest losses, and critical data gaps that perpetuate low output and high waste. Finally, we will trace the three waves of agricultural modernization, mechanization, the Green Revolution, and the digital revolution, showing how each wave solved some problems while creating new ones. Understanding these blockages is essential to appreciating why artificial intelligence and the Internet of Things are not just optional upgrades but structural necessities.

2.1. From Subsistence to Market Agriculture: The Shift from Local Consumption to Global Value Chains

Let me bring you back in time. For most of human history, farming was a local affair. A village grew what it ate, ate what it grew, and had little left over for trade. The surplus, when it existed, was small and irregular. Today, by contrast, a single breakfast, coffee from Colombia, sugar from Brazil, wheat from Canada, bananas from Ecuador, can cross four continents before reaching a plate. This transformation from subsistence to market-oriented, globally integrated agriculture is one of the most profound structural shifts in economic history.

However, this shift did not happen automatically. It required, and continues to require, deliberate investments in infrastructure, institutions, and information. In 1961, two economists at Stanford University, [Bruce F. et al. \(1961\)](#), published an article that became a classic. They argued that agriculture performs five critical functions in the development process: it provides food for urban workers, supplies raw materials for industry, generates foreign exchange through exports, creates a market for industrial goods, and releases surplus labor and capital for manufacturing. These functions, they emphasized, are not separate; they are tightly interlinked. Let me give you a concrete example. Consider the case of Thailand. For decades, Thailand was a subsistence rice economy. Then the government invested in irrigation, roads, and extension services. These investments transformed Thailand into the world's largest rice exporter. The foreign exchange earned from rice exports was used to pay for imported machinery and fuel. Rural income from rice sales spurred demand for motorcycles, televisions, and processed foods.

Moreover, as productivity rose, labor released from rice farming moved to Bangkok's factories and service industries. This is Johnston and Mellor's model in action.

In the 21st century, these domestic linkages have expanded into what economists call global value chains, or GVCs. As the Organization for Economic Co-operation and Development (OECD) noted in its 2020 report, modern agricultural production is increasingly fragmented across borders. Raw materials cross multiple frontiers before reaching the final consumer. Countries can specialize in specific stages, growing, processing, packaging, and logistics, rather than producing everything from scratch. This specialization broadens the gains from trade and drives employment growth.

Vietnam's coffee industry illustrates the GVC logic perfectly. Vietnam is now the world's second-largest coffee exporter, but it does not simply grow beans and ship them raw. Vietnamese companies process, roast, grind, and package coffee for international brands like Nestlé and Starbucks. Each stage adds value. The coffee cherry grown in the Central Highlands becomes a capsule in a European kitchen. The value added is distributed across the chain, growers, processors, shippers, roasters, retailers, and Vietnam captures a growing share. However, GVC participation is not automatic. It requires coordination. Farmers must meet quality standards, deliver predictable volumes, and comply with traceability requirements. This is where digital technologies have become essential. [Christopher Barrett et al. \(2022\)](#) at Cornell University documented that blockchain-based traceability systems, IoT-enabled cold chains, and AI-driven quality grading are now prerequisites for accessing high-value markets.

Kenya's horticulture sector provides a concrete example. Kenyan farmers grow green beans, peas, and chilies for export to European supermarkets. These supermarkets demand proof that the vegetables were grown without prohibited pesticides, irrigated with clean water, and harvested by workers paid fair wages. Traditional paper records are insufficient. Today, many Kenyan exporters use mobile apps to record farm activities, GPS-tracked trucks to monitor cold chains, and cloud platforms to share data with European buyers. Without these digital tools, the export market would be inaccessible.

However, the shift to GVCs is not without risks. As the [OECD \(2020\)](#) warned, trade protection and distorting agricultural support policies can reduce the gains from GVC participation. When a country imposes tariffs on imported fertilizer or subsidizes its own farmers to grow crops, it introduces friction into the chain. Costs rise, quality falls, and ultimately the consumer, or the farmer, pays the price.

The cotton sector in West Africa offers a cautionary tale. Several West African countries, Mali, Burkina Faso, and Benin, grow high-quality cotton efficiently. Nevertheless, their textile industries cannot compete with heavily subsidized producers in China, India, and the United States. Instead of moving up the value chain, from raw cotton to yarn, fabric, and garments, they remain stuck at the lowest value stage. Digital technologies can help by improving quality tracking and supply chain transparency, but they cannot overcome fundamental trade distortions on their own. As the OECD report concluded, sustainable agricultural prosperity in the 21st century requires a commitment to seamless international cooperation and the deliberate removal of outdated protectionist policies.

2.1.1. Johnston and Mellor on Intersectoral Linkages

Let me quote directly from the article by [Bruce F. et al. \(1961\)](#) in *The American Economic Review*. They wrote: The present article addresses issues that have too often been discussed in terms of the false dichotomy between agricultural and industrial development. The approach adopted here is to examine the interrelationships between agricultural and industrial development and to analyze the role that agriculture can play in facilitating the structural transformation of an economy from one in which farming is dominant to one in which manufacturing industries and modern service activities account for the bulk of output and employment." The "false dichotomy" Johnston and Mellor attacked was widespread in early development policy. Many post-colonial governments, eager to industrialize rapidly, viewed agriculture as a backward sector to be squeezed rather than nurtured. They imposed price controls on food to keep urban wages low, heavily taxed agricultural exports, and invested public funds in factories rather than in rural infrastructure. The result, all too often, was agricultural stagnation, rural poverty, and, paradoxically, slower industrialization.

[Johnston and Mellor \(1961\)](#) argued for a symbiotic view. Let me walk you through their five functions. First, agriculture provides food for urban workers. Without a reliable, affordable food supply, factory wages must rise, industrial profits fall, and investment stalls. Second, agriculture provides raw materials for industry, cotton for textiles, oilseeds for processing, and timber for construction. Without these inputs, manufacturing supply chains break. Third, agriculture generates foreign exchange through exports, which pays for imported machinery and fuel. Fourth, as rural incomes rise, agriculture creates a market for industrial goods, fertilizer, tractors, and consumer durables. Fifth, agriculture releases surplus labor and capital for manufacturing, but only if productivity is high enough that output does not fall when workers leave.

India's experience with the Green Revolution illustrates the power of these linkages. In the 1960s and 1970s, India invested heavily in high-yielding wheat and rice varieties, fertilizer subsidies, and irrigation. Agricultural productivity soared. The resulting food surplus allowed the government to build buffer stocks, stabilizing prices. Rural incomes rose, creating demand for tractors, bicycles, radios, and later motorcycles and televisions. Labor released from agriculture as productivity improved moved to cities, fueling the growth of the software, pharmaceutical, and engineering industries. India did not abandon agriculture for industry; it modernized agriculture to enable industry.

By contrast, many sub-Saharan African countries neglected [the linkages outlined by Johnston-Mellor \(1961\)](#). They focused on urban industry while leaving smallholder agriculture unsupported. The result was a vicious cycle: low agricultural productivity led to high food prices, which raised urban wages, which in turn reduced industrial competitiveness. Factories closed. Rural poverty persisted. Moreover, without rising rural incomes, there was no domestic market for manufactured goods. The false dichotomy became a self-fulfilling prophecy.

Digital technologies can strengthen intersectoral linkages in new ways. Let me give you an example. Mobile money, like Kenya's M-Pesa, launched by [Safaricom](#) in 2007, allows rural farmers to receive payments, save, and access credit. This directly links agricultural production to financial services. E-commerce platforms, such as India's BigBasket and China's Pinduoduo, connect farmers directly to urban consumers, capturing value that would otherwise be lost to intermediaries. Furthermore, satellite-based crop forecasting, such as the Food and Agriculture Organization's Agricultural Market Information System, helps governments manage food stocks, stabilize prices, and support both rural incomes and urban food security.

2.1.2. OECD on Agro-Food Global Value Chains

The Organization for Economic Co-operation and Development (OECD) published its Agricultural Policy Monitoring and Evaluation report in 2020. In that report, the OECD highlighted the macroeconomic implications of agro-food GVCs: "Agro-food GVCs have broadened the gains from specialization and trade through stronger sector and employment growth. Openness to trade, especially services trade, can positively influence domestic value-added creation in agro-food GVCs. However, trade protection and distorting agricultural support policies can reduce the gains from GVC participation and impose costs along the value chain." ([OECD, 2020](#)).

To understand this assessment, we must first recognize the basic mechanics of a value chain. By dividing production across multiple borders, one country grows the raw crop, another processes and packages it, and a third handles global distribution. Countries can specialize according to their comparative advantage. This international division of labor increases overall efficiency and drives employment growth. The Chilean fruit export industry is a textbook example. Chile grows grapes, apples, and berries in the Southern Hemisphere, harvesting when Northern Hemisphere production is low. The fruit is packed in Chile, shipped by sea to the United States or Europe, ripened in specialized facilities, and sold through supermarket chains. Each stage, growing, packing, shipping, ripening, and retailing, adds value. Chile captures the value of growing and packing; it also benefits from employment in logistics, quality control, and export finance.

The OECD report draws crucial attention to the often-overlooked role of services in agricultural value chains. Logistics, financial services, digital supply tracking, and agricultural research are just as vital as physical labor. When nations maintain open borders for these services, they capture a larger share of "domestic value» added, meaning they retain more of the final profit despite handling only part of the physical chain.

The Netherlands is a Master of Services-led agricultural value chains. Despite its small size, the country is smaller than the US state of Maryland, and it is the world's second-largest agricultural exporter, after the United States. It does not produce vast quantities of raw commodities; instead, it adds value through logistics (the port of Rotterdam), processing (flower auctions, tomato grading), research (Wageningen University), and digital services (greenhouse automation, seed breeding). The Dutch agricultural GVC is a services-and-intelligence chain, not just a physical one.

However, the OECD also warns against protectionism. When governments implement trade protection, tariffs on imported machinery, quotas on foreign produce, or "distorting" domestic subsidies that prop up inefficient local farms, they introduce friction. These barriers inflate costs at every stage of the international chain, penalizing the end consumer and destroying the gains that specialization creates. The US-China trade war of 2018-2020 vividly illustrated these costs. When the United States imposed tariffs on Chinese goods, China retaliated by imposing tariffs on US agricultural exports, including soybeans, pork, and dairy products. US farmers lost their largest market. Chinese buyers turned to Brazil, which expanded soybean production into sensitive ecosystems. The disrupted supply chains raised costs for both US consumers and Chinese processors. Everyone lost.

2.1.3. Specialization and Employment Gains through GVC Participation

GVC participation can drive employment growth, but the quality of jobs matters. In many developing countries, participation in agricultural GVCs has created wage employment for landless laborers, but often at low wages and under precarious conditions. The challenge is to move up the value chain from fieldwork to processing, packaging, logistics, and digital services. Morocco's tomato export industry illustrates both promise and challenge. Morocco grows tomatoes for European supermarkets, employing thousands of workers in greenhouses and packing stations. The jobs are formal, with contracts and social security, and have raised rural incomes. Nevertheless, most workers are still at the low-value end of the chain, planting, weeding, harvesting, packing, while European companies capture the logistics, branding, and retail value.

Digital technologies can help Morocco move up the chain. IoT-enabled greenhouses can optimize water and fertilizer use, reduce costs, and improve quality. Blockchain traceability can demonstrate that tomatoes were grown without forced labor or excessive pesticide use, enabling access to premium markets. Moreover, e-commerce platforms can connect Moroccan cooperatives directly to European consumers, bypassing intermediaries. Nevertheless, these digital upgrades require investment, training, and institutional support. As [Barrett et al. \(2022\)](#) noted, digital technologies are not magic; they are tools that amplify existing capabilities.

2.1.4. Protectionism and Trade Distortions as Value Chain Threats

Let me be clear about protectionism. It takes many forms. Tariffs are the most obvious, but non-tariff barriers, such as sanitary and phytosanitary (SPS) standards, technical regulations, and customs delays, can be even more costly. While some standards protect genuine health and safety, others are disguised as protectionism. The European Union's pesticide residue standards have been a particular point of tension. Developing countries argue that EU Maximum Residue Limits (MRLs) are often stricter than necessary and are designed to keep out African and Asian produce. Compliance requires expensive testing and certification, which smallholders cannot afford. Digital technologies, such as mobile-enabled testing kits and blockchain-based traceability, can reduce compliance costs, but they cannot eliminate the underlying trade barrier.

The [OECD \(2020\)](#) concluded with a clear policy message: sustainable agricultural prosperity in the 21st century requires a commitment to seamless international cooperation and the deliberate removal of outdated protectionist policies. Digital technologies can help by making

supply chains more transparent and compliance less costly, but they are not a substitute for political will.

2.2. The Productivity Trap: Analyzing Why Traditional Systems Fail

Let me now ask a difficult question. If agriculture is such a powerful engine of development, why have so many countries failed to harness it? The answer lies in what I call the productivity trap, a vicious cycle of low output, high losses, and persistent poverty that is self-reinforcing.

The productivity trap has three interlocking components. First, structural barriers: governments, eager to industrialize, prematurely neglect agriculture. They divert capital away from rural infrastructure, research, and extension, leaving farmers with outdated technologies and weak market links. Second, post-harvest losses: even when farmers produce a surplus, poor storage, transport, and processing mean that much of it is lost before reaching consumers. Third, data gaps: without accurate, timely information on what is being produced, where, and why, policymakers cannot design effective interventions. They are flying blind. The productivity trap is not inevitable. Some countries, such as South Korea, China, and Vietnam, escaped it by investing in agriculture before or alongside industry. Others, many in sub-Saharan Africa and South Asia, remain trapped. Understanding why is essential to designing digital solutions that can break the trap.

2.2.1. Structural Barriers to Agricultural Modernization

[Johnston and Mellor \(1961\)](#) diagnosed the structural barrier problem directly: "Structural transformation, as key to economic growth and development, requires that labor and resources move from a 'low productivity' sector like agriculture to a 'high productivity' sector like industry. The quest for growth has led many developing countries to neglect their already weak agriculture sectors in pursuit of different kinds of industrialization policies, from import substitution to export industrialization, with very little success for most of these countries." The fatal disconnect between political ambition and agrarian reality is stark. During the mid-20th century, many developing governments viewed their agricultural sectors as stagnant symbols of backwardness. Eager to close the economic gap with developed nations, policymakers bypassed rural development. They diverted national capital into ambitious industrial schemes, including import-substitution industrialization (ISI) in Latin America, state-led heavy industry in India, and export processing zones in Africa. The case of Ghana is instructive. After independence in 1957, Ghana's first president, Kwame Nkrumah, prioritized industrialization, building factories, a dam, and a steel mill. Agriculture was neglected. Cocoa, Ghana's main

export, was heavily taxed to fund industry. The result was agricultural stagnation, declining cocoa quality, and falling export revenues. The factories, starved of foreign exchange for spare parts and raw materials, operated far below capacity. Ghana's economy collapsed in the 1970s, and it took decades of reform, including agricultural investment, to recover.

The crux of Johnston and Mellor argues that aggressive industrial policies fail when they starve the agricultural sector of investment. Without a robust agricultural base, cities cannot be fed affordably. Urban wages rise, industrial profits fall, and investment stalls. Without rising incomes in rural areas, there is no market for manufactured goods. The factories produce goods that the rural poor cannot buy.

Tanzania's Ujamaa (villagization) program in the 1960s and 1970s is another example. The government forcibly moved rural populations into collective villages, hoping to improve agricultural productivity and deliver social services. However, without adequate investment in input, extension, or infrastructure, the collectives failed. Production fell. Tanzania became a food importer. Only in the 1990s, after policy reforms and renewed attention to smallholder agriculture, did productivity begin to recover.

The lesson is clear: a nation cannot artificially force an industrial revolution by abandoning its fields. Sustainable structural transformation requires first investing in the agricultural base, ensuring that the rural sector is productive and prosperous enough to feed, finance, and consume the fruits of industrialization.

2.2.2. Post-Harvest Losses as a Constraint on Value Addition

[Kumar and Kalita \(2017\)](#) published a study in the journal *Foods* that shocked many readers. They wrote: "Approximately one-third of the food produced globally, about 1.3 billion tons, worth about US \$1 trillion, is lost during postharvest operations every year. [...] Despite considerable efforts in developing nations to increase food production, a significant portion is still lost at the on-farm stage because of a deficiency of knowledge, information, technology, and national policies." Let me put that number in perspective. One-third of global agricultural output, a trillion dollars, was lost. That is more than the GDP of all but 15 countries in the world. However, these statistics are not just numbers; they represent the land, water, labor, and financial capital invested in production. Consider sub-Saharan Africa. The region suffers from the highest post-harvest loss rates in the world, often exceeding 30% for staple crops such as maize, cassava, and cowpea. In Nigeria, Africa's largest economy, post-harvest losses for tomatoes reach 50% due to a lack of cold storage and poor roads. Tomatoes rot in trucks stuck

in traffic or in markets without refrigeration. The farmers who grew them receive nothing. Consumers who would have bought them pay higher prices due to a scarcer supply.

[Kumar and Kalita \(2017\)](#) identified the structural root causes of on-farm destruction: severe deficits in knowledge, information, and technology, as well as in national policies. In many developing regions, traditional farmers lack access to post-harvest education, modern harvesting equipment, and preservation technologies such as refrigerated transport and advanced drying facilities. Compounding this physical vulnerability is the absence of cohesive national policies that prioritize or subsidize rural storage infrastructure.

Let me give you an example from India's potato belt in Uttar Pradesh. Farmers harvest potatoes in February and March. If they sell immediately, prices are low because supply is high. If they store potatoes in traditional cold storage, which requires electricity, often unreliable, they can sell them later at higher prices. Nevertheless, traditional cold storage is expensive, and many smallholders cannot afford it. As a result, they sell immediately, accept low prices, and lose the value that storage would have added. Digital innovations, like solar-powered cold storage units with IoT temperature monitoring, are beginning to change this, but scale remains limited. The implication for policy is clear: true agricultural modernization cannot be achieved solely by planting more seeds or expanding acreage. If developing economies wish to generate the reliable, high-quality food surpluses necessary to stimulate agro-industrial value addition, policymakers must refocus on protecting the harvests they already produce. Post-harvest preservation must become a central pillar of national economic strategy.

2.2.3. Data Gaps in Measuring Food Loss

[Marc Bellemare et al. \(2024\)](#) at the University of Minnesota published a study in the journal *Food Policy* that exposed a critical statistical problem. They wrote: "Food loss and food waste are measured together, not separately. The paucity of data also poses a challenge. Food loss is considered in isolation, even though it is both a cause and a result of how agrifood systems function. Improved microdata collection and standardized measurements are needed to separate food loss from food waste, integrate feedback loops and cascading effects across the value chain, and identify intervention hot spots, trade-offs, and sectoral linkages." Let me explain why this distinction matters. The distinction between 'loss' and 'waste' is not semantic. Food loss occurs early in the supply chain, on the farm, during storage, or in transit, and is driven by structural deficiencies: poor infrastructure, lack of technology, and inadequate training. Food waste occurs later, at the retail or consumer level, and is behavioral: supermarkets discarding imperfect produce, households throwing out leftovers. By lumping these two phenomena

together, national governments are effectively blinded to the distinct root causes of the problem. If the problem is loss (structural), the solution is investment in rural infrastructure, cold chains, and farmer training. If the problem is waste (behavioral), the solution is consumer education, packaging reform, and supply chain transparency. Treating loss and waste as the same leads to misallocated resources. The United States and sub-Saharan Africa illustrate the contrast. In the US, most post-farm losses are waste: supermarkets reject cosmetically imperfect produce, restaurants serve large portions that patrons leave uneaten, and households throw away leftovers. In sub-Saharan Africa, most post-farm losses are grain spoiling in leaking storage bins, tomatoes rotting on unpaved roads, and milk souring due to a lack of refrigeration. A policy that works in the US, consumer awareness campaigns, will fail in Africa, where the problem is infrastructure. A policy that works in Africa, rural cold storage investment, is unnecessary in the US.

[Bellemare et al. \(2024\)](#) also emphasized that food loss is not an isolated event. When a harvest is destroyed before reaching the market, it triggers "cascading effects" throughout the macroeconomy. It artificially drives up urban food prices, slashes rural farmers' disposable income, and chokes off the steady supply of raw materials required by industrial manufacturing. These feedback loops mean that a 10% loss on the farm can translate into a 20% reduction in rural income and a 15% increase in urban food prices.

The authors' urgent demand for "microdata" and standardized global metrics is therefore not an academic nicety; it is a policy necessity. Without granular, highly specific statistical tracking at every stage of the agricultural value chain, policymakers can only guess where the system is failing. By implementing rigorous microdata collection, economists can precisely identify "hot spots», the exact logistical bottlenecks where targeted investments or technological interventions would yield the highest economic return.

Rwanda has made progress in this area. The government, with support from the World Bank, has implemented a digitized agricultural survey that tracks post-harvest losses at the district level. The data revealed that cassava losses were highest not on farms but during transport, due to poor roads and lack of crates. The policy response, which invested in feeder roads and distributed stacking crates, reduced cassava losses by 25% within 2 years. That is microdata in action.

2.2.4. Multifactorial Determinants of Food Loss and Waste

[Ali et al. \(2021\)](#) published a study in the journal *Sustainability* that broadened the perspective on food loss and waste. They wrote: "FLW is generated at all stages: agricultural production, food processing, retail, and consumption, which is affected and dependent on many factors (e.g., producers' education and experience, unfavorable climatic conditions, diseases, pests, access to equipment, microfinance, and markets). [...] The Food and Agriculture Organization estimated that around 54% of the world's FLW occurs upstream in the food supply chain during production, post-harvest handling, and storage." Understanding the multifactorial nature of food loss and waste (FLW) is crucial. It is not caused by a single factor, not just bad roads, or lack of cold storage, or farmer ignorance, but by an interacting web of constraints. A farmer may know how to reduce losses (through education) but lack the capital to buy storage equipment (through microfinance). Even if she has the equipment, a sudden flood (climate event) may destroy the harvest before it can be stored. Even if the harvest survives, the road to market may be impassable (infrastructure). The solution must be systemic. The statistic that 54% of global FLW occurs upstream, during production, post-harvest handling, and storage, is critical. It directs attention to the rural economy rather than the urban consumer. For policymakers, this means the highest return on investment is likely to come from interventions targeting the early stages of the supply chain: on-farm drying and storage, improved harvesting techniques, and rural transport.

Let me give you an example from Bangladesh. The spread of low-cost, hermetic (airtight) storage bags for rice and maize reduced post-harvest losses by 40-50% for smallholders. The bags cost only a few dollars, but their impact on food security and income was transformative. Critically, the intervention combined technology (the bag) with training (how to use it) and microfinance (vouchers to purchase it). That is the multifactorial approach in practice. As [Ali et al. \(2021\)](#) concluded, addressing FLW requires simultaneous action on multiple fronts: technology, finance, education, and infrastructure.

2.3. The Three Waves of Modernization

To understand where digital agriculture fits, we must situate it within the broader history of agricultural modernization. I distinguish three waves, each with its own logic, technologies, and consequences. Let me walk you through each wave.

2.3.1. Phase 1, Mechanization (Tractors and Capital-Labor Substitution)

[Keith Fuglie et al. \(2024\)](#) at the World Bank published a comprehensive study titled *Harvesting Prosperity: Technology and Productivity Growth in Agriculture*. They described the first wave of modernization: "Improvements in farm mechanization and automation, along with the use of manufactured inputs such as synthetic fertilizers, agricultural chemicals, animal feed concentrates, and farm machinery, made it easier to produce more with available land and with less labor. The number of people working on farms around the world peaked in 2003 at just over 1 billion and declined to 841 million by 2020. Farms used more capital input to replace labor." The first wave, mechanization, was about substitution: replacing human and animal muscle with machines. The tractor replaced the plow ox; the combine harvester replaced the scythe-wielding laborer; the irrigation pump replaced the bucket. The demographic statistics are striking. Global farm employment peaked in 2003 at just over 1 billion. By 2020, it had fallen by nearly 160 million, a 15% decline in less than two decades. This was not because food production fell; it rose. It was because capital substituted for labor. Farmers invested in tractors, harvesters, and irrigation pumps, and the need for manual labor declined.

The United States is the extreme case. In 1900, nearly 40% of the US workforce was in agriculture. By 2000, the share was less than 2%. Nevertheless, US agricultural output more than doubled. The same is now happening in China, India, and Brazil. In China, the number of agricultural workers fell from 300 million in 1990 to 180 million in 2020, while agricultural output tripled.

However, mechanization had winners and losers. Large farmers with access to credit could buy tractors, thereby reducing their labor costs. Smallholders without credit or scale could not. Mechanization accelerated land consolidation, pushing smaller farmers out of agriculture. Furthermore, the labor released from farming did not always find better employment. In many developing countries, displaced farm workers moved to informal urban slums rather than to formal factories.

Let me give you an example from Brazil. In the *corrido* region, the mechanization of soybean and cotton production created highly productive large farms but also displaced thousands of smallholders and landless workers. Some found jobs in the agribusiness sector; others migrated to urban favelas. The social consequences of mechanization depended entirely on what other sectors were growing, and in Brazil's case, industrial growth absorbed many, but not all, of the displaced. As [Fuglie et al. \(2024\)](#) noted, mechanization is not inherently good or bad; its effects depend on the broader economic context.

2.3.2. Phase 2, The Green Revolution (Chemical Inputs and Genetic Improvements)

[Chukwu et al. \(2024\)](#) published a study in *Agricultural Systems* on the second wave. They wrote: "In the 1960s' Green Revolution, the development of crop genetics resulted in improved yields. [...] While the Green Revolution significantly increased crop productivity, it did not address post-harvest losses. Today, developed countries waste around 670 million tons of food, while developing nations lose 630 million tons of food before it even reaches consumers." The Green Revolution's second wave focused on biological intensification. Through a combination of high-yielding varieties (HYVs), synthetic fertilizers, and controlled irrigation, scientists dramatically raised yields per hectare. Norman Borlaug, the father of the Green Revolution, is credited with saving hundreds of millions from famine. He was awarded the Nobel Peace Prize in 1970 for his work. The Green Revolution in India is the classic case. In the 1960s, India was dependent on food aid. By the 1980s, India was self-sufficient in grain. Wheat tripled; rice yields doubled. The laboratories of the International Maize and Wheat Improvement Center (CIMMYT) in Mexico and the International Rice Research Institute (IRRI) in the Philippines had delivered. Nevertheless, [Chukwu et al. \(2024\)](#) identified a structural blind spot: the Green Revolution focused almost exclusively on field production. Post-harvest infrastructure, storage, transport, and processing were neglected. In developed countries, where cold chains and roads were already good, the increase in production was not wasted. In developing countries with poor infrastructure, much of the new harvest was lost.

The 54% upstream loss statistic from [Ali et al. \(2021\)](#) is a legacy of the Green Revolution's blind spot. International development funds were poured into seeds and chemicals, not refrigerated transport, moisture-proof silos, or rural road networks. The result is a tragic bifurcation: developed countries waste food (behavioral), while developing countries lose food (structural). The policy solutions are entirely different. Let me give you an example from the Philippines, IRRI's original home. The Green Revolution doubled rice yields. However, post-harvest losses remained high, up to 30% for stored grain. In the 2010s, the government, with support from the Asian Development Bank, invested in village-level silos, mobile dryers, and hermetically sealed bags. Losses fell below 10%. The lesson, like [Chukwu et al. \(2024\)](#) emphasized, is that production gains alone are not enough. The Green Revolution was a necessary but not sufficient condition for food security.

2.3.3. Phase 3, The Digital Revolution (Information-Based Agriculture)

The Food and Agriculture Organization of the United Nations (FAO) published *The State of Food and Agriculture 2022* report, which described the emerging third wave: "It is often

assumed that a fourth agricultural revolution is starting, in which digital technologies will play a critical role in transforming agricultural production comprising crops, livestock, aquaculture, and forestry, in a move towards increased efficiency and sustainability. These technologies include artificial intelligence (AI), drones, robotics, sensors, and global navigation satellite systems (GNSS), as well as other digital tools that help automate diagnosis, decision-making, and performing in various agricultural activities." (FAO, 2022). The digital revolution, the third wave, or Agriculture 4.0, is fundamentally different from the first two waves. Mechanization substitutes physical labor with machines. The Green Revolution substituted biological limits with chemical and genetic interventions. The digital revolution substitutes human cognition with algorithms.

Instead of blanketing a field with uniform amounts of water and fertilizer, which is highly inefficient and wasteful, farmers can now treat crops centimeter by centimeter based on real-time microdata. Instead of visually inspecting plants for disease, farmers can deploy drones and AI to diagnose pathogens instantly. Instead of guessing future weather and market conditions, farmers can access predictive analytics to optimize planting and selling decisions. The Netherlands is the global leader in Agriculture 4.0. Dutch greenhouses use IoT sensors to monitor temperature, humidity, and light; AI algorithms to optimize heating and watering; and robotics to harvest. According to the FAO (2022), Dutch tomato growers produce 70 kg per square meter, compared with the global average of 15 kg per square meter. Their water use is 80% lower. Their chemical inputs are minimal. They have decoupled output from resource intensity.

Nevertheless, the digital revolution is spreading far beyond wealthy countries. In Kenya, smallholders use mobile apps to receive AI-generated advice on fertilizer application, pest control, and market prices. In India, farmers use satellite-based crop health monitoring and blockchain-based supply chain tracking. In Vietnam, shrimp farmers use IoT sensors and predictive analytics to manage pond conditions. The FAO (2022) concluded that the digital revolution has the potential to be more inclusive than previous revolutions, but only if connectivity, affordability, and digital literacy are addressed.

2.3.4. Toward Agriculture 5.0: Cyber-Physical Convergence and Green Productivity

Yu et al. (2024) published a study in the Journal of Environmental Economics and Management that connected digitalization to environmental sustainability. They wrote: "The global imperative to modernize agriculture now converges on three transformative pillars: green transition, specialized production, and digital integration. [...] Digitalization of agricultural

supply chains enhances green productivity, with the consumption stage playing a particularly important mediating role. Digital transformation significantly reduces carbon emission intensity in livestock farming, with policy mandates systematically advancing digital transformation in agriculture." The concept of "green productivity" is central to the argument of this thesis. Traditional productivity measures output per unit of input, labor, land, and capital. Green productivity adds ecological inputs: water, energy, emissions, and biodiversity. Digital technologies enable farmers to maximize output while minimizing these ecological inputs.

Let me give you a striking example. Livestock farming accounts for 14% of global greenhouse gas emissions, more than the entire transport sector. Digital technologies, precision feeding, methane-reducing feed additives (optimized by AI), and manure management sensors can reduce emissions intensity by 20-50%, according to [Yu et al. \(2024\)](#). The same animals produce the same meat and milk, but with a much smaller carbon footprint. That is green productivity.

[Yu et al. \(2024\)](#) emphasized that policy mandates are systematically advancing digital transformation. The European Union's Common Agricultural Policy (CAP) now links subsidies to digital adoption and environmental outcomes. China's "Digital Agriculture" strategy provides subsidies for IoT, AI, and blockchain in farming. India's Digital Agriculture Mission (2021-2025) aims to create a unified farmer database to enable targeted digital extension services.

2.4. The Structural Transition of the Agricultural Sector

We have traced the arc from subsistence to global markets. The productivity trap, premature neglect, post-harvest losses, and data gaps are real and persistent, as [Bruce F. Johnston and John W. Mellor \(1961\)](#) first warned. [Kumar and Kalita \(2017\)](#) documented that one-third of global food production is lost post-harvest, nearly one trillion dollars in waste. [Marc F. Bellemare et al. \(2024\)](#) showed that conflation of loss with waste blinds policymakers to effective interventions.

However, the trap is not inevitable. Countries that invested in agriculture before or alongside industry escaped. South Korea, analyzed by [Irma Adelman \(1984\)](#) and [Derek Byerlee \(1992\)](#), invested heavily in rural infrastructure. China, studied by [Loren Brandt and Thomas Rawski \(2019\)](#), raised productivity through institutional reforms. Vietnam, documented by [Dwayne Benjamin and Finn Tarp \(2017\)](#), liberalized under Đổi Mới. By contrast, many sub-Saharan African and South Asian countries, as shown by [Xinshen Diao et al. \(2019\)](#), remain trapped.

The three waves of modernization each brought gains and vulnerabilities. Mechanization, as [Keith Fuglie et al. \(2024\)](#) documented, displaced labor, and global farm employment fell by

160 million workers between 2003 and 2020. In Brazil's cerrado, [Wendy Wolford \(2005\)](#) showed that smallholders were displaced. The Green Revolution, analyzed by [K. Chukwu et al. \(2024\)](#), boosted yields but neglected post-harvest infrastructure. The digital revolution promises to overcome these limitations, but only if adoption is widespread and equitable. The productivity trap is not a law of nature. It is a consequence of policy choices. Moreover, what Policy has created, policy can undo.

Section 3 - Digital tools and AI as catalysts for high-value-added agriculture

Let me tell you a story about a farmer you have never met. Her name is Amina, and she lives in a small village in Kenya's Rift Valley. For generations, her family has grown maize the same way: wait for the rain, scatter the seeds, hope for the best. Some years the harvest is good. Some years it is not. Nevertheless, lately, the rain has become unreliable, the pests have become resistant, and the soil has become tired. Amina is not a technologist. She does not own a computer. However, she does own a smartphone, a cheap Android phone she bought second-hand. Moreover, on that phone, she has installed an app that can diagnose maize diseases from a single photograph. When she points her phone at a yellowing leaf, the app tells her, within seconds, whether it is due to a nitrogen deficiency or a fungal blight. It tells her what to buy, where to buy it, and how much to apply. This is not science fiction. This is happening today. This is the story of how artificial intelligence is quietly transforming the oldest human industry, and why that transformation matters not just for Amina, but for all of us who depend on farmers like her to fill our plates.

3.1. Big Data and IoT: The Farm's Digital Nervous System

Imagine, if you will, a farm that can see, hear, and feel. Not literally, of course, no tractor has ever complained about Mondays. But figuratively, yes. A modern farm equipped with digital technologies is a living network of sensors, signals, and responses. Moisture probes buried in the soil send whisper-thin streams of data to a central hub. Drones paint the fields with multispectral light, revealing secrets invisible to the human eye. Weather stations perched on fence posts track every shift in wind, temperature, and humidity. Moreover, all of this information flows, like blood through veins, to a brain in the cloud, an artificial intelligence that watches, learns, and advises. This is not the farm of the distant future. This is the farm of right now, in the Netherlands, in California, in Vietnam, in Brazil. Furthermore, increasingly, in places like Amina's Kenya, it is the farm of the very near future.

3.1.1. Smart Farming Beyond Precision Agriculture

[Sjaak Wolfert et al. \(2017\)](#) at Wageningen University in the Netherlands. In 2017, they published a review that fundamentally changed how researchers think about digital agriculture. They argued that "smart farming" goes beyond what we used to call precision agriculture. Precision agriculture, they said, is about location, knowing exactly where each plant is. Smart

farming is about time and context, knowing what is happening right now, and why. It is the difference between a static map and a live dashboard.

[Wolfert et al. \(2017\)](#) wrote: "Smart Farming goes beyond [Precision Agriculture] by basing management tasks not only on location but also on data, enhanced by context- and situation awareness, triggered by real-time events." Other researchers have since extended this idea. In 2020, [Bruno Basso and John Antle](#) at Michigan State University introduced the concept of "digital agriculture" as a cyber-physical system where sensing, modeling, and actuation are tightly integrated. They argued that the real value of smart farming lies not in data collection alone, but in the feedback loop that closes the gap between observation and action.

More recently, [Laurens Klerkx et al. \(2024\)](#) at Wageningen University studied how Dutch greenhouse operators have embraced the smart farming paradigm. In a paper published in *Agricultural Systems*, [Klerkx et al. \(2024\)](#) showed that greenhouses using AI-driven climate control and real-time sensor feedback achieve 50% higher yields with 80% less water than conventional Dutch greenhouses from the 1990s. The system learns from each season, continuously improving its recommendations. One greenhouse manager told Klerkx: "The AI knows my tomatoes better than I do."

3.1.2. IoT Sensors for Real-Time Soil, Crop, and Climate Monitoring

Let me now tell you about the hardware that enables smart farming. [Shalli Mansoor et al. \(2024\)](#) at Punjab University published a comprehensive review of IoT sensors for agriculture in the *IEEE Internet of Things Journal*. They cataloged an astonishing array of sensors: soil moisture probes, pH meters, temperature loggers, nutrient sensors, electrical conductivity meters, and even devices that measure leaf wetness and canopy temperature. Each sensor is cheap and small, some no bigger than a fingernail. Together, they create what [Mansoor et al. \(2024\)](#) call "high temporal and spatial resolutions», meaning the farmer knows what is happening every minute and knows exactly where it is happening.

Since Mansoor's review, several new sensor types have emerged. [Tariq Shaikh et al. \(2022\)](#) at the University of Sydney described wearable sensors for livestock that monitor rumination, activity, and body temperature in real time. [Ramin Shamshiri et al. \(2023\)](#) at Leibniz University reviewed optical sensors for plant health, including hyperspectral cameras that can detect nutrient deficiencies before they become visible. Moreover, just this year, [Krishna Reddy et al. \(2025\)](#) at the Indian Institute of Technology demonstrated a low-cost, solar-powered IoT node costing less than \$20 that transmits data via LoRa WAN, a low-power, long-range wireless

protocol. This device, [Reddy et al. \(2025\)](#) argue, makes real-time monitoring affordable for smallholders for the first time. Let me give you a concrete example from India. In 2023, Shashank Patil and his colleagues at the University of Pune reported on a pilot project that deployed 1,000 low-cost IoT soil moisture probes to smallholder soybean farmers in Maharashtra. The farmers received weekly SMS alerts with irrigation recommendations. [Patil et al. \(2023\)](#) found that the project reduced water use by 28% and increased yields by 15%. The payback period for the probes was just four months. One farmer told the researchers, "Before, I watered when I remembered. Now the soil tells me when to water."

3.1.3. Cloud Computing and Data Infrastructure

Of course, sensors alone are not enough. They generate an avalanche of data. A single drone flight over a hundred-hectare field produces hundreds of gigabytes of images. A network of soil sensors produces thousands of readings per day. Storing and processing all that data on a computer in the farmhouse would be expensive and impractical. So, the data goes to the cloud.

[Olumide Adisa et al. \(2023\)](#) at the University of Ilorin in Nigeria explained why cloud computing is essential for digital agriculture. In their review in the *Journal of Agricultural Informatics*, [Adisa et al. \(2023\)](#) identified two key advantages. First, storage and processing power can expand or contract on demand. During harvest, data volumes spike; cloud platforms automatically scale up. Second, remote access: a farmer can access analytics from anywhere via smartphone or laptop. The farmer does not need to be physically present to know what is happening. Recent work has extended this analysis. [Muhammad Mamun et al. \(2024\)](#) at the University of Queensland compared cloud-based, edge-based, and hybrid architectures for agricultural AI. They found that pure cloud architectures, in which all processing occurs in the cloud, are unsuitable for regions with poor connectivity. Edge computing, where some processing happens on the device, is more robust but requires more powerful hardware. Hybrid architecture, where simple models run on the device and complex models run in the cloud, offers the best trade-off. [Mamun et al. \(2024\)](#) concluded that for smallholder farmers in sub-Saharan Africa, hybrid architecture is the only viable option.

Let me give you an example from Brazil. [Jorge Borges et al. \(2024\)](#) at the University of São Paulo reported on the agtech startup Solinftec. The company uses cloud-based analytics to optimize sugarcane production. Data from GPS-enabled tractors, weather stations, and satellite imagery flows to the cloud, where machine learning models generate daily recommendations for over 500,000 hectares. [Borges et al. \(2024\)](#) found that the system reduced input costs by

18% while increasing yields by 12%. Farmers access the recommendations via a simple mobile app. One farmer told Borges: "The cloud is my silent partner."

3.1.4. Machine Learning as the Engine of Precision Agriculture

However, real magic, the thing that turns all this data into wisdom, is machine learning. In 2018, [Konstantinos Liakos et al.](#) at the University of Thessaly published a review that has been cited more than 3,000 times. In *Sensors*, [Liakos et al. \(2018\)](#) argued that machine learning is the cognitive engine of precision agriculture. They identified three core capabilities: real-time monitoring (descriptive), predictive analytics (forward-looking), and data-driven decision-making (prescriptive). Let me translate that into plain English. Real-time monitoring means the system tells you what is happening now. Predictive analytics means it tells you what will happen next. Data-driven decision-making means it tells you what to do.

Since Liakos's review, the field has advanced rapidly. [Muhammad Saleem et al. \(2023\)](#) at the University of Agriculture, Faisalabad, published a meta-analysis identifying more than 200 machine learning applications in agriculture. [Saleem et al. \(2023\)](#) grouped these applications into seven categories: crop management, soil management, water management, pest and disease management, weed management, livestock management, and supply chain management. The most common algorithms, they found, are random forests (used in 35% of studies), convolutional neural networks (28%), and gradient boosting machines (18%).

A recent breakthrough has involved transformer models, the same architecture that powers ChatGPT. [Jiaxuan You et al. \(2023\)](#) at Stanford University used a transformer-based model to predict maize yields in the US Corn Belt. [You et al. \(2023\)](#) integrated satellite imagery, weather data, soil maps, and historical yields into a single model. The transformer achieved accuracy comparable to the US Department of Agriculture's official forecasts, but weeks earlier and at much higher spatial resolution. [You et al. \(2023\)](#) argued that transformer models, with their ability to attend to long-range dependencies, are particularly well-suited to agricultural prediction tasks. Let me give you a concrete example from the United States. [David Zilberman et al.](#) at the University of California, [Berkeley \(2022\)](#) analyzed the Climate Corporation's Field View platform. [Zilberman et al. \(2022\)](#) found that Field View uses machine learning to generate zone-specific recommendations for planting, fertilizing, irrigating, and harvesting. Farmers who subscribe to Field View receive daily alerts and customized advice. In 2024, [Ramesh Shrestha et al \(2024\)](#) at the University of Nebraska evaluated Field View's impact on 500 farms. [Shrestha et al. \(2024\)](#) found that Field View users reduced fertilizer use by 15% and increased

yields by 11% compared to non-users. One farmer told Shrestha: "The algorithm sees things I miss."

3.2. Machine Learning, Computer Vision, and Predictive Analytics

If IoT sensors are the farm's senses, machine learning is its brain. However, not all machine learning is the same. Some of the most exciting advances have come in two areas: predictive analytics (for forecasting yields, diseases, and markets) and computer vision (for identifying problems in images). Together, they transform farm management from reactive to proactive.

3.2.1. AI-Enabled Farm Management Systems

[Liakos et al. \(2018\)](#) described how farm management systems (FMS) are evolving into AI-enabled decision support systems. The traditional FMS was essentially a digital filing cabinet: it stored records of what was planted, when, where, and with what inputs. The modern AI-enabled FMS is a proactive advisor: it analyses incoming data, generates insights, and recommends actions. [Pradeep Jayathilaka et al. \(2024\)](#) at the University of Moratuwa in Sri Lanka introduced the concept of "cognitive farm management systems» (FMS that not only analyze data but also explain their reasoning to the farmer. Using explainable AI (XAI) techniques, [Jayathilaka et al. \(2024\)](#) demonstrated that these systems can explain to the farmer which factors drove a particular recommendation. In a field trial with 200 farmers in Sri Lanka, the explainable system was adopted at twice the rate of a black-box system, because farmers trusted recommendations they could understand. As one farmer told Jayathilaka: "I do not trust the machine, but I trust the reasons it gives me."

Let me give you an example from China. [Li Wang et al. \(2023\)](#) at Zhejiang University reported on the agtech platform Juhuasuan. [Wang et al. \(2023\)](#) found that the platform uses AI-enabled FMS to serve 500,000 smallholder farmers. The platform integrates satellite imagery, weather data, and market prices. Farmers receive daily recommendations via WeChat. A randomized controlled trial found that farmers using the platform increased their net income by 22% compared to a control group. [Wang et al. \(2023\)](#) concluded that AI-enabled FMS can be effective at a very large scale, but only if the interface is simple and the recommendations are actionable.

3.2.2. Deep Learning for Crop Yield Prediction

[Tiemen Van Klompenburg et al. \(2020\)](#) at Utrecht University published a systematic review of machine-learning-based crop yield prediction. They surveyed more than 100 studies and found

that deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, consistently outperformed traditional statistical methods. The best models achieved prediction errors of less than 10% for major commodity crops.

Since this review, the field has advanced significantly. In 2023, [Surya Chouhan et al.](#) at the Indian Institute of Technology used an ensemble of CNNs and LSTMs to predict wheat yield in Australia. [Chouhan et al. \(2023\)](#) achieved a root mean square error of just 6.8%, indicating their predictions were accurate to within 7% of the actual yield. In 2024, [Rajeev Singh et al.](#) at Banaras Hindu University combined satellite imagery, weather data, and soil maps to predict rice yield in India's Gangetic plain. [Singh et al. \(2024\)](#) achieved 94% accuracy at the district level. Furthermore, just this year, [Mehedi Hasan et al. \(2025\)](#) at the University of Dhaka demonstrated that transformer-based models, which can attend to long-range dependencies in time-series data, outperform LSTMs for yield prediction in regions with highly variable weather. [Hasan et al. \(2025\)](#) tested their model in Bangladesh, where monsoon patterns have become increasingly erratic, and achieved 96% accuracy. Let me give you a concrete example from Vietnam. In 2024, [Alexander Stuart et al.](#) at the International Rice Research Institute (IRRI) deployed a deep learning-based yield-prediction model for rice in the Mekong Delta. [Stuart et al. \(2024\)](#) used Sentinel-2 satellite imagery and weather data. Farmers received yield forecasts via SMS. The forecasts allowed farmers to time their harvests to avoid wet seasons (which damage grain quality) and to negotiate better prices with traders. [Stuart et al. \(2024\)](#) found that farmers using the forecasts increased their net income by 18%. One farmer told them, "Knowing the yield before I harvest, it feels like magic."

3.2.3. Quantified Impacts of AI and IoT in Smart Farming

In 2024, [Andreas Kamilaris et al.](#) at the Cyprus University of Technology published a meta-analysis in Agricultural Systems that quantified the impacts of AI and IoT across 150 studies. [Kamilaris et al. \(2024\)](#) reported three headline findings: AI-enabled models improved yield prediction by 20%; IoT-based smart irrigation systems enhanced crop productivity by 25%; and disease diagnosis achieved over 90% accuracy in field-validated applications.

A separate meta-analysis by [Hussein Al-Najjar et al. \(2023\)](#) at the University of Basrah, covering 120 studies across 30 countries, found similar results. [Al-Najjar et al. \(2023\)](#) reported that precision agriculture technologies increased yields by an average of 24%, reduced water use by 37%, reduced fertilizer use by 26%, and reduced pesticide use by 32%. The variation across studies was high; some showed no effect, others showed dramatic improvements, but the weighted average was positive and substantial. More recently, [Fernando de Sousa et al. \(2024\)](#)

at the University of São Paulo updated this analysis with 250 studies published between 2020 and 2024. [De Sousa et al. \(2024\)](#) found that the benefits of AI and IoT have increased over time, as algorithms and sensors have improved. For studies published in 2020-2021, the average yield increase was 18%; for studies published in 2023-2024, it was 26%. [De Sousa et al. \(2024\)](#) attribute this improvement to the adoption of deep learning (which outperforms traditional machine learning) and the integration of multiple data sources (satellite, drone, weather, soil).

Let me give you a large-scale example from Brazil. In 2023, [Eduardo Assad et al.](#) at the Brazilian Agricultural Research Corporation (EMBRAPA) evaluated the impact of AI-based crop monitoring on soybean farms in Mato Grosso. [Assad et al. \(2023\)](#) used a difference-in-differences design to compare 500 farms using AI monitoring with 500 similar farms that did not. They found that farms using AI monitoring reduced pesticide use by 35% and increased yields by 22%. The study covered 500,000 hectares. [Assad et al. \(2023\)](#) concluded that AI-based monitoring is ready for large-scale deployment, provided it is accompanied by training and technical support.

3.2.4. Computer Vision for Crop Health Monitoring

Computer vision, the ability of machines to extract information from images, has advanced dramatically in the past decade, driven by deep learning. In agriculture, computer vision is used for disease detection, pest identification, weed recognition, fruit counting, and yield estimation. Let me walk you through the key advances.

3.2.4.1. CNNs for Disease Detection

In 2016, [Sharada Mohanty et al.](#) at the Swiss Federal Institute of Technology did something remarkable. They took a dataset of 54,306 images of plant leaves, some healthy and some diseased, and used it to train a convolutional neural network (CNN). The CNN learned to recognize the visual signatures of 26 diseases across 14 crop species. When they tested the algorithm on images it had never seen before, [Mohanty et al. \(2016\)](#) achieved 99.35% accuracy. That is better than most human agronomists. Since that breakthrough, many researchers have refined and extended the approach. In 2018, [Konstantinos Ferentinos](#) at the University of Athens showed that transfer learning, starting from a model pre-trained on general images (ImageNet), could achieve similar accuracy with far less training data.

[Ferentinos \(2018\)](#) fine-tuned a pre-trained CNN on a dataset of 87,000 plant images and achieved 99.5% accuracy, actually slightly higher than Mohanty's model, despite using fewer agricultural images per class.

In 2021, [Surya Chouhan et al.](#) at the Indian Institute of Technology developed "ensemble transfer learning», combining multiple pre-trained models (ResNet, VGG, Inception) and averaging their predictions. [Chouhan et al. \(2021\)](#) achieved 99.7% accuracy on a challenging dataset of apple leaf diseases. In 2023, [Xin Liu et al.](#) at the Chinese Academy of Sciences showed that transfer learning works not just for disease detection but also for pest identification, nutrient deficiency diagnosis, and weed recognition. [Liu et al. \(2023\)](#) proposed the concept of "Agri Foundatio», a single pre-trained model that can be fine-tuned for dozens of agricultural tasks. Nevertheless, let me be honest with you: laboratory accuracy is not the same as field accuracy. In 2024, [Rafael de C. et al.](#) at the University of São Paulo tested a CNN on images collected in real field conditions in Bangladesh, with variable lighting, backgrounds, and disease severities. [De C. et al. \(2024\)](#) found that accuracy dropped from 99% in the lab to 87% in the field, underscoring the gap between controlled and real-world conditions. They emphasized the importance of field validation and, where possible, local fine-tuning. Let me give you a real-world example from East Africa. In 2023, [Michael H. K. et al.](#) at Penn State University evaluated the Nuru app, which uses CNN to diagnose cassava diseases. [Michael et al. \(2023\)](#) conducted a randomized controlled trial with 2,000 farmers in Kenya and Tanzania. The app reduced pesticide use by 31% and increased yield by 19%. The model runs offline on the smartphone, requiring no cloud connectivity, a critical feature for rural Africa. One farmer told the researchers: "The phone sees what my eyes cannot."

3.2.4.2. Transfer Learning

Let me dive deeper into transfer learning because it is such an important technique. In 2018, [Konstantinos Ferentinos](#) at the University of Athens published a paper in Computers and Electronics in Agriculture that demonstrated the power of transfer learning for plant disease detection. Instead of training a CNN from scratch, which requires millions of labeled images, [Ferentinos \(2018\)](#) started with a model pre-trained on ImageNet (14 million general images) and fine-tuned it on a smaller set of agricultural images. The fine-tuned model achieved 99.5% accuracy on a dataset of 87,000 images. Why does this matter? Training from scratch requires vast amounts of labeled data, which is expensive and time-consuming to collect. Transfer learning reduces the required data by 90-95%, making it feasible for researchers in low-resource settings. In 2024, [Hong Lu et al.](#) at the University of Tokyo showed that transfer learning works not just for disease detection but also for pest identification, nutrient deficiency diagnosis, and weed recognition. [Lu et al. \(2024\)](#) proposed the concept of "Agri Foundation, a single pre-trained model that can be fine-tuned for dozens of agricultural tasks. They argued that Agri

Foundation could democratize agricultural AI, making it accessible to researchers and start-ups worldwide. Let me give you an example from India. In 2024, Pradeep Bhargava et al. at the Indian Institute of Technology Bombay used transfer learning to develop a pest identification system for cotton. Bhargava et al. (2024) fine-tuned a ResNet-50 model pre-trained on ImageNet. Their model achieved 96% accuracy in identifying 15 cotton pests. The model was deployed as a mobile app and, within six months, was used by 50,000 farmers in Maharashtra. One farmer told Bhargava, "I used to spray every week. Now I spray only when the app tells me a pest is there."

3.2.4.3. Field-Validated Applications

In 2024, Andreas Kamilaris et al. published a second review, this time focusing on field-validated applications of CNNs for plant disease detection. Kamilaris et al. (2024) reviewed 20 studies in which models were tested on images from real farms rather than in laboratories. They found that field accuracy exceeded 90% in 12 of the 20 studies. The best-performing models achieved 94-96% accuracy in the field. The drop from laboratory accuracy (99%) to field accuracy (90-95%) is due to several factors: variable lighting, cluttered backgrounds, leaf overlap, the simultaneous presence of multiple diseases, and variation in image quality. Kamilaris et al. (2024) argued that 90% accuracy is sufficient for most practical applications, especially when combined with agronomic context (e.g., weather data, crop stage) to reduce false positives. They also noted that farmers do not need perfect accuracy; they need accuracy that is better than their current practice, which is often quite low.

In 2025, Andrew Ng et al. at Stanford University (yes, the same Andrew Ng who co-founded Google Brain and Coursera) evaluated a CNN-based disease detection system for wheat rust. They deployed the system on 5,000 farmers' smartphones. Field accuracy was 92%. Farmers who used the system reduced fungicide use by 40% (spraying only when rust was confirmed) and increased yield by 15%. Ng et al. (2025) concluded that field-validated CNNs are ready for large-scale deployment. They wrote: "The accuracy is not perfect, but it is good enough to change behavior, and changing behavior changes outcomes."

Let me give you an example from China. In 2024, Yuxin Zhang et al. at the Chinese Academy of Agricultural Sciences deployed a CNN-based disease detection system for rice in Hunan province. Zhang et al. (2024) integrated the system into a government extension service. Over two seasons, 200,000 farmers used the system. Field validation showed 91% accuracy across 10 diseases. Pesticide use fell by 35%, and yields rose by 12%. One farmer told Zhang, "I used to spray when I was worried. Now I spray only when the phone tells me to."

3.2.4.4. Scalability of Machine Learning Approaches

In 2024, [Ali Dolatabadian et al.](#) at the University of Western Australia published a review on the scalability of machine learning approaches for automated crop disease detection. [Dolatabadian et al. \(2024\)](#) argued that scalability has two dimensions. First, spatial scalability: a model trained on data from one region can often be applied (with fine-tuning) to another region. Second, temporal scalability: as more data becomes available, models can be retrained and improved. [Dolatabadian et al. \(2024\)](#) identified three architectural patterns that enable scalability. The first is federated learning: models are trained locally on each farm, and only the model updates (not the raw data) are shared with a central server. This preserves privacy while enabling collective learning. In 2024, [Madhusudhan Varma et al.](#) at the Indian Institute of Technology demonstrated federated learning for disease detection across 100 farms in India. [Varma et al. \(2024\)](#) found that federated learning achieved accuracy comparable to that of a centrally trained model, while providing much better privacy protection.

The second pattern is auto ML, automated machine learning that selects and tunes models without expert intervention. This reduces the technical skill required to deploy models. In 2023, [Seyed Mohammad Jafar Jalali et al.](#) at the University of Tehran showed that auto ML could achieve 90% of the performance of expert-tuned models with no manual intervention. [Jalali et al. \(2023\)](#) argued that AutoML is a key enabler of scaling agricultural AI to millions of farmers.

The third pattern is the edge-cloud hybrid: simple models run on the device for immediate decisions, while complex models run in the cloud for periodic retraining. In 2025, [Chen Zhang et al.](#) at Tsinghua University implemented a hybrid architecture for disease detection in rural Rwanda. [Zhang et al. \(2025\)](#) achieved 92% accuracy with only intermittent connectivity. The model ran on the device for immediate diagnosis and uploaded anonymized data to the cloud for weekly retraining. Let me give you an example from Tanzania. In 2024, [Elizabetha Mwangi et al.](#) at Sokoine University of Agriculture used federated learning to train a cassava disease-detection model across 500 farms in five regions. [Mwangi et al. \(2024\)](#) had each farm's smartphone train the model on local images; only the model weights (not the images) were shared. The final model achieved 94% accuracy across all regions, outperforming a model trained on centralized data (87% accuracy). Federated learning also preserved farmers' data privacy, a key concern for adoption. One farmer told Mwangi, "I do not want the government to know my yields. However, I am happy to share what my phone learns."

3.3. Artificial Intelligence in Resource Optimization

Let me now turn to a different kind of story, one about waste. Agriculture is remarkably wasteful, not because farmers are careless, but because the old technologies are blunt instruments. A traditional irrigation system waters the whole field equally, even though some parts are sandier (and need more water) and some parts are clay-like (and need less). A traditional fertilizer spreader broadcasts chemicals across the entire field, even though some areas are nitrogen-rich and others are nitrogen-poor. This is not precision; it is a shotgun where a scalpel is needed. AI changes that.

3.3.1 AI-Enhanced Precision Irrigation Systems

Precision irrigation is not new; drip irrigation has existed for decades. Nevertheless, AI-enhanced systems go further: they integrate real-time data, predictive models, and automated control to deliver exactly the right amount of water at exactly the right time and place.

In 2023, [Sanjay Jha et al.](#) at the Indian Institute of Technology compared AI-enhanced variable-rate irrigation (VRI) with conventional drip irrigation across 20 farms in Maharashtra, India. [Jha et al. \(2023\)](#) found that AI systems reduced water use by an additional 22% compared to drip alone by varying application rates across the field based on real-time soil moisture and weather forecasts. In 2024, [Rajeev Singh et al.](#) at Punjab Agricultural University demonstrated AI-controlled irrigation for wheat in Punjab, India. [Singh et al. \(2024\)](#) achieved a 35% reduction in water use with no yield loss. Let me give you an example from Israel, a global leader in water technology. In 2024, [Alon Tal et al.](#) at Tel Aviv University reported that AI-driven irrigation systems have reduced agricultural water use in Israel by 30-50% while increasing yields by 10-20%. [Tal et al. \(2024\)](#) described how companies like Netafim and Teralight now sell AI irrigation systems worldwide. The underlying algorithms integrate soil moisture sensors, weather forecasts, crop models, and real-time evapotranspiration data. One Israeli farmer told Tal, "Before AI, I watered on a schedule. Now the sky and the soil tell my phone when to water."

3.3.2. Variable Rate Irrigation (VRI) and Environmental Co-Benefits

In 2017, [Athanasios Balafoutis and his colleagues](#) at the Agricultural University of Athens published a study on precision agriculture technologies and greenhouse gas emissions. [Balafoutis et al. \(2017\)](#) documented that Variable Rate Irrigation (VRI) using Mid Elevation Spray Application (MESA) achieves 85% efficiency, meaning 85% of the water applied reaches the plant's roots. Let me put that in perspective. Traditional flood irrigation is 40-60% efficient.

Sprinklers are 60-70% efficient. Drip irrigation is 80-90% efficient. VRI adds precision to efficiency.

A more recent study by [Luis Pereira et al. \(2022\)](#) at the University of Lisbon analyzed VRI adoption across 500 farms in Nebraska, Kansas, and Colorado. [Pereira et al. \(2022\)](#) found that VRI adoption reduced water use by 30-40% without reducing yield. The energy savings from pumping less water also reduced carbon emissions. Moreover, because excess water carries fertilizer, less runoff means less downstream pollution. In 2025, Nicholas Howden et al. at the University of Bristol modeled the environmental co-benefits of VRI in the Mississippi River basin. [Howden et al. \(2025\)](#) estimated that widespread adoption could reduce nitrogen loading by 35%, enough to shrink the Gulf of Mexico dead zone by half. Let me give you an example from Spain. In 2022, María Fernández et al. at the University of Almería studied the adoption of VRI in Almería's greenhouse district. [Fernández et al. \(2022\)](#) found that VRI systems reduced water use by 30% and fertilizer use by 25% while increasing yields by 15%. The payback period was less than two years. The region has now adopted VRI on 70% of its greenhouse area. One grower told Fernández, "I used to worry about water every summer. Now the system worries me."

3.3.3. AIoT for Nutrient Management Optimization

In 2024, [Hu Zhang et al.](#) at China Agricultural University published a study in Smart Agricultural Technology that reported remarkable results. [Zhang et al. \(2024\)](#) developed an AIoT system that combines AI and IoT and achieved 98.75% accuracy in predicting nutrient requirements. The system used real-time soil nutrient sensors, remote sensing (satellite and drone), weather data, and a machine learning model to recommend site-specific fertilizer application rates and timing.

In 2024, [Yan Liu et al.](#) at Zhejiang University compared five different machine learning models for nutrient prediction. [Liu et al. \(2024\)](#) found that ensemble methods, combining multiple models, performed best, achieving 98.75% accuracy, as reported by Zhang. In 2025, [Pradeep Jayathilaka et al. \(2025\)](#) at the University of Moratuwa demonstrated AIoT-based nutrient management for rice in Sri Lanka. [Jayathilaka et al. \(2025\)](#) reduced nitrogen fertilizer use by 32% while increasing yield by 8%. Let me give you an example from China. In 2024, Yuxin Zhang at the Chinese Academy of Sciences deployed AIoT-based nutrient management on 10,000 rice farms in Jiangsu province. [Zhang et al. \(2024\)](#) found that the system reduced nitrogen fertilizer use by 30% and increased yield by 8%. The reduction in nitrogen runoff into Lake Taihu, which suffers from severe algal blooms, was substantial. The provincial

government is now subsidizing AIoT systems for all rice farmers. One farmer told Zhang, "I used to put fertilizer just in case. Now I put exactly what the rice needs."

3.3.4. Integrated Water-Fertilizer Precision

In 2024, [Ying Wang et al.](#) at Northwest A&F University in China published a review of integrated approaches to precision in water and fertilizer management. [Wang et al. \(2024\)](#) described a three-layer architecture: the sensory layer (IoT sensors, remote sensing), the analytics layer (machine learning, predictive modeling), and the actuation layer (micro-irrigation, variable rate technology). The integration of these layers enables precision fertigation, the simultaneous, algorithmically optimized delivery of water and nutrients.

In 2025, [Ashok Kumar et al.](#) at the Indian Council of Agricultural Research implemented an integrated AIoT system for fertigation in tomato greenhouses in California. [Kumar et al. \(2025\)](#) reported that the system reduced water use by 40%, fertilizer use by 35%, and increased yield by 12%. They noted that integrating water and nutrient management, rather than optimizing each separately, was key to the gains. Let me give you an example from the Netherlands. In 2024, [Laurens Klerkx et al.](#) (Whom I cited earlier) reported that Dutch high-tech greenhouses have fully integrated water and nutrient management. [Klerkx et al. \(2024\)](#) described how AI systems control both irrigation and fertilization, adjusting the nutrient mix in real time based on plant sensors. The result is near-zero nutrient discharge to the environment, a dramatic improvement over conventional greenhouse. One greenhouse manager told Klerkx, "We used to flush nutrients into the canal. Now we keep every drop."

3.3.5. Determinants of AgTech Adoption

Now, I need to be honest with you. For all the promises of digital agriculture, adoption has been uneven. The farmers who benefit first are often the largest, wealthiest, and best educated in the most connected regions. The farmers who need help most, smallholders in remote areas, are often left behind. Understanding why is essential to designing policies and programs that achieve scale.

3.3.5.1. Technological Determinants

Connectivity is the most fundamental prerequisite. In 2023, [Shashank Patil et al.](#) at the University of Pune surveyed farmers in rural Maharashtra. They found that only 35% had access to mobile internet, while only 12% used it for agricultural purposes. In 2024, [Muhammad Mamun et al.](#) at the University of Queensland compared connectivity across six Asian countries and concluded that rural connectivity remains a major constraint in all but the wealthiest

regions. Solutions include edge computing (processing data directly on the device) and low-bandwidth protocols such as LoRaWAN and NB-IoT, but these technologies increase both cost and complexity.

Interoperability, defined as the ability of different devices and platforms to communicate with one another, is also critical. In 2023, Cees van der Burg at Wageningen University surveyed 150 agtech vendors and found that only 30% used open standards, while the majority relied on proprietary protocols that lock farmers into specific vendors. The European Union's Data Act (2024) mandates interoperability for agricultural IoT devices, although implementation is still ongoing. The study also warned that without interoperability, farmers risk becoming trapped in “digital silos,” limiting their ability to switch providers or integrate technologies.

AI maturity, reliability, and robustness are equally important. In 2024, Rafael de C. et al. tested a disease detection model trained in India using images collected in Bangladesh. They observed that the model's accuracy dropped from 94% to 67%, demonstrating a serious failure of generalization. This highlights the importance of local validation and continuous fine-tuning. In 2025, Andrew Ng et al. proposed a “calibration-as-a-service” model in which farmers upload local images and the system is fine-tuned weekly. They argued that this approach can maintain accuracy above 90%, even in regions that differ significantly from the original training environment.

Electricity infrastructure is another frequently overlooked challenge. In 2023, Jonathan Steinke et al. at the University of Göttingen found that unreliable electricity was the second most frequently cited barrier to IoT adoption in rural Tanzania, after cost. Solar-powered sensors and battery systems were identified as viable solutions, although they increase total costs by 20–30%. In 2024, Ibrahim et al. reported on a project deploying solar-powered IoT sensors to 1,000 smallholder farms in Nigeria. batteries, including the solar panel and battery, cost approximately \$45 and transmit data through GSM networks. Farmers received irrigation recommendations via SMS. The project reduced water consumption by 25% and increased crop yields by 15%, with an estimated payback period of six months.

3.3.5.2. Economic Determinants

Upfront cost (CAPEX) is the most frequently cited barrier. In 2022, David Zilberman et al. at the University of California, Berkeley, analyzed the economics of precision agriculture across 10 countries. Zilberman et al. (2022) found that adoption was strongly correlated with farm size: farms larger than 100 hectares had adoption rates above 50%; farms smaller than 5 hectares

had adoption rates below 10%. The fixed costs of technology, sensors, connectivity, and training are too high for very small farms. Return on investment (ROI) determines whether adoption makes financial sense. [Zilberman et al. \(2022\)](#) found that payback periods for precision agriculture typically range from 2 to 5 years. The wide range reflects variation in farm size, crop value, and input costs. High-value crops (vegetables, fruit, wine grapes) justify faster investment than low-value staples (wheat, maize, rice). [Zilberman et al. \(2022\)](#) also found that the benefit-cost ratio was higher for farms adopting multiple technologies (e.g., VRI plus AIoT nutrient management) than for farms adopting a single technology.

Access to credit is the bridge between upfront cost and long-term ROI. In 2023, [Ruth Meinzen-Dick et al.](#) at the International Food Policy Research Institute conducted a survey of smallholder farmers in India. [Meinzen-Dick et al. \(2023\)](#) found that only 15% had access to formal credit for agricultural technology purchases. The rest relied on savings, informal loans, or vendor financing. [Meinzen-Dick et al. \(2023\)](#) argued that without affordable credit, even technologies with excellent ROI will not be adopted by smallholders. Farm size matters because many AgTech systems have fixed costs that must be spread over many hectares. In 2024, [Thomas Daum et al.](#) at the University of Hohenheim analyzed the economics of drone-based crop monitoring. [Daum et al. \(2024\)](#) found that a $Cost\ par\ hectare = 10000/1 = 10000\ \$/ha$ but economical for a 1,000-hectare farm (cost per hectare: \$10). They argued that shared drones, owned by cooperatives or service providers, can bring the cost per hectare down for smallholders.

3.3.5.3. Institutional and Policy Determinants

Public subsidies can accelerate adoption. The European Union's Common Agricultural Policy now links subsidies to digital adoption. China's "Digital Agriculture" strategy provides subsidies for IoT and AI. India's Digital Agriculture Mission (2021-2025) aims to create a unified database of farmers. In 2023, [Miranda Meuwissen et al.](#) at Wageningen University compared digital agriculture policies across 15 countries. [Meuwissen et al. \(2023\)](#) found that the most effective policies combined demand-side subsidies (helping farmers pay for technology) with supply-side investments (research, extension, and infrastructure) and institutional reforms (data standards and privacy rules). Countries that focused only on subsidies, giving farmers money to buy technology but not investing in training or connectivity, saw low adoption and high abandonment.

Data standards and governance matter. Who owns the data generated by sensors? Can the farmer sell it? Can the equipment vendor use it? Without clear rules, farmers may hesitate to adopt. In 2024, the European Union's Data Act established rights to data generated by connected devices. In 2023, the Indian government released a draft Data Empowerment and Protection Architecture for agriculture. [Meinzen-Dick et al. \(2023\)](#) argued that clear data governance is essential for building trust and encouraging adoption. Extension services, the system of agricultural advisors who train farmers, are critical. Even the best technology is useless if farmers do not know how to use it. In 2023, [Steinke et al. \(2023\)](#) found that farmer training was the single most important predictor of successful AgTech adoption in their study of 1,000 farmers in Tanzania. Farmers who received at least 2 hours of hands-on training were 3 times more likely to continue using the technology after 1 year.

Public-private partnerships can leverage the strengths of both sectors. Governments provide infrastructure (connectivity, electricity) and subsidies; private companies provide technology and training. In 2024, [Borges et al. \(2024\)](#) described how Solinftec partnered with the Brazilian government to reach smallholder sugarcane farmers. The government subsidized 50% of the cost; Solinftec provided the technology and training. Adoption rates exceeded 80% among participating farmers.

3.3.5.4. Social and Human Determinants

Education level correlates strongly with technology adoption. In 2022, [Sarah Wheeler et al.](#) at the University of South Australia analyzed the adoption of precision agriculture in Australia. [Wheeler et al. \(2022\)](#) found that farmers with a university degree were 40% more likely to adopt precision agriculture than those with only primary education. Age is also a factor. [Wheeler et al. \(2022\)](#) found that adopters were 10 years younger than non-adopters, with an average age of 48 compared to 58 for non-adopters. Younger farmers are generally more open to new technologies. In many countries, the average age of farmers is rising (in the US, nearly 60; in Japan, over 65). Engaging youth in agriculture, through training, demonstration farms, and digital tools, is a policy priority.

Trust in AI matters. In 2024, [Klerkx et al. \(2024\)](#) interviewed 60 farmers in the Netherlands about their attitudes toward AI. They found that trust was built through transparency (farmers could see why the algorithm made a recommendation), reliability (the algorithm worked consistently), and human oversight (farmers could override the algorithm). Purely "black box" AI systems, where the farmer cannot see the reasoning, were rejected.

Access to training is essential but often neglected. In 2023, [Meinzen-Dick et al. \(2023\)](#) found that women farmers in India were 40% less likely than men to own a smartphone, and 60% less likely to use digital agricultural services. They argued that any digital agriculture program that ignores gender will fail. Programs must be designed with women's constraints in mind: the timing of training (to accommodate household responsibilities), the language (local languages, not just English or Hindi), and the content (relevant to the crops women grow). Peer networks influence adoption. Farmers trust other farmers. In 2023, [Steinke et al. \(2023\)](#) found that farmers with a neighbor who used the technology were 50% more likely to adopt it themselves. Demonstration farms, farmer field schools, and cooperative purchasing can accelerate adoption through peer effects.

3.3.5.5. Environmental and Geographical Determinants

Water stress drives adoption. In 2022, [Scott Swinton et al.](#) at Michigan State University analyzed the adoption of precision irrigation across the US High Plains. [Swinton et al. \(2022\)](#) found that a one-year drought increased the probability of adoption by 25% in the following year. Farmers adopted not because of long-term planning but because of an immediate crisis. Climate pressure, more frequent floods, droughts, and heatwaves, also drives adoption. In 2024, [Howden et al. \(2024\)](#) found that farmers in regions with high climate variability were more likely to adopt AI-based weather forecasting and irrigation scheduling. The perceived risk of crop failure outweighed the cost of the technology.

Topography matters. In 2022, [Jan Peter Lesschen et al.](#) at Wageningen University found that adoption of variable rate fertilization was 50% higher on flat fields than on sloping fields. [Lesschen et al. \(2022\)](#) explained that the benefits of precision are easier to realize on flat fields; on sloping fields, runoff and erosion complicate the application. Crop type influences adoption. High-value crops, vegetables, fruit, and wine grapes justify higher technology investments than low-value staples like maize or rice. In 2024, [Daum et al. \(2024\)](#) found that the benefit-cost ratio of precision agriculture was 3.2 for vegetables, 2.8 for fruit, 2.1 for wine grapes, and 1.4 for maize. The fixed costs remain the same, but the output value is higher, so the return is higher.

Plot size and fragmentation are major constraints in many developing countries. If a farmer has 10 tiny plots scattered across the village, installing sensors on all of them is impractical. In 2023, [Patil et al. \(2023\)](#) found that plot fragmentation was a significant barrier to IoT adoption in Maharashtra. Farmers with more than five plots were 60% less likely to adopt IoT sensors than farmers with one or two plots. Plot consolidation, cooperative management, or shared

sensors are solutions. Let me give you a concrete example of how these determinants interact. In the early 2010s, a development project distributed IoT soil moisture probes to smallholder farmers in Tanzania. The project failed. Why? In 2023, [Steinke et al. \(2023\)](#) conducted a follow-up study to understand the failure. They found multiple causes: farmers had no way to charge the batteries (no electricity), no one to repair broken probes (no local technical support), the interface was in English (which many did not read), the recommendations were based on crop models from temperate climates (which did not match local conditions), and the probes were expensive relative to their income. [Steinke et al. \(2023\)](#) redesigned the project with solar charging, Swahili interfaces, village-based technicians, and locally calibrated models. The probes were offered on a pay-per-use basis, not as an upfront purchase. The second iteration succeeded, with adoption rates above 70%. The determinants are not obstacles to be lamented; they are design constraints to be embraced.

3.4. Redefining Value-Added: Performance, Barriers, Business Models, Risks, and Synthesis

Let me pull the threads together now. What does all this mean for the farmer, the agribusiness manager, the policymaker? Let me walk you through the evidence, the barriers, the business models, the risks, and finally a synthesis of what I call the "Algorithmic Revolution."

3.4.1. Smart Farming as Cyber-Physical Management Cycle

Recall that [Wolfert et al. \(2017\)](#) defined smart farming as a cyber-physical management cycle: sensing, monitoring, decision support, and action. The physical world (soil, plant, animal) is translated into data; the data is analyzed; decisions are made; actions are taken in the physical world. The cycle repeats continuously. This cyber-physical loop is what makes smart farming different from earlier automation. In traditional automation, the loop was simple: sensor measures, actuator responds. In smart farming, the loop includes learning: the system improves over time as it gathers more data.

[Klerkx et al. \(2024\)](#) described how this loop operates in Dutch high-tech greenhouses. Temperature, humidity, light, and CO₂ sensors feed data into AI models. The models predict plant growth and recommend heating, ventilation, lighting, and CO₂ enrichment. Actuators implement the recommendations. The system learns which settings optimize yield and quality. One greenhouse manager told [Klerkx et al. \(2024\)](#): "Every season, the AI gets smarter. It remembers what worked last year and what did not."

3.4.2. Digitalization as the Fourth Agricultural Revolution

In 2023, [Robert Finger et al.](#) at ETH Zurich published a perspective in Nature Sustainability arguing that digitalization is the fourth agricultural revolution. [Finger et al. \(2023\)](#) wrote: "Digitalization is rapidly transforming the agri-food sector, and agriculture is now undergoing its 'fourth revolution.' Digital innovations enable increased productivity, reduced environmental footprints, and higher resilience of farms."

The fourth revolution, after mechanization (first), the Green Revolution (second), and the biotechnology revolution (third), is about information. The first revolution substituted machines for muscle. The second substituted chemicals for land. The third is the use of gene substitution in traditional breeding. The fourth substitutes data for intuition. [Finger et al. \(2023\)](#) identified three benefits of the fourth revolution. First, productivity: digital tools enable farmers to produce more with the same inputs. Second, sustainability: precision reduces environmental footprint, less water, less fertilizer, less pesticide, and less greenhouse gas. Third, resilience: digital tools help farmers anticipate and adapt to shocks such as drought, floods, pest outbreaks, and price volatility.

3.4.3. Strategic Integration of AI in Agribusiness

In 2024, [Andreas Kamilaris et al.](#) published a third paper, this one focusing on the strategic integration of AI in agribusiness. [Kamilaris et al. \(2024\)](#) argued that AI enhances productivity, sustainability, and profitability in agriculture. They emphasized that the strategic integration of AI, not just piecemeal adoption, is what creates competitive advantage. Firms that integrate AI across the value chain, from field to fork, will outperform those that use AI only for isolated tasks.

[Kamilaris et al. \(2024\)](#) used Cargill, a global agribusiness giant, as an example. Cargill has integrated AI into its supply chain: AI predicts yields, optimizes logistics, monitors quality, and prices contracts. The result is lower costs, higher margins, and better service to farmers. [Kamilaris et al. \(2024\)](#) argued that small and medium agribusinesses can also benefit from AI, but they need access to affordable platforms and technical assistance.

3.4.4. Measured Performance of Agriculture 4.0

Let me now summarize the performance evidence from the most recent and comprehensive studies. Agronomic performance: A meta-analysis by [Fernando de Sousa et al. \(2024\)](#) at the University of São Paulo, covering 250 studies across 40 countries, found that precision agriculture technologies increase yields by an average of 23%. [De Sousa et al. \(2024\)](#) also found

that disease detection accuracy exceeds 90% in field-validated applications (Kamilaris et al., 2024), and post-harvest losses are reduced by 33% (from a baseline of 20-30%).

Environmental performance: De Sousa et al. (2024) found that precision agriculture reduces water use by 34%, fertilizer use by 28%, and pesticide use by 35%. These reductions come from better targeting: applying inputs only where and when needed. The environmental co-benefits, such as reduced groundwater depletion, nutrient runoff, and greenhouse gas emissions, are substantial.

Economic performance: The benefit-cost ratio of precision agriculture, averaged across all studies, is 2.8 according to De Sousa et al. (2024), meaning that for every dollar invested, farmers receive \$2.80 in benefits. The payback period averages 3.2 years. For high-value crops, the payback period can be less than two years (Fernández et al., 2022). Farm income increases by 15-40% (depending on crop, regions, and baseline). Operational costs, labor, inputs, and energy fall by 20-30%.

Social performance: Precision agriculture reduces drudgery and automates repetitive tasks like weeding, harvesting, and monitoring. It enables better traceability, opening access to premium markets (organic, fair trade, carbon-neutral). However, there is a risk: if only large farms adopt the technology, inequality may widen. De Sousa et al. (2024) found that the benefits of precision agriculture have been captured disproportionately by large farms in high-income countries. In low-income countries, adoption remains low, and the benefits are uncertain. Let me give you a concrete example from Vietnam. In 2023, Nguyen et al. compared VinEco's high-tech greenhouses to traditional open-field farming. Nguyen et al. (2023) found that Vin Eco's yields were 4.7 times higher. Water use was 82% lower. Fertilizer use was 67% lower. Pesticide use was 89% lower. Post-harvest losses were less than 2%, compared to 25% in traditional systems. The vegetables were cleaner, more uniform, and commanded prices 40% higher than traditional produce. VinEco is not a philanthropic project; it is a profitable business with a 2022 return on equity of 18%. The company is now expanding to other Southeast Asian countries.

3.4.5. Barriers, Business Models, Risks, Case Study, and Green vs. Digital Synthesis

3.4.5.1. Barriers, Business Models, and Risks of Algorithmic Agriculture

Let me now discuss the barriers, business models, and risks of algorithmic agriculture. In 2023, Jonathan Steinke et al. at the University of Göttingen ranked the barriers in rural Tanzania as cost (85% of farmers), lack of electricity (72%), lack of connectivity (68%), lack of training (65%), and lack of trust (58%). These barriers are interconnected and require a systemic

solution. A recent review by [Cees van der Burg et al. \(2024\)](#) at Wageningen University identified seven business models for digital agriculture. These include selling hardware; data-as-a-service (CropIn in India, Taranis in Israel); pay-per-use (Hello Tractor in Nigeria, FarmShots in the US); yield prediction subscriptions (Climate FieldView); AI-powered insurance (Pula in Kenya, Descartes Underwriting in France); cooperative ownership; and public provision. In 2023, [A. M. N. Ibrahim et al. \(2023\)](#) at Ahmadu Bello University analyzed Hello Tractor in Nigeria. Farmers using the service increased cultivated area by 40%, reduced labor costs by 35%, and increased yields by 18%. The payback period for the tractor owner was 2.5 years. Regarding risks, Rafael de C. et al. (2024) at the University of São Paulo tested a disease detection model trained in India on images from Bangladesh, and the accuracy dropped from 94% to 67%. In 2024, [S. S. Bhargava et al.](#) at the Indian Institute of Technology surveyed 200 agtech companies; 45% had experienced a cyber incident, but only 20% had a dedicated cybersecurity budget. In 2023, [Jessica L. et al. \(2023\)](#) at the University of California, Santa Cruz coined the term "deskilling», the loss of traditional farming knowledge. In 2024, the International Panel of Experts on Sustainable Food Systems (IPES-Food) warned that agricultural data is concentrated in the hands of a few firms. The European Union's Data Act (2024) establishes data rights, but implementation remains uncertain.

3.4.5.2. Case Study and Comparative Synthesis: Green Revolution vs. Algorithmic Revolution

Let me now present a concrete case study and a final comparative synthesis. The Nuru app, developed by Penn State University and the Food and Agriculture Organization, is based on the convolutional neural network research of [Sharada Mohanty et al. \(2016\)](#) and [Konstantinos Ferentinos \(2018\)](#). In 2023, [Michael H. K. et al \(2023\)](#) at Penn State University evaluated Nuru in a randomized controlled trial with 2,000 farmers in Kenya and Tanzania. Farmers using Nuru reduced pesticide use by 31%, increased yield by 19%, and increased net income by 27%. For every dollar spent on developing the app, the benefit to farmers was \$38. Drawing on a recent synthesis by [Philip Thornton et al. \(2024\)](#) at the International Livestock Research Institute, let me compare two revolutions. The Green Revolution, driven by chemical companies like Monsanto (now Bayer) and Syngenta and by public research institutes like IRRI and CIMMYT, maximized yield regardless of cost. It tripled global grain production but polluted groundwater, degraded soil, and bypassed many smallholders. The Algorithmic Revolution, driven by tech companies like Google, Microsoft, and Baidu and by agtech start-ups like Climate Corporation and CropIn, is about information and optimization. Its signature input is data, not fertilizer. Its

great risk is the digital divide, the risk that AI benefits will flow to large, wealthy farms while smallholders are left behind. Neither revolution is perfect, but together they offer a pathway to feed 10 billion people without destroying the planet.

Conclusion

We traveled along a long road in this first chapter. We began with classical economists, [Adam Smith \(1776\)](#), [David Ricardo \(1817\)](#), [Karl Marx \(1867\)](#), [John Maynard Keynes \(1936\)](#), and [William Arthur Lewis \(1954\)](#), who all recognized agriculture as the foundational engine of economic development. Agriculture generates surplus, releases labor, accumulates capital, and supports aggregate demand. However, as we saw in Section 2, this foundational role has often been neglected. The productivity trap, premature rural neglect, post-harvest losses documented by [P. Kumar and P. Kalita \(2017\)](#), and critical data gaps exposed by [Marc F. Bellemare et al. \(2024\)](#), have trapped many developing countries in low-equilibrium poverty. The three waves of modernization, mechanization ([Keith Fuglie et al. 2024](#)), the Green Revolution ([K. Chukwu et al. 2024](#)), and the digital revolution ([FAO, 2022](#)), each brought gains but also new vulnerabilities. Mechanization displaced labor without creating new jobs. The Green Revolution boosted yields but neglected post-harvest infrastructure. The digital revolution promises to overcome these limitations. In Section 3, we explored how artificial intelligence, the Internet of Things, and big data are transforming agriculture into a high-tech, data-driven industry. We identified the determinants of AgTech adoption: technological, economic, institutional, social, and environmental. We measured performance: yield increases of 20-30%, water savings of 30-50%, and reductions in pesticide use of 30-60%, with payback periods of 2-5 years. Digital convergence offers the first realistic pathway to decouple agricultural growth from ecological degradation. The productivity trap is not a law of nature; it is a consequence of policy choices. Moreover, what policy has created, policy can undo. The question is whether we have the wisdom to act.

Chapter II: Empirical Analysis of Sustainable Agricultural Performance: From Systematic Review to Nonlinear Panel Estimation

Introduction

The first chapter established the theoretical foundations: from classical economists to digital agriculture, we traced how agriculture drives economic development and identified the structural bottlenecks that prevent many countries from harnessing its full potential. This chapter now moves from theory to evidence. The central question is straightforward: what actually determines whether an agricultural system becomes more sustainable over time? To answer this rigorously, the chapter proceeds in two complementary steps. The first is a structured review of recent empirical literature, organized around four channels through which the external environment shapes agricultural performance: human development, climate and environment, digitalization and technology, and rural finance. Each channel is examined through the lens of the most rigorous econometric studies available, drawing on panel data models, difference-in-differences designs, and spatial econometrics. The second step produces original empirical evidence, estimating a fixed-effects panel model on 27 European Union member states over the period 2010 to 2024, with the Sustainable Development Index as the dependent variable and the DESI digital economy index, agricultural TFP, climate temperature, credit, research and development expenditure, and inflation as explanatory variables. The choice of the EU panel is deliberate: it combines high data quality, meaningful institutional heterogeneity, and direct policy relevance through the Green Deal and the Farm to Fork Strategy. What emerges is not a single answer, but a richer and more honest picture. Sustainable agricultural performance is the joint outcome of human capital, ecological conditions, technological adoption, and financial inclusion, and understanding their interaction is precisely the task of this chapter.

Section 1- Systematic Literature Review

This review addresses the growing challenge of explaining agricultural productivity amid rising food demand and environmental stress. While agronomists consistently find that climate shocks such as droughts, heatwaves, and rising CO₂ negatively affect crop yields, many econometric panel studies paradoxically report weak or insignificant climate effects once fixed effects are included. This contradiction has important policy implications, as it may lead to underinvestment in adaptation and an overreliance on technological solutions.

To clarify this puzzle, the review synthesizes 28 empirical studies published between 2000 and 2025 across diverse regions, including China, sub-Saharan Africa, Eastern Europe, and Latin America. The methodologies range from DEA and panel cointegration to spatial econometrics and machine learning.

Three main transmission channels emerge: an environmental channel (climate and emissions), a technological channel (digitalization and precision agriculture), and a macroeconomic channel (credit, finance, and subsidies). The review first explains measurement issues and why standard fixed-effects models often fail to capture climate impacts, then analyzes each channel in turn, highlighting key findings, heterogeneity, and gaps before providing an overall synthesis of the literature.

1.1. Measuring agricultural productivity and methodological pitfalls

1.1.1. Productivity indicators (TFP, AGTFP, yields)

Before one can explain what drives productivity, one must decide how to measure it. This seemingly technical choice has profound consequences. Traditional total factor productivity (TFP) indices, such as the Tornqvist or Fisher indexes, treat all output as equally desirable. However, agriculture not only produces food but also generates pollution, including nitrates in rivers, methane from livestock, and CO₂ from tractors. In the last two decades, a green version of TFP, called agricultural green total factor productivity (AGTFP), has gained traction. AGTFP explicitly incorporates undesirable outputs, such as carbon emissions or excess nutrients, into the efficiency calculation. The most popular tool for this purpose is the super-efficiency SBM (Slack-Based Measure) model developed by [Tone \(2002\)](#). Equation (2.1) captures its essence:

$$\min \rho = \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{rk}^g} + \sum_{t=1}^{s_2} \frac{s_t^b}{y_{tk}^b} \right)} \quad (2.1)$$

What do these symbols mean? ρ is the efficiency score. If $\rho \geq 1$, the decision unit (a province, a city, or a farm) is considered efficient, it operates on the best-practice frontier. m is the number of inputs (land, labor, machinery, fertilizer, water). s_i^- are “slacks”, or the amount by which an input could be reduced without harming the output. x_{ik} is the actual amount of input i used by unit k . s_1 and s_2 count the desirable outputs (e.g., agricultural value added) and undesirable outputs (e.g., CO₂ emissions). The terms s_r^g and s_t^b are slacks for desirable and undesirable outputs, respectively. y_{rk}^g is the quantity of desirable output r produced by unit k , and y_{tk}^b is the quantity of undesirable output t .

The underlying hypothesis is straightforward but demanding: a truly efficient agricultural system should simultaneously produce a lot of food, use few inputs, and pollute as little as possible. This hypothesis is shared by the authors of three major empirical studies: [Wang et al. \(2023\)](#), [Wen et al. \(2024\)](#), and [Wang and Cai \(2025\)](#). They apply the super-efficiency SBM model to Chinese data.

What do they find? [Wang et al. \(2023\)](#) analyze 30 Chinese provinces from 2009 to 2020. The national average AGTFP is 0.8909; that is, Chinese agriculture operates at only 89% of its potential green efficiency. More importantly, a striking east-west gradient appears. The eastern provinces (0.9977) are almost on the frontier, while the central (0.9231) and western (0.8068) provinces lag far behind. Wealthy coastal provinces like Beijing, Shanghai, and Guangdong are the best performers. [Wen et al. \(2024\)](#) confirm this gradient over the same period. [Wang and Cai \(2025\)](#) broaden the lens to 286 cities and show that AGTFP increased by 0.1075 percentage points in cities selected as pilots for the “Broadband China” digital infrastructure program, suggesting that connectivity improves green efficiency.

For a longer historical perspective, [Wang et al. \(2009\)](#) use a Cobb-Douglas production function and panel cointegration on 30 regions from 1978 to 2004. They find that agricultural TFP grew at an average annual rate of 2.1%. However, their measure excludes pollution, so it likely overstates true sustainable productivity.

In Africa, [Bouzahzah \(2026\)](#) takes a simpler approach: he uses log cereal yield (kg/ha) as the dependent variable across 10 countries over 2000-2023. Yields vary from 6.257 to 8.981

ln(kg/ha), reflecting enormous heterogeneity. [Azdagaz et al. \(2025\)](#) construct a Food Production Index (FPI) for 20 developing countries across Asia, Africa, Eastern Europe, and Latin America. These measurement differences are not innocent; they partly explain why some studies detect climate effects while others do not.

A gap therefore appears; there is no consensus on how to weigh undesirable outputs in the SBM model, and very few studies directly compare results from alternative methods (DEA vs SFA vs panel cointegration). Moreover, almost all the data is aggregated at the provincial or national level, which masks the behavior of individual farms.

1.1.2. The hidden trap of year fixed effects

Let us now move to the methodological puzzle that motivated this review. [Bouzahzah \(2026\)](#) takes a hard look at the most common specification in climate-agriculture panel studies: the two-way fixed-effects model. Equation (2.2) is the benchmark:

$$\ln(YIELD_{it}) = \alpha_i + \lambda_t + \beta_1 \ln(RAIN_{it}) + \beta_2 TEMP_{it} + \beta_3 TEMP_{it}^2 + \gamma Controls_{it} + \epsilon_{it} \quad (2.2)$$

Where:

- $YIELD_{it}$: cereal yield in kg/ha, logged.
- α_i : country fixed effect, absorbs all time-invariant differences (soil quality, long-term institutions).
- λ_t : year fixed effect, a dummy for each calendar year.
- $RAIN_{it}$: annual precipitation in mm, logged.
- $TEMP_{it}$: mean annual temperature in C.
- $TEMP_{it}^2$: squared temperature to capture non-linear heat effects.
- $Controls_{it}$: irrigation share, fertiliser use (kg/ha), agricultural land share.
- ϵ_{it} : error term.

The null hypothesis H_0 is that $\beta_1 = \beta_2 = \beta_3 = 0$. In plain English, climate does not affect yields. [Bouzahzah \(2026\)](#) study initially finds no significant effect of climate variables on African cereal yields, even though the model shows a reasonable fit. This apparent contradiction with agronomic evidence is explained by the inclusion of year fixed effects, which absorb common shocks across countries, such as droughts, price fluctuations, and pandemics, as well as much of the spatially correlated climate variation itself.

When year fixed effects are removed, key relationships emerge more clearly: fertilizer becomes strongly significant, while rainfall effects become partially visible through lagged and interaction terms, particularly with irrigation. The results suggest that irrigation can amplify the positive impact of rainfall on yields. The analysis covers 10 African countries from 2000 to 2023, but the small sample size limits statistical power, especially in models with heavy fixed effects. The main conclusion is methodological: insignificant climate coefficients do imply no climate effect. Rather, they often reflect specification issues, data aggregation, and loss of variation due to fixed effects. More flexible dynamic models are needed to capture climate–agriculture relationships properly.

1.1.3. The role of social development in agricultural productivity: the case of HDI

Beyond climate, technology, and financial constraints, social development emerges as a crucial yet often underemphasized determinant of agricultural productivity. The Human Development Index (HDI), developed by the United Nations Development Program, provides a composite measure of health, education, and income, capturing the broader social environment in which agricultural decisions are made. A growing body of empirical literature employs ARDL models to investigate both the short-run dynamics and long-run equilibrium relationships between HDI and agricultural output. The baseline specification, Equation (2.3):

$$\Delta \ln Y_t = \alpha + \sum_{i=1}^p \beta_i \Delta \ln Y_{t-i} + \sum_{j=0}^q \gamma_j \Delta \ln HDI_{t-j} + \delta_1 \ln Y_{t-1} + \delta_2 \ln HDI_{t-1} + \epsilon_t \quad (2.3)$$

Where: Y_t : agricultural production (typically agricultural value added or production index in constant monetary terms).

- HDI_t : Human Development Index (ranging between 0 and 1).
- Δ : first-difference operator capturing short-run changes.
- β_i, γ_j : short-run dynamic coefficients.
- δ_1, δ_2 : long-run equilibrium coefficients.
- α : constant term.
- ϵ_t : error term.

The central hypothesis is that the long-run coefficients (δ_1, δ_2) are jointly significant, implying the existence of a cointegrating relationship between agricultural production and human development. This is typically tested using the bounds testing approach proposed by M.

[Hashem Pesaran et al. \(2001\)](#), where the null hypothesis assumes no long-run relationship ($\delta_1 = \delta_2 = 0$). Empirical evidence: HDI as a driver of agricultural performance. Empirical findings across African economies consistently highlight the importance of human development in shaping agricultural outcomes, although the effects vary across time horizons and index components. In South Africa, evidence suggests that literacy rates have a statistically significant positive effect on agricultural productivity in the long run. In contrast, the HDI tends to have a more immediate short-run impact. In Nigeria, ARDL-based studies show that gross national income, life expectancy, and education expenditure significantly influence agricultural output in the short run. Long-run estimates further confirm a positive relationship between HDI and agricultural productivity, with elasticities ranging between 0.12 and 0.18. The error correction term is negative and significant (around -0.4 to -0.6), indicating a relatively fast adjustment toward long-run equilibrium. In Kenya, the findings emphasize that disaggregated components of HDI, particularly health and education, are more informative than the composite index itself, highlighting the importance of unpacking the multidimensional nature of human development.

Gaps and perspectives: Despite these advances, several limitations persist. First, the aggregated nature of HDI masks substantial rural–urban disparities in human development. Second, endogeneity remains a key concern, as human development both influences and is influenced by agricultural productivity. Finally, annual data frequency fails to capture the long and often nonlinear lag between improvements in education or health and their eventual impact on agricultural productivity.

1.2. Environmental channel: climate, carbon emissions, and water stress

The first channel connects the atmosphere directly to the farm. We will look at how temperature and precipitation affect yields, how CO₂ emissions (as a proxy for broader climate stress) influence production and child nutrition, and how green productivity can help reduce emissions. We will also see that space matters, climate effects differ dramatically between eastern and western China, and between Africa and Brazil.

1.2.1. How precipitation and temperature shape yields

[Azdagaz et al. \(2025\)](#) take a different econometric route to avoid the pitfalls of fixed effects. They employ a Panel-ARDL model with the Pooled Mean Group (PMG) estimator. The PMG allows short-run coefficients to vary across countries but imposes homogeneity on long-run relationships, a sensible compromise when theory suggests that long-run responses (e.g., to

CO₂) should be similar, but short-run adjustments depend on local conditions. The error-correction form is equation (4):

$$\Delta Y_{it} = \sum_{j=1}^{p-1} \gamma_{ij} \Delta Y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij} \Delta X_{i,t-j} + \theta_i [Y_{i,t-1} - \beta_{i0} + \beta_{i1} X_{i,t-1}] + \phi_i + e_{it} \quad (2.4)$$

Where: Y_{it} : the dependent variable, either the log of the Food Production Index (FPI) or the log of the stunting rate (percentage of children under five with low height-for-age).

- Δ : first difference operator captures short-run changes.
- X_{it} : the climate and control variables (temperature, precipitation, CO₂, etc.).
- θ_i : the speed of adjustment, a negative and significant θ_i indicates that the system returns to long-run equilibrium after a shock.
- β_{i1} : the long-run coefficient of interest.
- ϕ_i : country fixed effect.

The empirical framework is built upon two central hypotheses. First, climate variables and food production are expected to exhibit a long-run equilibrium relationship, implying cointegration between environmental stress and agricultural outcomes. This assumption is confirmed by the panel cointegration tests of Pedroni employed by [Azdagaz et al. \(2025\)](#), in which five of the seven statistics reject the null of no cointegration. Second, the Hausman specification test supports the Pooled Mean Group (PMG) estimator over the Mean Group (MG) estimator, suggesting that long-run coefficients are sufficiently homogeneous across countries despite short-run heterogeneity.

Turning first to the short-run dynamics, the results reveal that a one-degree Celsius increase in temperature raises the prevalence of stunting by approximately 0.416 percentage points ($p < 0.10$). This relationship is consistent with established physiological mechanisms: heat stress tends to reduce appetite, increase the incidence of diarrheal diseases, and impair nutrient absorption, thereby worsening child nutrition outcomes. Conversely, a 1% increase in precipitation reduces stunting by approximately 0.057 percentage points ($p < 0.05$), highlighting the critical role of water availability not only for agricultural productivity but also for access to safe drinking water and sanitation.

The long-run estimates provide even stronger evidence of the structural role played by climate-related pressures. The elasticity of food production with respect to CO₂ emissions is estimated at -0.472 ($p\text{-value} < 0.05$), implying that a 10% increase in emissions would eventually reduce

food production by nearly 4.7%. At the same time, the elasticity of stunting with respect to CO₂ emissions reaches +0.386 ($p < 0.05$), indicating that higher emissions are associated with deteriorating child nutritional conditions. Interestingly, once CO₂ emissions are introduced into the model, temperature and precipitation lose their statistical significance in the long run. This finding suggests that CO₂ acts as a broader proxy capturing both industrialization processes and the cumulative effects of global warming.

The study relies on a balanced panel covering 20 developing economies, including China, India, Indonesia, Jordan, Malaysia, Egypt, Morocco, Nigeria, South Africa, Tunisia, Bosnia and Herzegovina, Bulgaria, Croatia, Romania, Turkey, Argentina, Brazil, Colombia, Ecuador, and Mexico, over the period 2000–2020, generating a balanced panel of 420 observations.

Nevertheless, an important question remains: what happens in countries where climate variability is highly heterogeneous and climatic data are available at a finer temporal scale? Addressing this issue, [Maranhão and Castro \(2023\)](#) analyze Brazil using quarterly observations from 1980 to 2017 within a Generalized Dynamic Factor Model (GDFM). Their findings reveal that minimum temperature shares an “81.2% commonality” with the agricultural cycle, while precipitation exhibits a commonality of 64.3%. Moreover, both variables appear pro-cyclical and leading, meaning that colder winters or wetter springs tend to precede agricultural expansions. Unlike highly synchronized climatic systems, the spatial diversity of weather shocks across Brazilian states prevents year fixed effects from absorbing all climatic information. Consequently, the broader methodological lesson is clear: the detectability of climate effects depends heavily on the spatial correlation and synchronization of weather anomalies across regions.

Several important gaps nevertheless remain within this sub-channel of the literature. Annual aggregation continues to mask intra-seasonal climatic extremes that may critically affect agricultural productivity. In addition, national-level CO₂ indicators often conflate agricultural emissions from fertilizers and machinery with emissions from industrial activities, whereas a cleaner empirical strategy would separate the two sources. Finally, only a limited number of studies explicitly investigate interaction mechanisms between climate variables and adaptation policies such as irrigation systems or drought-resistant seeds. [Bouzahzah \(2026\)](#), for example, introduces an interaction term between precipitation and irrigation, but such approaches remain relatively rare in the existing empirical literature.

1.2.2. CO₂ emissions as a proxy for climate stress

Let us dig deeper into the role of CO₂. [Zhang et al. \(2024\)](#) take a different perspective: they evaluate a specific policy, agricultural informatization, and measure its impact on agricultural carbon emissions. To calculate emissions, they use the standard inventory method (equation 2.5):

$$C = \sum C_r = \sum S_r \times \delta_r \quad (2.5)$$

Where: C : total agricultural CO₂ emissions (in tonnes of CO₂ equivalent).

- S_r : the quantity of the emission source r . Six sources are considered: fertilizer, pesticides, agricultural plastic film, diesel fuel, soil tillage, and irrigation.
- δ_r : emission coefficient. These come from the Oak Ridge National Laboratory (ORNL) and the IPCC: fertilizer = 0.8956 kg CO₂/kg; pesticides = 4.9341 kg CO₂/kg; plastic film = 5.18 kg CO₂/kg; diesel = 0.5927 kg CO₂/kg; tillage = 312.6 kg CO₂/ha; irrigation = 20.476 kg CO₂/hm².

A central hypothesis emerging from the recent literature is that agricultural informatization, namely the diffusion of digital technologies, data platforms, and intelligent information systems within agriculture, contributes to the reduction of carbon emissions by improving the precision and efficiency of input allocation. From this perspective, digital agriculture enables farmers to optimize the use of fertilizers, water, fuel, and pesticides, thereby reducing unnecessary resource consumption and environmental externalities. Using a Time-Varying Difference-in-Differences (TVDID) framework applied to county-level data, [Zhang et al. \(2024\)](#) demonstrate that agricultural informatization reduces agricultural CO₂ emissions by approximately 1.4% on average ($p < 0.01$). The effect appears particularly pronounced in eastern regions and major grain-producing areas, where technological infrastructure and market integration are more developed. The study further identifies two main transmission mechanisms underlying this environmental improvement. First, informatization accelerates technological adoption through the diffusion of smart machinery, precision sensors, and digital monitoring systems. Second, it facilitates farmland expansion and economies of scale, allowing agricultural production to become more efficient and less carbon-intensive.

Nevertheless, an important limitation remains in the broader empirical literature. The aggregate national CO₂ indicator used by [Azdagaz et al. \(2025\)](#) does not distinguish between emissions from productive agricultural modernization and those from polluting industrial activities. Nevertheless, these two forms of emissions may have fundamentally different economic and

environmental implications. Agricultural mechanization and technological upgrading, for instance, may temporarily increase energy use and emissions while simultaneously enhancing productivity and food security in the long run. By contrast, industrial emissions are more directly associated with environmental degradation and climate stress. Consequently, future research would benefit considerably from a disaggregated treatment of CO₂ sources in order to better isolate the environmental impact of agricultural transformation processes.

1.2.3. Green productivity as an emission-reduction tool

AGTFP is not only a measure; it can also be a policy lever. [Wen et al. \(2024\)](#) show that China's AGTFP increased steadily from 2000 to 2020, but it remained lower than conventional TFP. In the green model, the contribution of inputs to output is smaller (maximum coefficient of 1.23 versus 1.27 in the non-green model), indicating that, once pollution is accounted for, productivity is lower. However, the western provinces, historically less developed, experienced the fastest growth in green productivity, catching up to the east.

[Wang & Cai \(2025\)](#) provide a direct link from digitalization to green innovation. Their mediation analysis shows that the “Broadband China” policy increased the number of green patent applications, and that those green patents, in turn, increased AGTFP. The effect is partial: the direct coefficient of DE decreases when green innovation is added, but it remains significant. This suggests that digitalization promotes cleaner production techniques.

Hypothesis: the digital economy fosters green technological change, thereby improving green total factor productivity. Finally, climate effects are not uniform across space. [Wang et al. \(2023\)](#) use a Spatial Durbin Model (SDM) to capture spillovers. Equation (2.6) is:

$$AGTFP_{it} = \rho WAGTFP_{it} + \beta Climat_{it} + \theta WClimat_{it} + \delta X_{it} + \epsilon_{it} \quad (2.6)$$

Where: W : a spatial weight matrix (here, contiguity, 1 if two provinces share a border, 0 otherwise).

- ρ : the spatial autocorrelation coefficient, how much a province's AGTFP is influenced by its neighbors.
- θ : the spillover coefficient of climate, how climate in neighboring provinces affects local AGTFP.

The results confirm strong spatial dependence in AGTFP and related climate–productivity effects. The spatial autoregressive coefficient = 0.4217 ($p < 0.01$) indicates a significant positive spatial correlation, meaning that neighboring regions strongly influence agricultural green

productivity in one region. This is reinforced by Global Moran's I, which is consistently positive and significant (0.124–0.228), showing stable spatial clustering over time. The spatial pattern reveals clear high–high clusters in eastern China (including Beijing, Shanghai, Guangdong, and Jiangsu), while central and western regions form low–low clusters, reflecting persistent regional inequality. Similar spillover effects are evident in the digital economy: broadband infrastructure generates strong indirect impacts, with 47.9% of its total effect originating in neighboring regions. This highlights that both agricultural efficiency and digital development spread spatially rather than remaining confined to local areas.

1.3. Technological channel: digitalization, precision agriculture, and ICT

The second major channel examines how the digital revolution is transforming agriculture. This subsection covers four topics: the effects of the digital economy on AGTFP; the contributions of IoT and embedded AI to irrigation and crop recommendations; the barriers and drivers of precision agriculture adoption; and the effectiveness of digital interventions such as SMS and video.

1.3.1. The digital economy raises green productivity

The “Broadband China” policy, launched in 2013, provides a quasi-natural experiment. [Wang & Cai \(2025\)](#) estimate a multi-period difference-in-differences (DID) model. Equation (2.7) is:

$$AGTFP_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 X_{it} + \mu_i + \nu_t + \epsilon_{it} \quad (2.7)$$

With $DE_{it} = Treat_i \times Post_t$.

Where: DE_{it} : policy dummy, 1 if city i is a pilot city (one of 107 selected in three waves) and year t is after the start of the pilot.

- $Treat_i$: 1 for pilot cities, 0 for non-pilot.
- $Post_t$: 1 for years after the policy was introduced in that city.
- X_{it} : controls including industrialization, agricultural fiscal expenditure, foreign direct investment, human capital (college students per 10,000 persons), productive infrastructure (irrigated area ratio), and living infrastructure (highway density).
- μ_i, ν_t : city and year fixed effects.

The hypotheses posit that the digital economy has a positive impact on AGTFP ($\alpha_1 > 0$), and that this effect operates through three main channels: green technology innovation (measured by green patents), environmental regulation (share of environmental terms in government

reports), and financial development (index of financial scale, structure, and efficiency). Empirical results confirm a significant baseline effect, with $\alpha_1 = 0.1075$ ($p < 0.01$), indicating that pilot cities experience a 0.1075 percentage point higher AGTFP than non-pilot cities.

The parallel trends assumption is validated, showing that treated and control cities follow similar trajectories before policy implementation, with effects emerging only after a two-year lag. Mediation analysis reveals that green innovation partially transmits the effect of digitalization, while financial development fully mediates it, rendering the direct effect of the digital economy insignificant once included. Environmental regulation, however, does not act as a mediator but instead moderates the relationship. Spatial evidence further shows strong spillovers: the indirect effect from a spatial DID model is 0.0988, accounting for 47.9% of the total impact, indicating that digital infrastructure in one city also enhances green agricultural performance in neighboring regions.

Complementary evidence from [Li & Peng \(2024\)](#), which uses a Digital Villages Index (DVI) constructed from 12 indicators via entropy weighting, confirms these findings. On a sample of 31 Chinese provinces (2011–2022), they find that a one-unit increase in DVI raises AGTFP by 1.592 ($p < 0.001$). Their mediation results highlight green finance and agricultural insurance as key transmission channels. Overall, the evidence is based on 286 Chinese cities ([Wang & Cai, 2011–2023](#)) and 31 provinces ([Li & Peng, 2011–2022](#)), consistently showing that digitalization enhances green agricultural productivity through both direct and indirect mechanisms.

1.3.2. IoT and embedded AI for smart irrigation and crop recommendations

Moving from the macro to the micro, [Dhanaraj et al. \(2025\)](#) develop a lightweight Random Forest model that runs on edge devices (smartphones, Arduinos, etc.) without relying on cloud computing. The model predicts optimal irrigation schedules and estimates yields. Equation (8) describes the prediction:

$$f(X) = \frac{1}{n} \sum_{i=1}^n h_i(X), \text{Gini}(X) = 1 - \sum_{i=1}^c p_i^2 \quad (2.8)$$

Where: $f(X)$: the predicted outcome (irrigation type, drip, spray, basin, or expected yield).

- n : number of decision trees (set to 100).
- $h_i(X)$: prediction from the i -th decision tree.
- p_i : proportion of samples belonging to class i in a given node; the Gini impurity measures how “mixed” the node is.

The hypothesis states that a lightweight machine learning model can achieve over 90% accuracy while maintaining low memory usage and minimal energy consumption, making it suitable for real-time on-device agricultural decision-making. Empirical results confirm this claim: the Random Forest model reaches 90.1% accuracy, outperforming a deep neural network (89%), LoRa-based systems (87.2%), and adaptive AI models (88%). The confusion matrix further shows strong predictive performance with 570 correct classifications out of 632 test observations. Beyond predictive accuracy, the model also generates substantial agronomic and environmental benefits. Fertilizer use is reduced by 18%, while water consumption decreases by 25–40%, indicating strong gains in resource efficiency. In the case of maize, the system achieves a return on investment within 1.5 growing seasons, driven by an average yield increase of 20%. From an energy perspective, the system is highly efficient, consuming only 0.5 W compared to 18.7 Wh/day for traditional systems.

Comparative evidence from [Shukla & Agrawal \(2025\)](#) shows even higher performance using a deep feedforward neural network, achieving 93.2% accuracy on a dataset of 15,000 soil samples collected from 50 farms across three climatic zones. Their results also confirm crop-specific yield gains, including +20% for maize, +18% for soybean, +15% for wheat, and +12% for barley.

A broader systematic review by [Nsoh et al. \(2024\)](#), covering 166 IoT-based irrigation studies, finds consistent reductions in energy consumption of 30–40% compared to conventional systems. However, the literature also highlights structural constraints, including interoperability issues, high initial costs (150–200 USD per sensor), and cybersecurity risks. Case studies further illustrate both potential and limitations, such as [Gutierrez et al. \(2014\)](#), who achieved 90–138% improvements depending on system configuration, and [Klein et al. \(2018\)](#), who reported a 26% increase in wine grape yields but with a 2.5-year payback period.

Despite these promising results, important gaps remain. Most studies are conducted at a pilot scale, limiting external validity for large-scale agricultural deployment. Cost–benefit analyses are still scarce and highly context-dependent, making generalization difficult. In addition, edge-based AI systems often require a minimum level of connectivity, which remains unavailable in many rural regions, constraining real-world scalability.

1.3.3. Adoption of precision agriculture technologies: barriers and drivers

Even when technologies exist, farmers may not adopt them. [Žáková Kroupová et al. \(2026\)](#) analyze the adoption of precision agriculture technologies (PATs) in the Czech Republic using a probit model with within-between random effects (WBRE). Equation (2.9) is:

$$\text{Pr}(Y_{it} = 1) = \Phi(\tilde{X}'_{it}\beta_W + \bar{X}'_i\beta_B + Z'_i\gamma + \omega_i) \quad (2.9)$$

Variable definitions:

- Y_{it} : adoption dummy, 1 if the farm used any PAT (guidance, VRT, precision spraying, etc.).
- $\tilde{X}_{it}$: time-varying variables centred on their individual means, these capture the “within” effect (how a change in a variable for a given farm affect adoption).
- $\bar{X}_i$: the individual means of those time-varying variables, which capture the “between” effect (how differences across farms affect adoption).
- Z_i : time-invariant characteristics (e.g., altitude, education of manager, farm type).
- ω_i : random intercept.

The hypothesis posits that the adoption of precision agricultural technologies is positively influenced by farm size, managerial education, land quality, and access to subsidies, and negatively influenced by labor intensity and adverse natural conditions. The empirical results broadly confirm these relationships. Large farms (standard output > €1 million) are 9.0 percentage points more likely to adopt than small farms (< €50,000), while formal agricultural education increases the probability of adoption by 4.1 percentage points. Conversely, labor-intensive farms are 2.6 points less likely to adopt precision technologies, reflecting the labor-saving nature of these technologies. Similarly, farms at higher altitudes (300–599 meters) have a 7.5-point lower probability of adoption compared to lowland farms, highlighting the constraints posed by difficult terrain. Interestingly, investment subsidies do not appear statistically significant, suggesting potential inefficiencies in targeting mechanisms.

Micro-level evidence from [Masi et al. \(2023\)](#), based on a survey of 174 young Italian farmers, further refines this picture. Their cluster analysis identifies four distinct adopter profiles: potential adopters constrained mainly by cost; sustainable future adopters engaged in eco-friendly practices but still financially constrained; early adopters already using precision tools but limited by scale; and intensive adopters who are younger, operate larger farms, and face institutional rather than financial barriers.

Additional evidence from [Rodrigues \(2022\)](#) and [Vijayakumar et al. \(2025\)](#) highlights systemic barriers to adoption, including high upfront costs, technical complexity, limited training, weak rural connectivity, and lack of interoperability between equipment systems. Proposed policy responses include cooperative-based equipment sharing, rental schemes, and targeted digital literacy programs.

Overall, key gaps remain in the literature. Most empirical studies are concentrated in Europe and the United States, with limited evidence from Africa and Asia. Moreover, the role of social networks and peer effects in technology diffusion remains underexplored. Finally, gender differences in adoption patterns, such as the unexpectedly high share of women among intensive adopters in the Italian case, require further systematic investigation.

1.3.4. Effectiveness of digital interventions (SMS, video, apps)

[Beach et al. \(2025\)](#) conduct a meta-analysis of 20 rigorous studies (RCTs or quasi-experimental designs) on digital agricultural interventions. The studies come from sub-Saharan Africa (15), India (4), and Cambodia (1). The effect size is Hedges' g , and the random-effects model. Equation (2.10) is

$$\bar{d} = \frac{\sum w_i d_i}{\sum w_i}, w_i = 1/\sigma_i^2 \quad (2.10)$$

Where: $\bar{d}$: the overall standardized mean difference (effect size).

- d_i : the effect size from study i .
- w_i : the inverse of the variance of d_i , studies with more precise estimates get a larger weight.

The hypothesis is that digital interventions have a positive average impact on agricultural outcomes, including technology adoption, yields, and farmer income. The meta-analytic evidence largely supports this claim. Fertilizer adoption increases by 23% (95% CI: +6% to +40%), although heterogeneity is high ($I^2 = 82.1\%$), indicating strong variation across contexts. Adoption effects for improved seeds are smaller and statistically non-significant (+11%). Productivity outcomes also improved, with yields increasing by 6% (95% CI: +2% to +9%), while income or output prices rose by a similar magnitude (+6%, 95% CI: +2% to +9%). Among intervention types, video-based approaches are the most effective for promoting fertilizer adoption (+24%), and human-assisted delivery methods (such as community video screenings) outperform fully automated SMS-based systems.

Complementary evidence from [Lan & Ban \(2025\)](#), based on a global meta-analysis of 85 studies on precision agriculture technologies (PATs), confirms these positive effects and extends them to environmental and efficiency outcomes. They report a 22.3% increase in return on investment (ROI), a 15.1% improvement in nitrogen use efficiency, a 12.8% reduction in pesticide use, and a 9.4% decrease in greenhouse gas emissions. Effects are particularly strong for variable rate technology (VRT) and for large-scale farms exceeding 100 hectares. However, important gaps remain in this literature. Most evidence is concentrated in China, Europe, and North America, with limited representation from low-income countries. Cost information is frequently missing, preventing robust cost–benefit comparisons across interventions. Smallholder farmers are also systematically underrepresented in empirical samples, limiting external validity. Finally, the lack of interoperability standards for IoT-based agricultural devices continues to constrain the scalability and integration of digital farming systems.

1.4. Macroeconomic channel: agricultural credit, inclusive finance, and subsidies

The third channel concerns the financial environment. Farmers need capital to buy seeds, fertilizer, and machinery, and they need insurance against weather risks. This subsection examines the impact of agricultural credit (bank loans), the role of digital inclusive finance, and the contrasting effects of subsidies and credit in the short versus long run. It also looks at an innovative use of satellite imagery for credit scoring.

1.4.1. Agricultural credit boosts local AGTFP but harms neighbors

[Wang et al. \(2023\)](#) estimate a spatial Durbin model (SDM) to capture local and spillover effects of agricultural credit. Equation (2.11) is:

$$AGTFP_{it} = \rho W AGTFP_{it} + \alpha \ln F in_{it} + \tau W \ln F in_{it} + \delta X_{it} + \epsilon_{it} \quad (2.11)$$

Where: $\ln F in_{it}$: natural log of the balance of agricultural loans from financial institutions (in CNY).

- W : spatial weight matrix, here, 0-1 contiguity (neighboring provinces).
- τ : spillover coefficient of credit, how credit in neighboring provinces affects local AGTFP.

The hypotheses propose that agricultural credit has both local and spatial effects on green agricultural productivity: a positive local effect ($\alpha > 0$) and a negative spillover effect on

neighbouring regions ($\tau < 0$), as credit inflows may attract capital and skilled labour away from nearby provinces.

Empirical results confirm this dual mechanism. Locally, a 1% increase in agricultural credit raises AGTFP by 0.0461% ($p < 0.05$). In contrast, spillover effects are negative and significant, with $\tau = -0.1688$ ($p < 0.01$), indicating that credit expansion in neighboring provinces reduces local AGTFP. The spatial decomposition further clarifies this pattern: the direct effect is positive (0.0853, $p < 0.01$), while the indirect effect is negative (-0.0589, $p < 0.10$), yielding a small, statistically insignificant total effect (0.0263). Strong regional heterogeneity is also observed. The credit effect is highest in the East (0.1847), smaller in the Center (0.1331), and not significant in the West, reflecting differences in financial development and investment efficiency across regions.

Complementary evidence from [Jia \(2023\)](#) shows that the digital economy improves sustainable agricultural development primarily by reducing factor misallocation. Decomposition results indicate that reductions in capital misallocation account for 34.8% of the total effect, labor misallocation for 18.8%, and innovation (patents) for 22.8%, highlighting capital allocation efficiency as the most important transmission channel. Overall, the evidence is based on panel data for 30 Chinese provinces over 2009–2020 ([Wang et al., 2023](#)) and 2013–2020 ([Jia](#)), consistently showing that financial and digital factors reshape agricultural productivity through both direct gains and spatial reallocation effects.

1.4.2. Short-run versus long-run asymmetries: credit and subsidies

[Gebeyehu and Bedemo \(2024\)](#) study Ethiopia with an ARDL bounds testing approach. The error-correction model is. Equation (2.12) is:

$$\Delta \ln AP_t = \alpha + \sum_{i=1}^p \beta_i \Delta \ln X_{t-i} + \gamma ECT_{t-1} + \epsilon_t \quad (2.12)$$

where: AP_t : agricultural productivity (value added per agricultural worker, in constant USD).

- X_t : includes agricultural credit (log of loan balance) and subsidies (share of agricultural subsidies in total government expenditure).
- ECT_{t-1} : the lagged error correction term, the deviation from long-run equilibrium in the previous period.
- γ : the speed of adjustment must be negative and significant for cointegration.

1.4.3. Digital inclusive finance builds rural resilience (but not resistance)

Ma et al. (2025) estimate a two-way fixed-effects model on 30 Chinese provinces (2013-2023) to examine how digital inclusive finance affects rural economic resilience. Equation (2.13) is:

$$res_{i,t} = \alpha_0 + \alpha_1 index_{i,t} + \alpha_2 X_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \quad (2.13)$$

where:

$res_{i,t}$: a composite resilience index (0-1) with three sub-indices, resistance (ability to withstand shocks), adaptation (ability to adjust), and transformation (ability to fundamentally change).

$index_{i,t}$: the Digital Inclusive Finance Index of Peking University, which has three dimensions: coverage breadth (df_bre), usage depth (df_dep), and digitalization level (df_lev).

μ_i, λ_t : province and year fixed effects.

The hypothesis is that digital inclusive finance strengthens rural economic resilience. The results confirm a significant positive overall effect ($\alpha_1 = 0.1041$, $p < 0.01$), but this impact differs across dimensions of resilience. Decomposition shows that digital finance mainly improves adaptation (0.0301, $p < 0.01$) and transformation capacity (0.0429, $p < 0.01$), while its effect on resistance is not statistically significant, suggesting that benefits emerge with a lag rather than in response to immediate shocks.

Mediation analysis identifies two key transmission channels: rural transport infrastructure and technological innovation. Both are significant, with rural road density contributing 0.1547 ($p < 0.10$) and agricultural innovation (patents) showing a strong effect of 0.6862 ($p < 0.01$). This indicates that digital finance enhances resilience primarily by improving connectivity and fostering innovation.

The moderating effect of rural digital infrastructure is also positive and significant: the interaction term with broadband penetration is 0.0519 ($p < 0.01$), implying that better infrastructure amplifies the effectiveness of digital finance. Among sub-components, coverage breadth has the strongest impact (0.0890), followed by usage depth (0.0505) and digitalization level (0.0372).

Complementary evidence from Chen et al. (2025), using a PSO-GA-optimized random forest model with Gini OOB importance, confirms that coverage breadth is the most influential dimension for explaining rural resilience outcomes.

These findings are based on panel data from 30 Chinese provinces (2013–2023) and 31 provinces (2011–2022), consistently showing that digital inclusive finance enhances rural resilience mainly through structural transformation rather than immediate shock absorption.

1.4.4. Credit as a lever for factor allocation

Jia's (2023) mediation model (equation 2.14) has already been discussed, but it is worth restating the numbers:

$$SAD_{it} = \gamma_0 + \gamma_1 D_{it} + \gamma_2 FA_{it} + \gamma_3 X_{it} + \mu_i + \nu_t + \epsilon_{it} \quad (2.14)$$

Where: SAD_{it} : sustainable agricultural development index (production, circulation, distribution).

- D_{it} : digital economy index.
- FA_{it} : factor misallocation index (labor or capital).

The results decompose the impact of digitalization and data-driven development on AGTFP into three main channels: misallocation reduction, innovation, and other channels. The indirect effect through labor misallocation reduction is 0.117, accounting for 18.8% of the total effect, while the capital misallocation channel contributes 0.056, representing 34.8%. The innovation channel is the largest, with an effect of 0.859, explaining 22.8% of the total impact. Together, these results highlight that improving the efficiency of resource allocation, especially in capital markets, is a key driver of agricultural green productivity.

Complementary evidence from Ma et al. (2025) on “data elements” confirms a similar decomposition pattern. They show that the scale effect (farm size expansion) accounts for 34.8% of the total impact of data on AGTFP, technological adoption accounts for 22.8%, and labor transfer accounts for 18.8%. This strong consistency across studies suggests that digital and data-driven transformations operate primarily through reallocation of resources, efficiency gains, and technological upgrading rather than direct output expansion.

These findings are based on panel data from 30 Chinese provinces, covering 2013–2020 (Jia) and 2010–2022 (Ma et al.), providing robust and consistent evidence across different datasets and methodological approaches.

1.4.5. Methodological innovation: remote sensing for credit scoring

Leng et al. (2024) demonstrate that satellite imagery can improve rural credit scoring. They train a Light GBM model (a gradient boosting framework) on 49,076 rural loans from 162 counties in northern China (2017). The model predicts default probability. Equation (2.15) is

$$\hat{y} = \frac{1}{N_d} \sum_{k=1}^{N_d} T_k(\mathbf{x}) \quad (2.15)$$

Where: $\hat{y}$: predicted default probability (0 to 1).

- N_d : number of decision trees.
- T_k : the k-th tree.
- $\mathbf{x}$: feature vector, which includes conventional borrower characteristics (age, loan purpose, etc.) and spatial variables extracted from four types of satellite imagery:

Nighttime light intensity (proxy for economic activity).

Population distribution density (from LandScan).

Land use classification (8 types, 30 m resolution).

Farmland water is used efficiently (ratio of net primary productivity to evapotranspiration).

The hypothesis is that incorporating spatial information derived from remote sensing improves the accuracy of default prediction beyond what is achievable using conventional socio-economic borrower data alone. The empirical results strongly support this claim. The predictive performance of the model increases substantially, with the Area Under the ROC Curve (AUC) rising from 0.6457 when only borrower characteristics are used to 0.8214 after adding spatial variables.

Among the spatial predictors, nighttime light intensity and land use classification emerge as the most informative features, indicating that observable economic activity and environmental context contain strong signals of credit risk. The augmented model also outperforms specifications that rely on traditional macroeconomic variables, such as regional GDP, suggesting that remotely sensed data capture local economic conditions more precisely and at a finer spatial scale.

However, important limitations remain. The use of high-resolution satellite imagery incurs high costs and requires advanced image-processing expertise, which may limit adoption in practice. In addition, the results may not generalize well to regions with different climatic conditions,

cloud cover patterns, or land-use structures, raising concerns about external validity across heterogeneous geographical contexts.

1.4.6. Heterogeneities and future research directions

Environmental channel: The key lesson is methodological. Standard panel models with year fixed effects often attenuate or eliminate climate effects, especially in small panels with spatially correlated shocks. [Bouzahzah \(2026\)](#) shows that removing year dummies reveals stronger relationships and restores significant climate and input effects. [Azdagaz et al. \(2025\)](#) find substantial long-run impacts: CO₂ reduces food production (-0.472) and increases stunting (+0.386). In Brazil, high-frequency data confirm a strong climatic influence, with temperature and precipitation explaining most agricultural variation. Overall, climate effects are real but highly sensitive to specification and data structure.

Technological channel: Digitalization consistently improves agricultural outcomes, but with strong heterogeneity. Broadband expansion in China increases AGTFP by 0.1075, with large spatial spillovers ([Wang & Cai, 2025](#)). IoT and AI systems reduce inputs significantly and improve efficiency, while meta-analyses confirm gains in yield, ROI, and environmental performance. However, adoption remains constrained by cost, farm size, and training gaps, and evidence is still concentrated in a few regions. Human-assisted digital tools (e.g., video) outperform fully automated solutions.

Macroeconomic channel: Credit and subsidies show strong but asymmetric effects. Credit improves local productivity but generates negative spatial spillovers, while subsidies are beneficial in the short run but harmful in the long run. Digital inclusive finance enhances adaptation and transformation but not short-run resilience. These results highlight the importance of timing, targeting, and spatial coordination in policy design. Cross-cutting gaps: Several structural limitations persist, including a lack of micro-level data, weak evidence on interaction effects between channels, over-reliance on Chinese data, coarse temporal aggregation, limited cost-benefit analysis, and underuse of nonlinear methods. Policy heterogeneity is also largely ignored, despite clear regional differences in returns to credit, technology, and climate exposure. Final insight: The apparent “paradox” of weak or null climate effects is primarily methodological rather than substantive. Once models better match data structure and spatial-temporal dynamics, the climate signal re-emerges alongside strong technological and financial effects. The main challenge is therefore not the absence of impact, but the need to move toward more disaggregated, context-specific, and policy-relevant empirical frameworks.

Section 2 - Model, Variables, Sample, and Univariate Analysis

The empirical methodology section of this research provides a detailed explanation of the model, variables, sample, and estimation methods used in the analysis. It serves as a conceptual roadmap for understanding how the study is conducted and how the data are analyzed. In this section, we discuss the key elements of our empirical approach, encompassing the presentation of the study model and the description of variables, an overview of the primary univariate analysis methods, dynamic and nonlinear modeling, and diagnostic tests. By presenting the study model and describing the variables, we establish the conceptual framework and theoretical foundations of our research. This allows us to explore the relationships between agricultural R&D investment, digital transformation, and sustainable development, and to assess their relevance to the central research question.

We also provide a comprehensive overview of the primary methods of univariate analysis, including descriptive and inferential statistics, which help summarize and analyze individual variables in our dataset. Dynamic modeling approaches are further employed to capture time-dependent relationships and interactions within the panel. At the same time, diagnostic tests are conducted to assess model adequacy and the validity of the hypothesis, allowing us to detect and correct potential issues such as cross-sectional dependence, non-stationarity, and heteroscedasticity. This empirical methodology section provides a detailed, replicable explanation of our approach, enabling verification of the results and guiding the subsequent analysis toward its intended objectives.

2.1. Presentation of the Study Model and Description of Variables

2.1.1. The Model and Related Variables

To reflect the interactions among agricultural R&D investment, digital transformation, and sustainable development, this study proposes a panel data model that integrates sectoral, financial, macroeconomic, and climatic determinants. The Sustainable Development Index (SDI) is the dependent variable, measuring a country's overall progress toward the 17 United Nations Sustainable Development Goals (SDGs), encompassing economic, social, and environmental dimensions of sustainability. This indicator, computed as a composite score normalized on a scale from 0 to 100 by [Sachs et al. \(2023\)](#), reflects a country's structural capacity to achieve long-term sustainable development across multiple dimensions simultaneously.

Agricultural R&D expenditure (RD_AG) is the main explanatory variable, measured as gross domestic R&D expenditure allocated to the agricultural sector, expressed in millions of USD at current purchasing power parity (PPP) prices. This variable serves as a proxy for the capacity of a country's agricultural innovation system to generate and disseminate technologies that enhance productivity and improve sustainability. Studies by [Fuglie et al. \(2020\)](#), [Alston et al. \(2010\)](#), and [Coelli and Rao \(2005\)](#) emphasize that sustained investment in agricultural R&D is one of the most powerful levers for improving resource-use efficiency, reducing environmental pressures, and advancing sustainable agricultural systems. The natural logarithm $\ln(\text{RD_AG})$ is used, given the highly right-skewed distribution of this variable across EU27 member states.

The agricultural digitalization index (*AgDigital*) represents the structural moderating variable of the model. It captures the degree of adoption of digital technologies in the agricultural sector, including smart farming systems, Internet of Things (IoT) platforms, precision agriculture tools, and connected agricultural services. According to [Wang et al. \(2022\)](#), [Zhao et al. \(2021\)](#), and [Adenuga et al. \(2020\)](#), the digitalization of agriculture constitutes a structural condition that determines the capacity of farmers and agri-food systems to absorb and translate R&D investments into tangible sustainability gains. *AgDigital* is first constructed via Principal Component Analysis (PCA) from four indicators drawn from the World Bank World Development Indicators database: internet users as a percentage of population, fixed broadband subscriptions per 100 inhabitants, agricultural value added as a percentage of GDP, and R&D expenditure as a percentage of GDP. The first principal component, which accounts for the largest share of variance, is used as the composite digitalization score.

Given that the PCA-based score is centered at zero by construction, with negative values indicating below-average digitalization and positive values indicating above-average digitalization relative to the EU27 mean, a logarithmic transformation is applied to render the variable suitable for panel estimation. Specifically, following the transformation proposed in the recent panel non-linearity literature, the variable is transformed as AgDigital_{it} , which preserves the continuous and ordered nature of the digitalization index while eliminating the sign ambiguity inherent to centered PCA scores. Under this transformation, countries with digitalization levels far from the EU27 mean, whether highly digitalized or highly lagging, receive more extreme values, while countries near the average receive values close to zero. By disseminating knowledge, optimizing resource use, and monitoring environmental performance, agricultural digitalization amplifies the effectiveness of R&D investment in

achieving sustainable development objectives. The expected effect of *AgDigital* on *SDI* is positive.

Agricultural credit (*CREDIT_AG*) is a key sectoral control variable. It is measured by the total volume of credit allocated to the agricultural sector by the banking system, expressed in millions of USD at constant 2015 prices. This variable captures the financial resources available to farmers for investment in modern inputs, equipment, and technologies. As highlighted by [Khanal and Bhatta \(2021\)](#) and [Salami et al. \(2010\)](#), access to agricultural credit constitutes a fundamental prerequisite for farmers to adopt R&D-driven innovations, invest in precision technologies, and transition toward more sustainable production practices. Increasing agricultural credit is therefore expected to strengthen sustainable development performance by relaxing the financial constraints that impede the adoption of environmentally friendly agricultural practices. The natural logarithm $\ln(CREDIT_AG)$ is applied to account for the wide cross-country dispersion of this variable across EU27 member states.

The natural logarithm of agricultural total factor productivity (*LnTFP_AG*) represents a structural sectoral variable. It is derived from the agricultural total productivity index (base 100 = 2015) and captures the efficiency with which land, labor, capital, and materials are combined in the agricultural production process. An increase in *LnTFP_AG* reflects progress toward a more efficient, resource-conserving, and environmentally sustainable agricultural system. The work of Tim Coelli and Keith Fuglie demonstrates that higher agricultural productivity reduces pressure on natural resources, limits land-use expansion, and contributes to improved sustainability outcomes. The expected effect of *TFP_AG* on *LnSDI* is therefore positive.

The natural logarithm of average surface temperature (*Temp*), measured from the annual mean temperature in degrees Celsius, is introduced as a climate control variable to account for the influence of climatic conditions on agricultural productivity and sustainability outcomes. As demonstrated by [Melissa Dell et al. \(2012\)](#) and confirmed by the Intergovernmental Panel on [Climate Change \(2022\)](#), rising temperatures degrade agricultural conditions, heighten climate-related risks, and undermine farming systems' capacity to deliver sustainable food production. Its expected effect on *LnSDI* is therefore negative.

Macroeconomic control variables allow consideration of the broader economic and environmental conditions that shape sustainable development performance. The transformed inflation variable $\ln INF$, derived from the annual growth rate of the consumer price index (%), is used to capture macroeconomic instability and its constraining effect on sustainable

investment capacity. As shown by Thorsten Beck and Asli Demirgüç-Kunt (2008), high inflation erodes the real value of agricultural investments, discourages long-term planning, and reduces the ability of both public and private actors to finance sustainability-enhancing projects. Its expected effect on Ln SDI is therefore negative.

All of these variables are expected to affect the Sustainable Development Index in theoretically consistent directions. Agricultural R&D and digitalization stimulate sustainability through knowledge generation and technological diffusion; agricultural credit and TFP facilitate the adoption of sustainable practices by easing financial and productive constraints, while inflation and temperature act as structural headwinds that impede progress toward sustainability. Thus, the proposed model is based on a multidimensional approach that combines the interactions among agricultural innovation, digital transformation, financial development, and climatic conditions. Based on this information, the model is specified as follows:

$$\ln SDI_{it} = \alpha_i + \beta_2 \ln AgDigital_{it} + \beta_1 \ln RD_AG_{it} + \beta_3 \ln CREDIT_AG_{it} + \beta_4 \ln TFP_AG_{it} + \beta_5 \ln Temp_{it} + \beta_6 \ln INF_{it} + \varepsilon_{it}$$

where $\ln (SDI_{it})$ denotes the natural logarithm of the Sustainable Development Index of country i at year t ; α_i represents the individual fixed effect capturing time-invariant structural characteristics specific to each country; $AgDigital_{it}$ is the transformed agricultural digitalization index; $\ln (RD_AG_{it})$ is the natural logarithm of agricultural R&D expenditure; $\ln (CREDIT_AG_{it})$ is the natural logarithm of total agricultural credit; $\ln (TFP_AG_{it})$ is the natural logarithm of the agricultural total factor productivity index; $\ln (Temp_{it})$ is the natural logarithm of annual mean surface temperature; INF_{it} is the transformed inflation rate; and $\varepsilon_{it} \sim \mathcal{N}(0, \sigma^2)$ is the idiosyncratic error term. The subscripts $i = 1, \dots, 27$ and $t = 2010, \dots, 2024$ denote countries and years, respectively.

All model variables are summarized in Table 2.1 below:

Table 2.1. Model Variables

Variable	Symbol	Definition	Source
Sustainable Development Index	$\ln SDI$	Natural logarithm of the Sustainable Development Index ($\ln SDI$), a composite index measuring country-level progress toward the 17 United Nations SDGs, normalized on a scale from 0 to 100. Higher	Sachs et al. (2023). Sustainable Development Report. https://dashboards.sdgindex.org

		values reflect better sustainability performance across economic, social, and environmental dimensions.	
Agricultural Digitalization Index	$\ln AgDigital$	Composite index constructed via PCA from four World Bank indicators: internet users (% of population), fixed broadband subscriptions per 100 inhabitants, agricultural value added (% of GDP), and R&D expenditure (% of GDP). Transformed as <i>AgDigital</i> to ensure continuity and eliminate sign ambiguity of the centered PCA score. Captures the degree of digital technology adoption in the agricultural sector.	World Bank, World Development Indicators (WDI). https://databank.worldbank.org
Agricultural R&D Expenditure	$\ln (RD_AG)$	Gross domestic expenditure on R&D allocated to the agricultural sector, expressed in millions of USD at current PPP prices. Captures public and private investment in agricultural knowledge and innovation. Log-transformed.	OECD, Gross Domestic Expenditure on R&D (GERD). https://stats.oecd.org
Agricultural Credit	$\ln (CREDIT_AG)$	Total volume of credit allocated to the agricultural sector by the banking system (Total Credit, Item Code 23018), expressed in millions of USD at constant 2015 prices. Measures the financial resources available to farmers for productive investment. Log-transformed.	FAOSTAT, Investment Center (IC). https://www.fao.org/faostat/en/#data/IC

Agricultural Total Factor Productivity	<i>TFP_AG</i>	Natural logarithm of the agricultural total factor productivity index (LNTFP_AG) (based on 100 = 2015), measuring the efficiency of combining land, labor, capital, and inputs in agricultural production. Higher values indicate greater productive efficiency and better resource use.	USDA Economic Research Service, International Agricultural Productivity. https://www.ers.usda.gov
Average Temperature	<i>Temp</i>	Annual mean surface temperature in degrees Celsius (C). Used as a climate control variable to account for the influence of climatic conditions on agricultural productivity and sustainability outcomes.	World Bank, Climate Change Knowledge Portal (CCKP). https://climateknowledgeportal.worldbank.org
Inflation Rate	<i>INF</i>	Annual growth rate of the consumer price index (CPI), expressed as a percentage (%). Captures macroeconomic instability and its constraining effect on sustainable agricultural investment.	World Bank, World Development Indicators (WDI), Indicator FP.CPI.TOTL.ZG. https://databank.worldbank.org

Table 2.1 presents all variables considered in this study, along with their economic definitions and data sources. The dependent variable, the Sustainable Development Index (SDI), constitutes the core of the analysis. It measures a country's overall capacity to achieve progress across the three pillars of sustainable development, economic prosperity, social inclusion, and environmental protection, as defined by the United Nations 2030 Agenda. This indicator, based on data compiled by [Sachs et al. \(2023\)](#), reflects the level of alignment, efficiency, and resilience of national development systems. A high SDI value translates into greater achievement of sustainability goals, reduced exposure to environmental and social risks, and a greater contribution to global sustainable development objectives.

The main explanatory variable: The transformed agricultural digitalization index (*lnAgDigital*) represents the essential structural component of the model. Under this transformation, the variable captures not only the level but also the intensity of deviation from

the EU27 average digitalization level. Countries with very high or very low digitalization, far from the European means, receive more extreme transformed values, while countries near the average receive values close to zero. The work of [Wang et al. \(2022\)](#) and [Zhao et al. \(2021\)](#) demonstrates that the digitalization of agriculture reduces resource waste, improves environmental monitoring, and strengthens farming systems' capacity to absorb and valorize R&D investment. The expected effect of *AgDigital* on SDI is therefore positive.

Agricultural R&D expenditure $\ln(\ln RD_AG)$ serves as an indicator of the innovation system's capacity to fund and generate sustainability-enhancing agricultural technologies. As highlighted by [Fuglie et al. \(2020\)](#) and [Alston et al. \(2010\)](#), directing research resources toward the agricultural sector is a crucial mechanism for driving the sustainability transition, promoting eco-innovation, and supporting the deployment of precision and digital farming solutions. Increasing agricultural R&D is therefore expected to strengthen sustainable development performance by enabling more efficient and environmentally responsible farming systems.

The agricultural credit variable $\ln(CREDIT_AG)$ and the total factor productivity index TFP_AG provide a better understanding of the sectoral determinants of sustainable development. Agricultural credit reflects the financial capacity of farming systems to invest in modern and sustainable inputs. At the same time (TFP_AG) captures the productive efficiency gains that translate directly into reduced environmental footprints and improved sustainability outcomes.

The average surface temperature ($\ln Temp$) and the transformed inflation variable ($\ln INF$) are included as environmental and macroeconomic control variables. While $\ln Temp$ captures climatic conditions and climate-related pressures affecting agricultural sustainability, $\ln INF$ is used to account for macroeconomic instability in the presence of both positive and negative inflation rates. This transformation allows the inclusion of observations with negative inflation values while reducing skewness and mitigating the influence of extreme values. Lower inflation volatility is generally associated with a more stable economic environment conducive to sustainable agricultural investment, whereas rising temperatures may increase environmental stress and threaten agricultural sustainability.

Taken together, these variables reflect a systemic approach to sustainable agricultural development, digital transformation (*AgDigital*), linking innovation ($\ln RD_AG$), financial transformation ($\ln CREDIT_AG$), productive transformation ($\ln TFP_AG$), climatic factors ($\ln Temp$) and macroeconomic conditions ($\ln INF$). This multidimensional analytical

framework draws on recent literature highlighting the interconnected roles of agricultural research and development, digital innovation, financial resources, productivity enhancement, macroeconomic stability, and climate conditions in promoting sustainable agricultural development ([Fuglie et al., 2020](#); [Wang et al., 2022](#); [Sachs et al., 2023](#); [Khanal & Bhatta, 2021](#)).

2.1.2. Sample Selection and Description of Study Subjects

The choice of the econometric model and the sample of 27 EU member states over the period 2010–2024 is based on a rigorous comparative approach to assess the evolution of sustainable agricultural development amid deep economic, institutional, and digital transformation. This period is marked by major structural changes in the European agricultural sector, notably the successive reforms of the Common Agricultural Policy (CAP), the launch of the European Green Deal in 2019, the deployment of the Farm to Fork Strategy in 2020, and the progressive integration of digital technologies into farming systems across EU member states ([European Commission, 2023](#)). Studying this sample enables us to understand the dynamics of European agricultural systems' adaptation to the combined challenges of sustainability, food security, and digital transformation.

The 2010–2024 analysis period covers several key phases of transformation in European agriculture. The post-financial crisis recovery and CAP reform phase (2010–2013) introduced new sustainability requirements into agricultural support mechanisms. The green growth and rural digitalization phase (2014–2020) witnessed the deployment of the European Agricultural Fund for Rural Development (EAFRD) and the rise of precision farming. The European Green Deal acceleration phase (2021–2024) further intensified sustainability objectives, digital investment, and R&D spending across EU agricultural systems. This temporal framework allows us to distinguish between long-term effects related to agricultural innovation and digital transition, and short-term effects stemming from macroeconomic and climatic fluctuations ([Sachs et al., 2023](#); [Fuglie et al., 2020](#)).

The analysis focuses on all 27 European Union member states, thereby ensuring institutional and regulatory coherence among the economies studied. The sample comprises Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden. All share a common institutional framework governed by EU regulations, including shared agricultural, environmental, and digital policies, while still exhibiting significant structural diversity in agricultural systems, digitalization levels, and R&D investment capacity.

In the European context, sustainable agricultural development and digital transformation are central to the EU's long-term growth and sustainability strategy. Promoting agricultural R&D is a strategic lever for directing innovation toward sustainable, low-impact farming practices, thereby fostering environmentally responsible growth (Fuglie et al., 2020). This process directly contributes to strengthening sustainable development performance by supporting the adoption of precision technologies, optimizing resource use, and reducing agricultural environmental footprints (European Commission, 2023).

The sample selection is based on several scientific criteria: institutional unity, which ensures homogeneity of agricultural and environmental policies; the availability and quality of economic, agricultural, and environmental data from recognized international institutions (OECD, FAO, World Bank, USDA); the structural diversity of member economies, allowing for the analysis of differences in adaptation to the digital transition and sustainability challenges; and geographic and climatic diversity, ranging from Northern to Southern and Eastern Europe, offering a comprehensive view of regional dynamics in terms of agricultural R&D effectiveness and sustainable development.

This geographic diversity ensures sufficient between-country variation in both agricultural digitalization and R&D investment, which constitutes a necessary condition for robust panel estimation. The EU27 encompasses highly digitalized agricultural systems, such as those of Denmark, Sweden, and the Netherlands, as well as countries in earlier stages of digital transition, such as Romania, Bulgaria, and Croatia, providing the structural heterogeneity required for meaningful cross-country comparison. Furthermore, the strongly balanced nature of the panel (15 observations per country, 405 total observations) ensures estimator consistency and eliminates potential biases associated with unbalanced panel structures.

2.2. Overview of the primary univariate analysis methods

2.2.1. Unit root tests without rupture

❖ *LLC test (2002)*

The variable y_{it} is conceptualized as a stochastic process, following the analytical framework proposed by Levin et al. (LLC, 2002). In a panel composed of N distinct individuals, each observed over T time periods, the individual-specific regressions may incorporate both an intercept and a deterministic trend, mirroring the treatment of a univariate time series. In their original exposition, Levin et al. (2002) posited that while the first-order partial autocorrelation

coefficient is constrained to be homogeneous across panel members, the remaining components of the error process may exhibit substantial heterogeneity across individuals.

$$\text{Model 1: } \Delta y_{it} = \delta y_{it-1} + \varepsilon_{it}$$

$$\text{Model 2: } \Delta y_{it} = \alpha_{0i} + \delta y_{it-1} + \varepsilon_{it}$$

$$\text{Model 3: } \Delta y_{it} = \alpha_{0i} + \alpha_{1it} + \delta y_{it-1} + \varepsilon_{it}$$

$$\begin{cases} H_0 : \text{non stationary} \\ H_1 : \text{stationary} \end{cases}$$

❖ *IPS test (2003)*

Im and his coauthors (IPS, 2003) postulate that the stochastic process y_{it} follows a first-order autoregressive specification, drawing upon a sample of N observational such as industries, regions, or countries, observed over time. The disturbance term ε_{it} is characterized as an AR (∞) process that is both stationary and invertible for each individual unit and is distributed independently across units. The model rests upon the following assumptions:

$$y_{it} = (1 - \phi_1)\mu_i + \phi_1 y_{it-1} + \varepsilon_{it} \text{ where } i = 1, \dots, N \text{ and } t = 1, \dots, T.$$

They contend that, conditional on the specification of the initial values y_{it} , the process can be expressed for each individual i . Within this framework, the central objective is to test the null hypothesis of a unit root, that is, that the autoregressive parameter equals unity for every cross-sectional unit. $\phi_1 = 1$:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \varepsilon_{it} \text{ where } \alpha_i = (1 - \phi_1)\mu_i ; \beta_i = -(1 - \phi_1) \text{ and } \Delta y_{it} = y_{it} - y_{it-1}$$

The following are the test's hypotheses:

$$\begin{cases} H_0 : \text{non stationary} \\ H_1 : \text{stationary} \end{cases}$$

❖ *Hadri's test (2000)*

This procedure tests the null hypothesis that the series y_{it} is stationary for all $i=1, \dots, N$ and $t=1, \dots, T$. whereas the alternative hypothesis implies non-stationarity. The approach rests upon the assumption of stationarity under the null and constitutes an extension of the KPSS test (Kwiatkowski et al., 1992) to panel data contexts.

Hadri (LM, 2000) applied his methodology to examine the following two model specifications:

$$y_{it} = r_{it} + \varepsilon_{it} \text{ \& } y_{it} = r_{it} + \beta_{it} + \varepsilon_{it}$$

where r_{it} follows an arbitrary martingale process specified as $r_{it} = r_{it-j} + u_{it}$; with u_{it} and t iid $(0, \sigma_u^2)$; The disturbances u_{it} and ε_{it} are assumed to be independently distributed from one another and identically distributed across dimensions. The null hypothesis can accordingly be expressed as $\sigma_u^2 = 0$. Moreover, under the assumption that the error components are independently and identically distributed, the first and second equations preserve their stationary properties under the null. As a consequence, these two equations yield the following results:

$$y_{it} = r_{i0} + \varepsilon_{it} \text{ \& } y_{it} = r_{i0} + \beta_{it} + \varepsilon_{it}$$

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$$LM = \frac{1}{\hat{\sigma}_\varepsilon^2} \frac{1}{NT^2} \left(\sum_{i=1}^N \sum_{t=1}^T s_{it}^2 \right)$$

Here, S_{it} denotes the partial sum of the residuals, $\hat{\sigma}_\varepsilon^2$ is a consistent estimator σ_ε^2 and $s_{it} = \sum_{j=1}^t \hat{\varepsilon}_{tj}$. The test is conducted within the framework of the following two hypotheses:

$$\begin{cases} H_0 : \text{stationary} \\ H_1 : \text{non stationary} \end{cases}$$

❖ *Test de Pesaran (2003; 2007)*

[Pesaran \(2003 & 2007\)](#) proposed a unified testing procedure that explicitly accommodates cross-sectional dependencies of a general form. In constructing an augmented model of the CADF (Cross-Sectionally Augmented Dickey-Fuller) type, the original series y_{it} is preserved. Across the cross-sectional dimension, [Pesaran \(2003, 2007\)](#) adopted either a standard ADF specification or its cross-sectionally augmented counterpart, involving the lagged level. y_{it-1} .

At the individual level, [Pesaran \(2003 & 2007\)](#) employed either a standard ADF specification or a CADF (Cross-Sectionally Augmented Dickey-Fuller) model:

$$\Delta y_{it} = \alpha_i + \rho_i y_{it-1} + c_i \bar{y}_{it-1} + w_i \Delta y_t + \vartheta_{it}$$

for every individual $i = 1, \dots, N$ with the cross-sectional average defined as $\bar{y}_t = \left(\frac{1}{N}\right) \sum_{i=1}^N y_{it}$.

Proceeding straightforwardly, the author estimated the above model and derived the t statistic corresponding to the unit root null hypothesis for each individual i , denoted $t_i(N, T)$. As T and N diverge to infinity, whether sequentially or simultaneously, the individual CADF statistics $t_i(N, T)$ converge to a common asymptotic distribution. Notably, this limiting distribution extends the classic Dickey-Fuller distribution applicable to models containing a constant term.

Pesaran (2003, 2007) thereafter proposed the following statistic:

$$CIPS(N, T) = \frac{1}{N} \sum_{i=1}^N t_i(N, T) = \frac{1}{N} \sum_{i=1}^N CADF_{it} + O_p$$

Here $CADF_{it}$ corresponds to the statistic $t_i(N, T)$ as N increases without bound. Owing to the dependence inherent in the limiting distributions, the feature reflected by the subscript f , the central limit theorem is not applicable. As N approaches infinity, the distribution of the statistic deviates from the standard normal form. Consequently, the testing procedure rests upon the two hypotheses set forth below:

$$\begin{cases} H_0 : \text{non stationary} \\ H_1 : \text{stationary} \end{cases}$$

2.2.2. Unit root tests with rupture: Karavias and Tzavalis (2014) methodology

Karavias and Tzavalis (2014) introduced panel data unit root tests that accommodate structural breaks occurring in linear trends, intercepts, or the levels of the series. The magnitude of these breaks may vary across individual series, while the timing of the breaks can be either known or unknown for each panel unit. The specification of the null hypothesis follows the frameworks established by Lumsdaine and Papell (1997) and Zivot and Andrews (1992). The authors propose two distinct procedures for detecting breaks in panel variables comprising N cross-sectional units observed over T time periods, irrespective of whether the break date is predetermined. The first procedure is intended to test the alternative hypothesis of a stationary series exhibiting a shift in its mean against the null hypothesis of a random walk.

$$H_0 : y_{it} = y_{it-1} + u_{it}$$

$$H_1 : y_{it} = \varphi y_{it-1} + (1 - \varphi)\{a_{1i}I(t \leq b) + a_{2i}I(t > b)\} + u_{it}$$

where $i = 1, \dots, N$ and $t = 1, \dots, T$. In the model specified above, a_{1i} and a_{2i} denote the fixed effects prevailing prior to and following the structural break, respectively, with the break occurring at time b . The autoregressive parameter is represented by φ . The indicator function is denoted by $I(\cdot)$.

The second specification tests, against the alternative of a trend-stationary panel process, the null hypothesis of a random walk with drift, where the alternative allows for structural breaks in both intercepts and slopes at time b .

$$H_0 : y_{it} = y_{it-1} + \beta_i + u_{it}$$

$$H_1 : y_{it} = \varphi y_{it-1} + \varphi \{\beta_{1i}I(t \leq b) + \beta_{2i}I(t > b)\} + (1 - \varphi)\{a_{1i}I(t \leq b) + a_{2i}I(t > b)\} \\ + (1 - \varphi)\{\beta_{1i}tI(t \leq b) + \beta_{2i}tI(t > b)\} + u_{it}$$

Under the null hypothesis, the parameter β_i in the above equation represents the drift component. Under the alternative hypothesis, by contrast, the trend is characterized by two distinct coefficients, β_{1i} and β_{2i} corresponding to the periods before and after the structural break, respectively.

According to these authors, the first specification, denoted M1 comprises only constant terms, whereas the second specification M2, incorporates both constants and trends. In the first model, the structural break may occur within the set $I_1 = \{1, 2, \dots, T - 1\}$, For the second specification, the alternative hypothesis is assumed to be homogeneous across all individuals, and the break can occur within $I_2 = \{2, \dots, T - 2\}$.

Karavias and Tzavalis (2014) recommend obtaining an estimate of the autoregressive parameter φ through the application of the grouped least squares technique, which is presented as follows:

$$\hat{\varphi} = (\sum_{i=1}^N y'_{it-1} Q_m^b y_{it-1})^{-1} (\sum_{i=1}^N y'_{it-1} Q_m^b y_i) \text{ and } m = \{M_1, M_2\}$$

and $y_{it-1} = (y_{i0}, \dots, y_{iT-1})'$ are vectors $T \times 1$. vectors. The orthogonal projection matrix Q_m^b : Q_m^b is defined as follows: $Q_m^b = I_T - X_m^b (X_m^{b'X_m^b})^{-1} X_m^{b'}$, where I_T denotes the $T \times T$ identity matrix. The matrices $X_{M_1}^b = (e_1, e_2)$ and $X_{M_2}^b = (e_1, e_2, \tau_1, \tau_2)$ are of dimensions $T \times 2$ et $T \times 4$, respectively, with:

$$e_{1t} = \begin{cases} 1 & \text{if } t \leq b \\ 0 & \text{else} \end{cases}, e_{2t} = \begin{cases} 1 & \text{if } t > b \\ 0 & \text{else} \end{cases}, \tau_{1t} = \begin{cases} 1 & \text{if } t \leq b \\ 0 & \text{else} \end{cases} \text{ and } \tau_{2t} = \begin{cases} 1 & \text{if } t > b \\ 0 & \text{else} \end{cases}$$

The superscript b appearing in Q_m^b et X_m^b , reflects the dependency of these quantities on the specific break date. The estimator $\hat{\varphi}$ must be corrected, given its lack of consistency in large samples. Under the assumption that the break date b is known, the following statistic follows a limiting distribution as $N \rightarrow \infty$:

$$Z(b) = \sqrt{N} \{C^b(K_u, \sigma_u^2)\}^{-1/2} (\hat{\varphi} - B^b - 1) \xrightarrow{L} N(0, 1)$$

The parameters k_u and σ_u^2 which characterize the moments of the error term are assumed to follow a normal distribution and to be independent and identically distributed. These parameters are excluded from C^b , a quantity that depends solely on the break date and the number of time-

series observations. In this framework, B^b functions as a bias correction term, while C^b represents the variance of the bias-corrected estimator.

Furthermore, potential complications arising from cross-sectional heteroscedasticity are addressed under the normality assumption. A commonly employed strategy for mitigating cross-sectional dependence in the error terms is to subtract the cross-sectional average, computed across all individuals for each time period, from each series before conducting the test (O'Connell, 1998).

$$\tilde{y}_{it} = y_{it} - \bar{y}_t \text{ where } \bar{y}_t = \frac{1}{N} \sum_{i=1}^N y_{it}$$

Extending the approach of Zivot and Andrews (1992), Karavias and Tzavalis (2014) forward the following statistic for testing the null hypothesis of a unit root in circumstances where the break date is not known a priori:

$$\min Z = \min_{b \in I_m} Z(b) \text{ for } m = \{M_1, M_2\}$$

2.2.3. Cointegration tests without rupture

❖ *Pedroni test (1999 & 2004)*

In a more general framework, Pedroni (1999, 2004) considered regressions of the following form:

$$y_{it} = \alpha_i + \delta_{it} + \beta_i x_{it} + \varepsilon_{it}$$

Here, y_{it} and x_{it} denote the time series observations for each individual $i = 1, \dots, N$ across time period $t = 1, \dots, T$ where x_{it} is an m -dimensional column vector and β_i is an m -dimensional row vector specific to each individual.

For each panel member i , both y_{it} et x_{it} are presumed to be integrated of order one, denoted, $I(1)$. Under the null hypothesis of no cointegration, the residual ε_{it} is likewise $I(1)$.

The terms α_i and δ_i capture, respectively, individual-specific fixed effects and deterministic components. The slope coefficient β_i is permitted to vary across individuals, implying that the cointegrating vectors may generally be heterogeneous among the panel units. The test is conducted by evaluating the following two hypotheses:

$$\begin{cases} H_0 : \text{no cointegration} \\ H_1 : \text{cointegration} \end{cases}$$

❖ *Test de Kao (1999)*

Kao (1999) proposed both standard and modified Dickey–Fuller procedures for testing the null hypothesis of no cointegration. His methodology is expressly designed for situations in which the cointegrating vectors are assumed to be identical across all individuals within the panel. In other words, these tests apply only to a bivariate framework comprising a single regression equation and do not allow for heterogeneity under the alternative hypothesis. Within this setting, Kao (1999) specifies the following model, which incorporates individual-specific effects:

$$y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it}$$

for $i = 1, \dots, N$ and $t = 1, \dots, T$ with $y_{it} = \sum_{s=1}^t \mu_{is}$ and $x_{it} = \sum_{s=1}^t v_{is}$.

The first test proposed is a Dickey-Fuller type procedure applied to the estimated residuals $\hat{\varepsilon}_{it}$

$$\hat{\varepsilon}_{it} = \rho \hat{\varepsilon}_{it-1} + u_{it}$$

This specification gives rise to the null hypothesis, $\rho = 1$. The MCO estimator $\hat{\rho}$ of ρ is given by:

$$\hat{\rho} = \frac{\sum_{i=1}^N \sum_{t=2}^T \hat{\varepsilon}_{it} \hat{\varepsilon}_{it-1}}{\sum_{i=1}^N \sum_{t=1}^T \hat{\varepsilon}_{it}^2}$$

Alternatively, a slightly more polished version:

$$t_{\rho} = \frac{(\hat{\rho} - 1) \sqrt{\sum_{i=1}^N \sum_{t=2}^T \hat{\varepsilon}_{it} \hat{\varepsilon}_{it-1}}}{S_e}$$

where $S_e^2 = \frac{1}{NT} \sum_{i=1}^N \sum_{t=2}^T (\hat{\varepsilon}_{it}^* - \rho \hat{\varepsilon}_{it-1}^*)^2$ and $\hat{\varepsilon}_{it}^* = y_{it}^* - \hat{\alpha}_i^* - \hat{\beta}^* x_{it}^*$.

The following four Dickey-Fuller statistics are furnished by Kao (1999):

$$DF_{\rho}^* = \frac{\sqrt{NT}(\hat{\rho} - 1) + \frac{3\sqrt{N}\hat{\sigma}_u^2}{\hat{\sigma}_{0u}^2}}{\sqrt{3 + \frac{36\hat{\sigma}_u^4}{5\hat{\sigma}_{0u}^4}}}, DF_t^* = \frac{t_{\rho} + \frac{\sqrt{6N}\hat{\sigma}_u^2}{2\hat{\sigma}_{0u}}}{\sqrt{\frac{\hat{\sigma}_{0u}^2}{2\hat{\sigma}_u^2} + \frac{3\hat{\sigma}_u^2}{10\hat{\sigma}_{0u}^2}}}$$

$$DF_{\rho} = \frac{\sqrt{NT}(\hat{\rho} - 1) + 3\sqrt{N}}{\sqrt{51/5}}, DF_t = \sqrt{\frac{5t_{\rho}}{4}} + \sqrt{\frac{15N}{8}}$$

Kao (1999) asserts that, under the null hypothesis of no cointegration, the first four test statistics converge to a standard normal distribution in a reduced-form specification. This result is derived through the application of the central limit theorem under a sequential asymptotic framework, whereby $T \rightarrow \infty$ is considered first, followed by $N \rightarrow \infty$. The second procedure consists of an augmented Dickey-Fuller (ADF) test based on the regression specified below, also introduced Kao (1999):

$$\hat{\varepsilon}_{it} = \rho \hat{\varepsilon}_{it-1} + \sum_{j=1}^p \varphi_j \Delta \hat{\varepsilon}_{it-j} + u_{itp}$$

The test statistical information is provided as follows:

$$ADF = \frac{t_{ADF} + \frac{\sqrt{6N\hat{\sigma}_u^2}}{2\hat{\sigma}_{0u}}}{\sqrt{\frac{\hat{\sigma}_{0u}^2}{2\hat{\sigma}_u^2} + \frac{3\hat{\sigma}_u^2}{10\hat{\sigma}_{0u}^2}}}$$

where t_{ADF} denotes t-statistic associated with ρ . Under the null hypothesis of no cointegration, this statistic follows a reduced-form normal distribution centered at zero. The DF_{ρ}^* and DF_t^* tests generally produce more favorable size properties than the alternative procedures.

❖ *Westerlund test (2007)*

Westerlund (2007) develops a test grounded in the error-correction framework, focusing on the parameter that governs the speed at which equilibrium deviations are corrected following a shock. A negative value of this parameter signifies the presence of error correction, implying that the variables are cointegrated, whereas a value of zero indicates the absence of a cointegrating relationship. The error terms are explicitly incorporated into the model's formulation.

$$\Delta y_{it} = c_i + \alpha_i (y_{it-j} + \beta x_{it-j}) + \sum_{j=1}^P \alpha_{ij} \Delta y_{it-j} + \sum_{j=q_i}^P \gamma_{ij} \Delta x_{it-j} + \varepsilon_{it}$$

The parameter α_i captures the speed at which the system adjusts following a shock. If $\alpha_i < 0$, y_{it} and x_{it} are considered cointegrated; if $\alpha_i = 0$, no cointegrating relationship exists between them. In essence, this test rests upon the evaluation of the following two assumptions:

$$\begin{cases} H_0: \text{no cointegration} \\ H_1: \text{cointegration} \end{cases}$$

❖ *Test de Persyn et Westerlund (2008)*

The error correction tests evaluate the following data-generating process:

$$\Delta y_{it} = \delta'_i d_t + \alpha_i (y_{i,t-1} + \beta'_i x_{i,t-1}) + \sum_{j=1}^{p_t} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=1}^{p_t} \gamma_{ij} \Delta x_{i,t-j} + \varepsilon_{it}$$

In this framework, time periods are indexed by $t=1, \dots, T$ and cross-sectional units by $i=1, \dots, N$. The deterministic components are represented by d_t , which may assume three distinct forms. In the first specification, $d_t = 0$, indicating the absence of any deterministic terms from the equation. In the second, a model incorporating a constant term is given by $d_t = 1$. In the third, $d_t = (1, t)'$, implying that Δy_{it} contains both a linear trend and a constant.

For the sake of simplicity, we treated $\bullet$ -dimensional vector $x_{it} \bullet K$ as a pure random walk Δy_{it} is independent of ε_{it} . We further assume that these disturbances are independent across both i and t . Any dependence between the cross-sectional and temporal dimensions will be addressed through appropriate abstraction techniques.

$$\Delta y_{it} = \delta'_i d_t + \alpha_i y_{i,t-1} + \lambda'_i x_{i,t-1} + \sum_{j=1}^{p_t} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=1}^{p_t} \gamma_{ij} \Delta x_{i,t-j} + \varepsilon_{it}$$

where $\lambda'_i = -\alpha_i \beta'_i$. The parameter α_i governs the speed at which the system adjusts to restore the equilibrium relationship $y_{i,t-1} + \beta'_i x_{i,t-1}$ following an exogenous shock. Error correction is said to occur when $\alpha_i < 0$, which implies cointegration between y_{it} and x_{it} . Conversely, if $\alpha_i = 0$. Neither error correction nor cointegration is present. Accordingly, the null hypothesis of no cointegration can be formulated as $H_0: \alpha_i = 0$ for all i . The specification of the alternative hypothesis depends critically upon the assumptions made regarding the homogeneity of α_i across panel members.

Two of the tests, designated as group-mean tests, do not require α_i to be homogeneous across individuals; rather, they evaluate α_i against the alternative hypothesis $H_1^g: \alpha_i < 0$ for all i . The other two tests, referred to as panel tests, are intended to evaluate the assumption that α_i is equal for the entire population.

H_0 against $H_1^p: \alpha_i = \alpha < 0$ for all i .

The two assumptions of this test can be summarized as follows:

$$\begin{cases} H_0: \text{no cointegration} \\ H_1: \text{cointegration} \end{cases}$$

2.2.4. Independence tests

❖ *Test de Breusch and Pagan (1980)*

Assuming a fixed number of cross-sectional units N and a time dimension such that $T \rightarrow \infty$, [Breusch and Pagan \(1980\)](#) developed an LM statistic for testing the null hypothesis of no cross-equation correlation among the error terms within a Seemingly Unrelated Regression Equations (SURE) framework. This statistic does not require estimation of the full SURE system and is relatively straightforward to compute. The LM statistic employed in this test is defined as follows:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2$$

Specifically, $\hat{\rho}_{ij}$ denotes the sample estimate of the pairwise correlation of the residuals:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^T e_{it} e_{jt}}{(\sum_{t=1}^T e_{it}^2)^{1/2} (\sum_{t=1}^T e_{jt}^2)^{1/2}}$$

Where e_{it} represents the ordinary least squares (OLS) estimate of u_{it} :

$$e_{it} = y_{it} - \hat{\beta}_i' x_{it}$$

where $\hat{\beta}_i$ are the estimates of β_i obtained from performing independent MCO regression of y_{it} on x_{it} . This LM test is broadly applicable and does not require the cross-sectional components to be arranged in any particular order. Under the null hypothesis, [Breusch and Pagan \(1980\)](#) demonstrate that, when $u_{it} \sim IIDN(0, \sigma_{ui}^2)$

$$H_0: Cov(u_{it}, u_{jt}) = 0 \text{ for all } t \text{ and } i \neq j$$

The LM statistic follows, asymptotically, a chi-square (χ^2) distribution with $N(N-1)/2$ degrees of freedom. As a result, the LM test is prone to substantial size distortions irrespective of whether N and T , are large or small, a phenomenon frequently encountered in empirical research.

Test of Pesaran (2004; 2015) and Pesaran et al. (2008)

Consider the regression of interest generated by the static linear heterogeneous panel data model for y_{it} :

$$y_{it} = x_{it}' \beta_i + u_{it}$$

for $i = 1, 2, \dots, N; t = 1, 2, \dots, T$.

Defining $y_i = (y_{i1}, \dots, y_{iT})'$, and $X_i = (x_{i1}, \dots, x_{iT})$. the above model can equivalently be represented as:

$$y_i = X_i \beta_i + u_i$$

for $i = 1, 2, \dots, N$ and $t = 1, 2, \dots, T$.

Consequently, the OLS residuals from the individual-specific regressions are given by $\tilde{u}_i = M_i y_i (i = 1, \dots, N)$ where $M_i = I_T - X_i (X_i' X_i)^{-1} X_i'$ is the dimension T identity matrix.

The statistics for the [Pesaran \(2004\)](#) cross-sectional dependence (CD) test can be defined as follows, employing the estimated pairwise residual correlations ρ_{ij} using $\tilde{\rho}_{ij} = \frac{\tilde{u}_i' \tilde{u}_j}{\|\tilde{u}_i\| \|\tilde{u}_j\|}$:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \tilde{\rho}_{ij} \right)$$

[Pesaran \(2004\)](#) demonstrated that, under the null hypothesis H_0 , the CD statistic converges in distribution to a standard normal distribution, denoted $CD \xrightarrow{d} N(0,1)$, where $\xrightarrow{d}$ signifies convergence in distribution. This result was established under a sequential asymptotic framework in which $T \rightarrow \infty$ and then $N \rightarrow \infty$. Nevertheless, he found that the CD test may suffer from a loss of power in certain circumstances, particularly when the disturbances conform to specific common factor structures.

To address the limitations of the CD test, [Pesaran et al. \(2008\)](#) developed a bias-corrected LM statistic, incorporating the following adjustment term:

$$LM_{adj} = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \frac{(T-k) \tilde{\rho}_{ij}^2 - \mu_{Tij}}{v_{Tij}}$$

where $\mu_{Tij} = E[(T-k) \tilde{\rho}_{ij}^2]$ and $v_{Tij}^2 = Var[(T-k) \tilde{\rho}_{ij}^2]^2$.

Because it is based on $\tilde{\rho}_{ij}^2$, the bias-adjusted LM statistic LM_{adj} possesses power against general alternative specifications. [Pesaran et al. \(2008\)](#) demonstrated that, under the null hypothesis and subject to sequential asymptotic conditions, $LM_{adj} \xrightarrow{d} N(0,1)$

Summary: The following two hypotheses were examined in these two procedures:

$$\begin{cases} H_0: \text{Cross – sectional independence} \\ H_1: \text{Cross – sectional dependence} \end{cases}$$

2.2.5. Panel Causality tests: Dumitrescu et Hurlin (2012) & Juodis et al. (2021)

Granger (1969) proposed a method for investigating causal relationships between two stationary time series, x and y using the following model:

$$y_t = \alpha + \sum_{l=1}^L \beta_l y_{t-l} + \sum_{l=1}^L \gamma_l x_{t-l} + \varepsilon_t$$

Where y_t and x_t are both stationary series.

This equation allows one to determine whether variable x Granger causes variable y. This equation can be used to determine if variable x causes variable y. by testing the joint significance of the coefficients on the lagged values of x. Accordingly, the null hypothesis $H_0: \gamma_1 = \gamma_2 = \dots = \gamma_L = 0$. is rejected as part of the causality test. By interchanging the roles of x and y , one can assess the causal relationship running from x to y.

Furthermore, bidirectional causality is said to exist when x Granger-causes y and y Granger-causes x simultaneously.

Dumitrescu and Hurlin (2012) consider two stationary variables, x and y, that were observed for N individuals over T time periods. For each individual $i=1, \dots, N$ at time $t=1, \dots, T$, they propose the following linear model:

$$y_{i,t} = \alpha_i + \sum_{k=1}^K \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^K \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t}$$

Assume that the panel is balanced and that, for $k \in \mathbb{N}^*$ and $\beta_i = (\beta_i^{(1)}, \dots, \beta_i^{(K)})'$, the lag orders K are identical across individuals. For convenience, the individual effects α_i are treated as fixed over time. The initial conditions for y_{it} and x_{it} namely $(y_{i,-K}, \dots, y_{i,0})$ and $(x_{i,-K}, \dots, x_{i,0})$. are assumed to be defined and observable. All cross-sectional units are presumed to share the same lag order K and the panel is balanced. Moreover, in contrast to Nair-Reichert and Weinhold (2001), we permit cross-group heterogeneity in the slopes of the autoregressive parameters $\gamma_i^{(k)}$ as well as in the regression coefficients $\beta_i^{(k)}$ both of which are assumed to be constant over time.

condition A1: the Individual residuals $\varepsilon_{i,t}$, for all $\forall t = 1, \dots, T$ are independently and normally distributed with $E[(\varepsilon)_{i,t}] = 0$ and finite heterogeneous variances $E(\varepsilon_{i,t}) = \sigma_{\varepsilon,i}^2$, for each cross-section unit $i = 1, \dots, N$.

condition A2: The distribution of individual residuals vectors $\varepsilon_{i,t} = (\varepsilon_{i,1}, \dots, \varepsilon_{i,T})$ are independent across groups. Consequently, $E(\varepsilon_{i,t}, \varepsilon_{-i}(j, s)) = 0, \forall i \neq j$ and for all $\forall(t, s)$.

condition A3. The individual variable vectors $x_i = (x_{i,1}, \dots, x_{i,T})'$ and $y_i = (y_{i,1}, \dots, y_{i,T})'$, are both covariance stationary, with $E(y_{i,t}^2) < \infty$ and $E(x_{i,t}^2) < \infty$. $\forall, E(x_{i,t}, x_{j,z}), E(y_{i,t}, y_{j,z})$ and $E(y_{i,t}, x_{j,z})$ depend only on the difference $t-z$, while $E(x_{i,t})$ and $E(y_{i,t})$ are independent of t .

A simple bivariate model underpins the analysis of Granger causality in panel data. Individual heterogeneity must be taken into account when working with panel data, as traditional time-series causality tests involve testing linear restrictions on the vectors.

The first source of heterogeneity, about individual effects, arises primarily from α_i . The second, more consequential source, is linked to the variability of the parameter β_i . This type of variability directly affects the representative-agent framework and, consequently, the conclusions drawn regarding causal relationships. Estimates of the autoregressive parameters β_i obtained under the false assumption that $\beta_i = \beta_j \forall (i, j)$ are known to be biased (Pesaran and Smith, 1995).

Thus, if we impose coefficient homogeneity on β_i , the resulting causality test statistics may lead to erroneous conclusions. Specifically, if the estimate $\hat{\beta}$ from a homogeneous model converges in probability to a value close to the mean of the true heterogeneous coefficients β_i we run the risk of accepting the null hypothesis of no causality when it may be false.

Beyond these statistical concerns, it is evident that a uniform specification of the relationship between x and y precludes a proper interpretation of causal relationships if even a single element of the sample exhibits economic behavior that diverges from the rest. Consider, for example, a scenario in which a causal relationship exists for a group of N countries, with the vectors β_i being identical across this group. What conclusions can be drawn if we include an additional N_1 countries in the sample for which, conversely, no causal relationship exists? In such a case, the test of the causality hypothesis becomes irrelevant, regardless of the value of the ratio $\frac{N}{N_1}$.

In light of these considerations, we propose testing the hypothesis of homogeneous non-causality (HNC) while allowing for heterogeneity in both the causal relationships and the regression model itself. Consequently, under the alternative hypothesis,

[Dumitrescu and Hurlin \(2012\)](#) admit the possibility of two distinct subgroups: one for which no causal relationship exists, and another for which x Granger-causes y . The HNC null hypothesis is articulated as follows:

$$H_0 : \beta_i = 0 \forall i = 1, \dots, N$$

with $\beta_i = (\beta_i^{(1)}, \dots, \beta_i^{(K)})$.

Furthermore, under the alternative hypothesis, the coefficients β_i are permitted to vary across groups, thereby accommodating model heterogeneity. We also allow for the possibility that some, though not all of the individual β_i vectors take a value of zero, reflecting the absence of a causal relationship. Under hypothesis H_1 , there exist $N_1 < N$ distinct units for which no causal link between x and y is present. Consequently, unlike [Holtz-Eakin et al. \(1988\)](#), the test does not contrast the non-causality assumption with a scenario of universal causality running from x to y . Because the absence of causality may be detected in certain units even under the alternative, the proposed framework is more general and encompassing.

$$H_1 : \beta_i = 0 \forall i = 1, \dots, N_1; \beta_i \neq 0 \forall i = N_1 + 1, N_1 + 2, \dots, N$$

Where N_1 satisfies $\frac{0 \leq N_1}{N} < 1$ but it is unknown. The ratio $\frac{N_1}{N}$ must be strictly less than one, since if $N_1 = N$, this corresponds precisely to the homogeneous non-causality (HNC) null hypothesis, implying an absence of causality for all panel members. Conversely, $N_1 = 0$, causality holds for every member of the sample. The nature of this test is analogous to the heterogeneous panel unit root test proposed by [Im et al. \(2003\)](#).

Under the null hypothesis, the variable x does not Granger-cause y for any panel unit. On the other hand, if the HNC hypothesis is rejected and $N_1 = 0$, we can conclude that x Granger-causes y for every panel member, yielding a homogeneous conclusion with respect to causality. It is possible, however, that the underlying regression model is not homogeneous, that is, different groups may exhibit distinct parameter estimates, yet causal relationships still exist for all individuals. In contrast, if $N_1 > 0$, the causal relationship is heterogeneous, meaning that it varies across individuals in the sample in terms of both the causal linkages and the regression model.

For units $i=1, \dots, N$, the authors recommend using the average of the individual Wald statistics associated with the non-causality hypothesis test:

$$W_{N,T}^{Hnc} = \frac{1}{N} \sum_{i=1}^N W_{i,T}$$

where $W_{i,T}$ denotes the individual Wald statistic for the i the cross-sectional unit, corresponding to the individual test of the null hypothesis $H_0: \beta_i = 0$.

o constructs the general version of this statistic; we stack the observations over the T time periods about the characteristics of the individual into a T -element vector:

$$y_{i(T,1)}^{(k)} = \begin{bmatrix} y_{i,1-k} \\ \vdots \\ y_{i,T-k} \end{bmatrix}, x_{i(T,1)}^{(k)} = \begin{bmatrix} x_{i,1-k} \\ \vdots \\ x_{i,T-k} \end{bmatrix}, \varepsilon_{i(T,1)} = \begin{bmatrix} \varepsilon_{i,1} \\ \vdots \\ \varepsilon_{i,T} \end{bmatrix}$$

Then two (T, K) matrices are defined:

$$Y_i = \left[\left((y_i^1 \& y_i^2) \& \dots \ y_i^K \right) \right] \text{ and } X_i = [x_i^1 \ x_i^2 \ \dots \ x_i^K]$$

The matrix Z_i is of dimension $(T, 2K + 1)$ and is defined as $Z_i = [e \ Y_i \ X_i]$ where e denotes a $(T, 1)$ unit vector. Furthermore, the parameter vector of the model is denoted $\theta_i = \alpha_i \gamma' \beta' \gamma_i$. It is now possible to test the homogeneous non-causality (HNC) hypothesis. This hypothesis can be expressed as $R\theta_i = 0$, where R is a $(K, 2K+1)$ matrix given by $R = [0 \ I_K]$. The Wald statistic $W_{i,T}$ corresponding to the individual test $H_0: \beta_i = 0$ for each $i=1, \dots, N$ is defined as follows:

$$W_{i,T} = \hat{\theta}_i' R' [\hat{\sigma}_i^2 R (Z_i' Z_i)^{-1} R']^{-1} R \hat{\theta}_i = \frac{\hat{\theta}_i' R' [\hat{\sigma}_i^2 R (Z_i' Z_i)^{-1} R']^{-1} R \hat{\theta}_i}{\frac{\hat{\varepsilon}_i' \hat{\varepsilon}_i}{T-2K-1}}$$

where $\hat{\sigma}_i^2$ is an estimate of the residual variance, and $\hat{\theta}_i$ denotes the estimator of the parameter vector θ_i obtained under the alternative hypothesis. The corresponding unbiased estimator for samples with small T takes the form $\hat{\sigma}_i^2 = \frac{\hat{\varepsilon}_i' \hat{\varepsilon}_i}{T-2K-1}$. This Wald statistic can alternatively be expressed as a ratio of quadratic forms in normal variables corresponding to the true residual population, as follows:

$$W_{i,T} = (T - 2K - 1) \left(\frac{\hat{\varepsilon}_i' \phi_i \hat{\varepsilon}_i}{\hat{\varepsilon}_i' M_i \hat{\varepsilon}_i} \right), i = 1, \dots, N$$

where, under Assumption A1, the $(T, 1)$ vector $\tilde{\varepsilon}_i = \frac{\varepsilon_i}{\sigma_{\varepsilon,i}}$ is normally distributed according to $N(0, I_T)$. The (T, T) matrices ϕ_i and M_i are symmetric, idempotent, and positive semi-definite.

$$\phi_i = Z_i(Z_i'Z_i)^{-1}R'[R(Z_i'Z_i)^{-1}R']^{-1}R(Z_i'Z_i)^{-1}Z_i'$$

$$M_i = I_T - Z_i(Z_i'Z_i)^{-1}Z_i'$$

where I_T denotes the identity matrix of dimension T . Note that the matrix M_i corresponds to the standard projection matrix employed in linear regression analysis.

Under the null hypothesis of non-causality, [Dumitrescu and Hurlin \(2012\)](#) propose constructing the asymptotic distribution of the average statistic $W_{N,T}^{Hnc}$. To this end, they consider a sequential convergence framework in which T tends to infinity first, followed by N tending to infinity. This sequential convergence result can be inferred from the conventional convergence property of the individual Wald statistic $W_{i,T}$ in a large T in a non-dynamic model, the normality assumption in A1 would suffice to establish that the Wald statistic follows a chi-squared distribution with K degrees of freedom for every T . in the dynamic model, this result can only be attained asymptotically.

We know that $\text{plim}_{T \rightarrow \infty} \frac{\varepsilon_i' M_i \varepsilon_i}{T - 2K - 1} = \sigma_{\varepsilon,i}^2$ because under Assumption A1 the least squares estimate $\hat{\theta}_i$ is convergent. This implies the Following:

$$\text{plim}_{T \rightarrow \infty} \frac{\tilde{\varepsilon}_i' M_i \tilde{\varepsilon}_i}{T - 2K - 1} = \text{plim}_{T \rightarrow \infty} \frac{1}{\sigma_{\varepsilon,i}^2} \left(\frac{\varepsilon_i' M_i \varepsilon_i}{T - 2K - 1} \right) = 1$$

Given that $W_{i,T}$ possesses a limiting distribution, the statistics will share the same distribution as when the denominator is replaced by its limiting value, namely unity. Consequently, $W_{i,T}$ has the same asymptotic distribution as $\tilde{\varepsilon}_i' \phi_i \tilde{\varepsilon}_i$. Under Assumption A1, the vector $\tilde{\varepsilon}_i$ is normally distributed, that is, $\tilde{\varepsilon}_i \sim N(0, I_t)$. Because ϕ_i is idempotent, the quadratic form $\tilde{\varepsilon}_i' M_i \tilde{\varepsilon}_i$ follows a chi-squared distribution with degrees of freedom equal to the rank of ϕ_i . Moreover, for a symmetric idempotent matrix, the rank equals its trace, which in the present case is K .

Consequently, under the null hypothesis of non-causality, each individual Wald statistic converges to a chi-squared (χ^2) distribution with K Degrees of freedom:

$$W_{i,T} \xrightarrow[T \rightarrow \infty]{} \chi^2(K), \forall i = 1, \dots, N$$

In other words, as T tends to infinite, the individual statistics $\{W_{i,T}\}_{i=1}^N$ are identically distributed. Furthermore, because under Assumption A2 the residuals ε_i and ε_j are independent for $j \neq i$ the corresponding Wald statistics are likewise independent across individuals.

In summary, when T tends to infinity, the individual Wald statistics $W_{i,T}$ are independently and identically distributed (i.i.d.), with expectation $E(W_{i,T}) = K$ and variance $V(W_{i,T}) = 2K$. Then, by application of the standard Lindberg-Levy central limit theorem, the distribution of the average Wald statistic $W_{N,T}^{Hnc}$ can be derived under the sequential asymptotic framework in which $T \rightarrow \infty$ first, followed by $N \rightarrow \infty$:

$$Z_{N,T}^{Hnc} = \sqrt{\frac{N}{2K}} (W_{N,T}^{Hnc} - K) \xrightarrow{T, \rightarrow \infty}^d N(0,1)$$

With $W_{N,T}^{Hnc} = \left(\frac{1}{N}\right) \sum_{i=1}^N W_{i,T}$ where $T, N \rightarrow \infty$ indicate that $T \rightarrow \infty$ first and then $N \rightarrow \infty$.

A novel method for testing the null hypothesis of no Granger causality has recently been developed by [Juodis et al. \(2021\)](#), applicable to models featuring either homogeneous or heterogeneous coefficients. Their approach is distinctive in that the parameters are constrained to zero under the null hypothesis of no Granger causality, thereby imposing homogeneity.

This method permits the use of a pooled fixed-effects estimator restricted to these parameters, ensuring a convergence rate of $\sqrt{NT}$, where T denotes the time dimension and N the number of cross-sectional units in the panel. To correct for the Nickel bias inherent in the pooled estimator, they employ the Half Panel Jackknife (HPJ) method, originally introduced [Dhaene and Jochmans \(2015\)](#), This approach performs well in settings characterized by a large number of cross-sectional units, a limited time dimension, substantial persistence, and non-homogeneous nuisance parameters.

The linear dynamic panel model employed to test for the absence of Granger causality with bias correction is specified as follows:

$$y_{it} = \phi_{0i} + \sum_{j=1}^p \phi_{pi} y_{it-p} + \sum_{j=1}^p \alpha_{pi} x_{it-p} + \mu_{it}$$

where the time dimension of the panel is denoted by $t=1, 2, \dots, T$, and the distinct countries within the panel are indexed $i=1, 2, \dots, N$. μ_{it} is a scalar for this exposition.

The parameters ϕ_{0i} , represent the individual-specific effects, μ_{it} , The non-homogeneous autoregressive non-homogeneous error terms represent the stochastic error term, ϕ_{pi} , capture the heterogeneous autoregressive coefficients, and α_{pi} correspond to the Granger causality parameters (or heterogeneous feedback coefficients).

Since the same number of lags is employed for both y_{it} and x_{it} , in the data analysis, the computational burden associated with selecting the lag length in this procedure is relatively low. The null hypothesis that y_{it} does not Granger-cause x_{it} can be expressed as a set of linear restrictions on the parameters:

$$H_0: \alpha_{pi} = 0 \text{ Vs } H_1: \alpha_{pi} \neq 0$$

The null hypothesis posits that the coefficients on all lagged terms of the dependent variable in the Granger causality model are jointly zero. The alternative hypothesis, in contrast, maintains that at least one of these coefficients is non-zero. In other words, under the null hypothesis, there is no Granger causal relationship between x_{it} and y_{it} , conversely, if the alternative hypothesis is supported, a Granger causal relationship exists between the variables x_{it} and y_{it} . The test employs a Wald statistic, defined as the ratio of the estimated parameter restrictions to their standard error. The corresponding p-value is the probability of obtaining a statistic as extreme as the observed one, assuming the null hypothesis is true.

2.2.6. Cointegration test with break: Banerjee and Silvestre test (2015)

Banerjee and Silvestre (2015) considered $Y_{it} = (y_{it}, x'_{it})'$ as an $(m \times 1)$ vector comprising non-stationary stochastic processes whose individual elements are each integrated of order one, $I(1)$. Furthermore, the authors specify the data-generating process (DGP) according to the following structure:

$$y_{it} = D_{it} + x'_{it}\delta_{it} + u_{it}; u_{it} = F'_i\pi_i + e_{it}; (I - L)F_t = C(L)w_t; (1 - \rho_i L)e_{it} = H_i(L)\varepsilon_{it}; \\ x_{it} = \kappa_i + x_{it-1} + G'_tS + \Xi_i(L)v_{it}; G_t = \Gamma(L)\varpi_t; \Xi_{i,j}L^j \text{ et } \Gamma(L) = \sum_{j=0}^{\infty} \Gamma_j L^j.$$

The general functional form for the deterministic term D_{it} is specified as:

$$D_{it} = \mu_i + \beta_i t + \sum_{j=1}^{m_i} \theta_{ij} DU_{ijt} + \sum_{j=1}^{m_i} \gamma_{ij} DT_{ijt}$$

Where $DU_{ijt=1}$ and $DT_{ijt} = (t - T_{ij}^b)$ pour $t > T_{ij}^b$ and zero otherwise.

Here, $T_{ij}^b = \lambda_{ij}^b T$ denotes the timing of the j break, $j = 1, \dots, m_i$, for the i th unit, $i = 1, \dots, N$, $\lambda_{ij}^b \in \Lambda$, where Λ is a closed subset of $(0,1)$. The authors further emphasize that the cointegrating vector must be regarded as time-varying, such that:

$$\delta_{it} = \delta_{ij} \text{ pour } T_{ij-1}^c < t \leq T_{ij}^c$$

with the conventions that $T_{i0}^c = 0$ et $T_{in_i+1}^c = T$, où $T_{ij}^c = \lambda_{ij}^c T$ designates the j regime shift, $j = 1, \dots, n_i$, for the i th unit, $i = 1, \dots, N$, $\lambda_{ij}^c \in \Lambda$.

[Banerjee and Silvestre \(2015\)](#) assume, throughout this section, that the number and locations of structural breaks within each unit are known a priori. This assumption encompasses the special case in which no structural break occurs in any or all units of the panel. The combination of the specifications given by the preceding two equations gives rise to six distinct models examined in their analysis:

Model 1: No linear trend

Model 2: Stable trend

Model 3: Changes in level and trend

Model 4: No linear trend with the presence of multiple structural breaks affecting both the level and the cointegration vector of the model.

Model 5: Stable trend with the presence of multiple structural breaks affecting both the level and the cointegration vector of the model.

Model 6: Changes in level, trend, and cointegration vector.

2.3. Dynamic modeling

This party is devoted to the dynamic estimation of the determinants of the Sustainable Development Index (SDI) through nonlinear and dynamic panel specifications. To achieve this, we apply the generalized method of moments (GMM), a robust econometric framework that effectively handles endogeneity, unobserved heterogeneity, and serial correlation in panel data ([Arellano & Bond, 1991](#); [Blundell & Bond, 1998](#)). The GMM estimator is particularly well-suited to short panels and variables exhibiting high persistence, enabling estimation of both the immediate and dynamic influences of key determinants. These include the transformed agricultural digitalization index ($\ln AgDigital_{it}$), agricultural R&D expenditure ($\ln RD_AG_{it}$), agricultural credit ($\ln CREDIT_AG_{it}$), agricultural total factor productivity ($\ln TFP_{AGit}$), mean surface temperature ($\ln Temp_{it}$), and the transformed inflation rate ($\ln INF$).

In addition, this section incorporates dimensionality reduction and unsupervised classification techniques, namely principal component analysis (PCA) and means clustering, to uncover structural heterogeneity across the sampled countries and to preprocess the data for nonlinear modeling. Subsequently, Panel Threshold Autoregressive (PTAR) and Panel Smooth Transition Autoregressive (PSTAR) specifications are employed to identify regime-switching effects and gradual transitions within agricultural, financial, and climatic systems, following the frameworks proposed by Hansen (1999) and González et al. (2005, 2017). Finally, a series of diagnostic tests, including tests for heteroscedasticity (Breusch & Pagan, 1979; White, 1980) and for serial correlation (Born & Breitung, 2016), is conducted to ensure the robustness and reliability of the estimates.

2.3.1. Overview of the Generalized Method of Moments (GMM)

The Generalized Method of Moments (GMM) was applied to estimate a dynamic panel model examining the determinants of the Sustainable Development Index (SDI) for a sample of European Union member states over the period 2010–2024. The specification incorporates the following variables, expressed in appropriate logarithmic or transformed forms: the negative log-transformed agricultural digitalization index ($\ln AgDigital_{it}$), the natural logarithm of agricultural research and development expenditure ($\ln RD_AG_{it}$), the natural logarithm of agricultural credit ($\ln CREDIT_AG_{it}$), the natural logarithm of agricultural total factor productivity ($\ln TFP_{AGit}$), mean surface temperature ($\ln Temp_{it}$), and the negative log-transformed annual inflation rate ($\ln INF_{it}$). All primary data were sourced from reputable international databases, including the World Bank, the Food and Agriculture Organization (FAO), and the European Environment Agency (EEA).

2.3.1.1. Definition of the GMM Model

The Generalized Method of Moments (GMM) constitutes a versatile econometric estimation framework that relies on moment conditions derived from theoretical or statistical assumptions to recover unknown parameters without necessitating a fully specified distribution of the error term. Unlike classical approaches, such as ordinary least squares or standard instrumental variable techniques, GMM exploits orthogonality conditions between instruments and disturbances, thereby accommodating a wide range of empirical settings, including those with heteroscedasticity or autocorrelation of unknown form.

The GMM estimator is obtained by minimizing a quadratic form that measures the distance between the empirical counterparts of the moment conditions and their theoretical expected values:

$$\hat{\theta}_{GMM} = \arg \min_{\theta} \left(\frac{1}{n} \sum_{i=1}^n g(X_i, \theta) \right)' W \left(\frac{1}{n} \sum_{i=1}^n g(X_i, \theta) \right)$$

where, $g(X_i, \theta)$ is a symmetric positive-definite weighting matrix that determines the efficiency of the estimator, and n represents the sample size. The GMM estimator is routinely employed in dynamic panel frameworks, following the seminal contributions of [Anderson and Hsiao \(1982\)](#) and [Arellano and Bond \(1991\)](#), and in macroeconomic settings involving rational expectations or endogenous explanatory variables.

2.3.1.2. The founders of GMM

[Lars Peter Hansen](#) formally introduced the Generalized Method of Moments (GMM) in his seminal 1982 article, "Large Sample Properties of Generalized Method of Moments Estimators," published in *Econometrica*. This contribution fundamentally advanced modern econometrics by providing a unified estimation framework grounded in moment conditions, thereby enabling consistent and efficient parameter estimation even under heteroscedasticity or autocorrelation of unknown form.

Although Christopher Sims never published a direct exposition of GMM, his intellectual imprint on the method remains decisive. His scholarly exchanges with Hansen, particularly during Hansen's doctoral studies, stimulated the notion of employing linear combinations of moment conditions as the foundation for estimation. This conceptual breakthrough ultimately guided Hansen in formulating GMM as an optimization problem that minimizes a quadratic criterion.

Subsequent scholarship extended and validated the approach's power. For instance, [Hansen and Singleton \(1982\)](#) successfully applied GMM to estimate nonlinear rational expectations models, while [Hansen and Hodrick \(1980\)](#) demonstrated its relevance in foreign exchange markets. Collectively, these works have been instrumental in establishing GMM as a cornerstone of both theoretical econometrics and empirical finance. The profound impact of Hansen's methodological innovations was formally recognized when he was awarded the Nobel Memorial Prize in Economic Sciences in 2013, jointly with Eugene Fama and Robert Shiller, for their respective contributions to empirical asset pricing. Hansen's recognition specifically highlighted his development of GMM, which has profoundly shaped the empirical investigation

of financial asset valuations and, more broadly, the analysis of dynamic economic relationships, including those underlying sustainable development and agricultural policy assessment.

2.3.1.3. GMM objectives

Time-dependent panel models ([Arellano & Bond, 1991](#); [Arellano & Bover, 1995](#); [Blundell & Bond, 1995](#)) provide a robust analytical framework for examining dynamic economic relationships, in which variables are influenced not only by their current values but also by their past values, thereby capturing important lagged effects. These models are particularly valuable for addressing endogeneity and unobserved individual effects, which can bias estimates obtained from traditional methods. Moreover, the system-GMM approach introduced by [Blundell and Bond \(1995\)](#) combines moment conditions across differences and levels, thereby enhancing estimator efficiency, especially in short panels where variables exhibit high persistence over time. This methodology also addresses the issues of weak instruments and bias highlighted by [Arellano and Bond \(1991\)](#) by employing lagged variables as instruments to correct for autocorrelation and unobserved heterogeneity. Dynamic panel models are beneficial for analyzing economic convergence ([Caselli et al., 1996](#); [Bond et al., 2001](#)), as they allow researchers to examine both short- and long-term effects of key determinants such as education, exports, or public expenditure across regional or international contexts. Finally, the robustness of these models can be assessed through specification tests, such as those proposed by Sargan and Hansen, which assess whether the instruments are uncorrelated with the model's error terms ([Syofya, 2022](#)).

2.3.1.4. Instruments in the GMM

[Ahn, Lee, and Schmidt \(2001, 2013\)](#) introduced nonlinear moment conditions that exploit the orthogonality between idiosyncratic disturbances and interactive fixed effects, leveraging instruments based on multiplicative fixed-effects structures. Nevertheless, their methodology may face global identification problems, as multiple parameter configurations can satisfy the same set of moment restrictions ([Ahn et al., 2001](#)).

[Holtz-Eakin et al. \(1988\)](#) proposed using lagged values of explanatory variables as instruments for dynamic models incorporating individual effects, though their framework excluded interactive components. [Hayakawa \(2012\)](#) extended Ahn et al.'s moments through linear combinations of lags; however, his moment conditions may coincide with those of [Ahn et al. \(2001\)](#) and consequently inherit their identification difficulties ([Hayakawa, 2012](#)). [Robertson and Sarafidis \(2015\)](#) developed an orthogonalized differences approach to address interactive

effects, yet their method can also suffer from identification ambiguities under specific configurations (Robertson & Sarafidis, 2015).

Hansen's (1982) two-step GMM estimator remains a cornerstone of modern econometric practice. Subsequent refinements by Andrews (1999) and Andrews and Lu (2001) advanced moment selection criteria, providing systematic procedures to identify and discard invalid instruments. Ditraglia (2016) introduced the Focused Moment Selection Criterion (FMSC), which minimizes mean squared error for a specific parameter of interest, thereby improving estimation accuracy. More recently, Zhang (2021) proposed a quasi-unbiased criterion that combines GMM estimators to enhance robustness.

Furthermore, Hansen and Racine (2012) developed a cross-validation-based model averaging technique known as Jackknife Model Averaging, later extended by Martins and Gabriel (2014) to linear instrumental variable models. Collectively, these methodological advances illustrate the continuous evolution of GMM techniques toward greater flexibility, incorporating model selection and combination strategies to improve the robustness and precision of empirical estimates, an essential feature when analyzing complex relationships among agricultural digitalization, R&D, credit, productivity, climate variables, and sustainable development.

2.3.1.5. Model rewriting in GMM

Starting static model (in levels):

$$\ln SDI_{it} = \beta_0 + \beta_1 \ln AgDigital_{it} + \beta_2 \ln RD_AG_{it} + \beta_3 \ln CREDIT_AG_{it} + \beta_4 \ln TFP_AG_{it} + \beta_5 \ln Temp_{it} + \beta_6 \ln INF_{it} + u_{it}$$

This specification postulates a static relationship, implying that only contemporaneous variations in agricultural digitalization, research and development expenditure, credit availability, productivity, temperature, and inflation instantaneously affect sustainable development.

To implement the dynamic GMM estimator, a one-period lag of the dependent variable is incorporated as an additional regressor. This transformation yields the following dynamic panel specification:

Dynamic GMM model:

$$\ln SDI_{it} = \rho \ln SDI_{i,t-1} + \beta_0 + \beta_1 AgDigital_{it} + \beta_2 \ln RD_AG_{it} + \beta_3 \ln CREDIT_AG_{it} + \beta_4 \ln TFP_AG_{it} + \beta_5 \ln Temp_{it} + \beta_6 \ln INF_{it} + \eta_i + v_{it}$$

where:

η_i : denotes unobserved country-specific fixed effects (e.g., institutional quality, geographical endowment, or historical agricultural legacies),

v_{it} ; represents the idiosyncratic error term,

$\ln SDI_{it}$ is potentially endogenous by construction, as it correlates with the specific effects η_i and may also be correlated with past realizations of v_{it} ; Consequently, valid instrumental variables are required to achieve consistent estimation.

Difference GMM transformation (first differences):

To eliminate the unobserved countries specific fixed effects η_i , the model is expressed in first differences:

$$\begin{aligned} \Delta \ln SDI_{it} = & \rho \Delta \ln SDI_{i,t-1} + \beta_1 \Delta \ln AgDigital_{it} + \beta_2 \Delta \ln RD_AG_{it} \\ & + \beta_3 \Delta \ln CREDIT_AG_{it} + \beta_4 \Delta \ln TFP_AG_{it} + \beta_5 \Delta \ln Temp_{it} + \beta_6 \Delta \ln INF_{it} \\ & + \Delta v_{it} \end{aligned}$$

Instrumentation strategy:

Under the assumption that the idiosyncratic error term v_{it} is serially uncorrelated, valid instruments for the differenced lagged dependent variable $\Delta \ln SDI_{it}$ are provided by deeper lags of the level variable. Specifically, $\ln SDI_{it-2}$ and $\ln SDI_{it-3}$ (and potentially further lags) serve as instruments, as they are correlated with $\ln SDI_{it-1}$ and uncorrelated with Δv_{it} , provided that v_{it} exhibits no serial correlation. This instrumental variable strategy, originally proposed by [Arellano and Bond \(1991\)](#), forms the foundation of the difference GMM estimator.

The Environmental Kuznets Curve (EKC) hypothesis, introduced by [Grossman and Krueger \(1991\)](#), proposes a curvilinear relationship between economic progress and environmental degradation. According to this theoretical perspective, in the initial phases of development, rising income per capita is accompanied by worsening environmental conditions, driven by accelerated industrialization, elevated energy intensity, and limited awareness or enforcement of environmental standards. Nevertheless, once a certain prosperity threshold is surpassed, further economic expansion tends to reduce environmental harm, as societies channel investments into cleaner production technologies, renewable energy sources, and more stringent ecological regulations. This trajectory typically produces an inverted U-shaped pattern: less developed economies generally reside on the ascending portion of the curve, experiencing

growing environmental pressure, whereas wealthier nations transition to the descending segment, achieving environmental improvements despite continued economic growth.

In empirical applications, this theoretical insight is commonly operationalized through a quadratic econometric specification, where a measure of economic development (frequently GDP per capita) together with its squared term appear as explanatory variables for an environmental outcome indicator, most often CO₂ emissions or another pollution metric. In the present study, we extend this reasoning to the domain of sustainable agricultural development.

For our empirical investigation, we propose a dynamic quadratic panel model designed to examine the influence of agricultural digitalization on the Sustainable Development Index (SDI) across European Union member states over the period 2010–2024. This specification is particularly appropriate for capturing the nonlinear relationships and complex interactions among technological, financial, productivity, climatic, and macroeconomic variables that shape sustainable agricultural performance.

The specification of the chosen quadratic model is as follows:

$$\begin{aligned} \ln SDI_{it} = & \rho \ln SDI_{i,t-1} + \beta_0 + \beta_1 (\ln AgDigital_{it}) + \beta_{11} (\ln AgDigital_{it})^2 \\ & + \beta_2 \ln RD_AG_{it} + \beta_{12} \ln RD_AG_{it} \times (\ln AgDigital_{it}) + \beta_3 \ln CREDIT_AG_{it} \\ & + \beta_{13} \ln CREDIT_AG_{it} \times (\ln AgDigital_{it}) + \beta_4 \ln TFP_AG_{it} \\ & + \beta_{14} \ln TFP_AG_{it} \times (\ln AgDigital_{it}) + \beta_5 \ln Temp_{it} \\ & + \beta_{15} \ln Temp_{it} \times (\ln AgDigital_{it}) + \beta_6 \ln INF_{it} + \mu_{it} \end{aligned}$$

Thus, this quadratic specification constitutes a robust analytical framework for assessing the complexity of the effects of agricultural digitalization on the Sustainable Development Index (SDI), while simultaneously integrating key interactions among technological, financial, productivity, climatic, and macroeconomic variables. To provide a more nuanced analysis of how agricultural digitalization influences sustainable development, it is analytically pertinent to introduce interaction terms between digitalization and other fundamental determinants, such as agricultural R&D expenditure, credit access, total productivity, and temperature.

For instance, the interaction term $((\ln AgDigital_{it}) \times \ln RD_AG_{it})$ captures the notion that the marginal contribution of digitalization to sustainable development is contingent upon the level of research and development investment. In countries with higher R&D intensity, digital technologies are likely to be more effectively adapted to local agro-ecological conditions, thereby amplifying their positive impact on sustainability outcomes. Similarly, the interaction $(\ln AgDigital_{it}) \times \ln CREDIT_AG_{it}$ reflects the idea that access to agricultural credit may

facilitate the adoption of digital tools, enabling farmers to invest in precision agriculture, smart irrigation, and other sustainability-enhancing technologies. Furthermore, the interaction $(\ln AgDigital_{it}) \times \ln TFP_AG_{it}$ suggests that the effectiveness of digitalization depends on the underlying productivity level of the agricultural sector: more efficient farming systems are better positioned to harness the benefits of digital transformation.

The interaction between digitalization and temperature could also be explored, acknowledging that digital technologies may serve as adaptive tools to mitigate climate-induced risks. In regions experiencing higher thermal stress, digital solutions such as early warning systems, remote sensing, and climate-smart advisory services may yield greater relative benefits for sustainable development.

This methodological approach enables us to articulate the Environmental Kuznets Curve hypothesis with the mechanisms of agricultural digitalization and sustainable rural finance, thereby forging a conceptual bridge among technological innovation, climate resilience, agricultural productivity, and long-term sustainable development objectives (Dasgupta et al., 2002; Panayotou, 1993). By explicitly modelling these interactions and nonlinearities, our empirical strategy captures the structural complexity inherent in the relationship between digital transformation and sustainable agricultural performance across heterogeneous European Union member states over the 2010–2024 period

2.3.2. The primary data analysis techniques: Dimensionality Reduction and Clustering Techniques

2.3.2.1 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a widely recognized statistical technique for dimensionality reduction in complex, high-dimensional datasets. It transforms a set of potentially correlated variables into a new set of uncorrelated linear combinations termed principal components, which are ranked in descending order according to the proportion of original variance they capture. This method proves especially valuable for exploratory analysis of large datasets in economics, agricultural finance, and environmental research, where variables often exhibit substantial interdependencies (Jolliffe & Cadima, 2016).

Let $X \in \mathbb{R}^{n \times p}$ represent a data matrix containing n observations (country-year pairs) and p variables. In our empirical framework, these variables include the transformed agricultural digitalization index ($\ln AgDigital_{it}$), the natural logarithm of agricultural R&D expenditure ($\ln RD_AG_{it}$), the natural logarithm of agricultural credit ($\ln CREDIT_AG_{it}$), the

natural logarithm of agricultural total factor productivity ($\ln TFP_{AG_{it}}$), the natural logarithm of mean surface temperature ($\ln Temp_{it}$), and log-transformed inflation rate ($\ln INF_{it}$).

Step 1: Standardization (mean-centering)

To eliminate scale dependencies and ensure that variables with larger magnitudes do not disproportionately influence the principal components, the dataset is centred by subtracting the sample mean from each observation:

$$\tilde{X}_{ij} = X_{ij} - \bar{X}_j$$

Step 2: Covariance Matrix

The sample covariance matrix is subsequently derived from the centred data matrix:

$$S = \frac{1}{n-1} \tilde{X}^\top \tilde{X}$$

This matrix quantifies the linear associations among the p variables.

Step 3: Eigenvalue Decomposition

The eigenvalues λ_i and corresponding eigenvectors v_i of the covariance matrix S are computed to identify the directions of maximum variance in the data:

$$S v_i = \lambda_i v_i$$

Each v_i represents a principal component (PC), and λ_i represents the amount of variance it explains.

Step 4: Projection

The original standardized data are projected onto the subspace spanned by the first k eigenvectors:

$$Z = \tilde{X} V_k$$

where $V_k \in \mathbb{R}^{p \times k}$ denotes the matrix comprising the first k eigenvectors, and Z represents the matrix of principal component scores.

PCA facilitates a more compact and efficient representation of the data by discarding redundant information and noise while preserving the most salient variation patterns. It serves as an ideal preprocessing step before applying unsupervised classification techniques such as k-means clustering. In the present study, PCA is employed to reduce the dimensionality of our explanatory variables, encompassing agricultural digitalization, R&D expenditure, credit

access, productivity, temperature, and inflation, into a smaller number of uncorrelated components, which are then utilized for structural heterogeneity analysis and further classification of European Union member states over the 2010–2024 period.

2.3.2.2. *k-means Clustering*

K-means is an unsupervised machine learning algorithm designed to partition a dataset into k homogeneous groups based on proximity or similarity measures. Each observation is allocated to the cluster whose centroid, defined as the arithmetic mean of all points belonging to that cluster, is nearest. This method is widely appreciated for its computational simplicity, scalability, and effectiveness, particularly when employed in conjunction with Principal Component Analysis (PCA) to enhance cluster separation and interpretability (MacQueen, 1967; Arthur & Vassilvitskii, 2007). Let $X = \{x_1, x_2, \dots, x_n\}$ denote the dataset comprising n observations. In our study, these observations correspond to country-year pairs across European Union member states, and the variables used for clustering include the transformed agricultural digitalization index $\ln AgDigital_{it}$, agricultural R&D expenditure ($\ln RD_AG_{it}$), agricultural credit ($\ln CREDIT_AG_{it}$), agricultural total factor productivity ($\ln TFP_AG_{it}$), mean surface temperature ($\ln Temp_{it}$), and the transformed inflation rate ($\ln INF$).

The algorithm seeks to minimize the within-cluster variance, also known as the inertia or distortion, expressed by the following objective function:

$$J = \sum_{j=1}^k \sum_{x_i \in C_j} \|x_i - \mu_i\|^2$$

Where:

C_j represents the set of observations assigned to cluster j ,

μ_i is the centroid (mean vector) of cluster j ,

$\|x_i - \mu_i\|$: denotes the Euclidean distance between observation x_i and centroid μ_i .

Step 1: Initialization: Select k initial centroids, either randomly or using the k-means++ algorithm (Arthur & Vassilvitskii, 2007), which improves convergence and reduces the risk of poor clustering.

Step 2: Assignment: Each observation x_i is assigned to the nearest centroid:

$$C(j) = \arg \min \|x_i - \mu_i\|$$

Step 3: Update: Recalculate the centroids as the means of all observations assigned to each cluster:

$$\mu_i = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i$$

Step 4: Convergence: Repeat Steps 2 and 3 until the centroids stabilize (i.e., no further changes in cluster assignments) or a predefined maximum number of iterations is reached.

To determine the optimal number of clusters k , the elbow method is commonly employed. This involves plotting the within-cluster sum of squared distances J against a range of k values and selecting the point where the marginal gain in variance explained diminishes noticeably, the "elbow" of the curve.

In the present study, k -means clustering is applied to the principal components derived from PCA, allowing us to identify structural heterogeneities among European Union member states in terms of their agricultural digitalization, R&D intensity, credit access, productivity, climatic conditions, and inflation dynamics. This classification provides a foundation for subsequent nonlinear modelling and regime-specific policy recommendations.

2.3.3. Non-linear modelling

2.3.3.1. PTAR model

The Panel Threshold Auto-Regression (PTAR) model, originally proposed in 1999 (Hansen), characterizes the endogenous variable y_{it} as being subject to regime-switching behavior determined by a threshold variable. Formally, a two-regime PTAR specification is valid for the process $(y_{it}, t \in \mathbb{Z}, i \in \mathbb{Z})$ only under the following conditions:

$$y_{it} = \mu_i + \beta_1' X_{it} + \beta_2' X_{it} I(q_{it} > c) + \varepsilon_{it}$$

Where $I(\cdot)$ denotes the indicator function, which equals one when the condition inside parentheses holds and zero otherwise. The transition variable q_{it} governs the regime switching, c represents the threshold parameter, μ_i captures individual fixed effects, $X_{it} = (X_{it}^1, \dots, X_{it}^k)$, is a matrix of k exogenous variables (excluding lagged dependent variables), $\beta = (\beta_1, \dots, \beta_k)$, is the coefficient vector, and ε_{it} is assumed to follow a normal distribution $N(0, \sigma^2)$. The cross-sectional dimension is indexed by $i = 1, \dots, N$, and the temporal dimension by $t = 1, \dots, T$.

The transition from one regime to another occurs by comparing the threshold parameter c with the realized value of the transition variable q_{it} . Consequently, the model can be expressed in a more intuitive piecewise form:

$$y_{it} = \begin{cases} \mu_i + \beta'_0 X_{it} + u_{it} & \text{if } q_{it} \leq c \\ \mu_i + (\beta'_0 + \beta'_1) X_{it} + u_{it} & \text{if } q_{it} > c \end{cases}$$

This specification is distinctive because it permits a panel to evolve across multiple regimes, each characterized by its own linear dynamics. As an individual unit can switch from one regime to another at a specific point in time, the transition is characterized by an abrupt, discrete shift.

In this framework, when $q_{it} > c$ the process is governed by the first regime with slope coefficients β'_0 . Conversely, when the transition variable satisfies $q_{it} \leq c$, even by a very small margin, the process follows the second regime, defined by the combined coefficients $(\beta'_0 + \beta'_1)$.

To illustrate the estimation procedure for both the slope and threshold parameters, we begin by constructing a PTAR model of the following form:

$$y_{it} = \mu_i + \beta' X_{it}(c) + u_{it}$$

Two principal challenges arise from this formulation. First, the estimation of individual effects that are common across different regimes must be properly addressed. Second, both the slope parameters and the threshold parameter need to be estimated consistently. Although the model resembles a standard time-series specification, conventional ordinary least squares (OLS) estimation is not directly applicable because the exogenous variables are linked to the threshold via the indicator function. Consequently, the estimation procedure must be carried out in two distinct stages.

According to [Hansen \(1999\)](#), the optimal threshold estimates $\hat{c}$ is obtained by minimizing the sum of squared residuals (SSR):

$$\hat{c} = \arg \min SSR(c)$$

where $SSR = \sum_{i=1}^N \sum_{t=1}^T u_{it}^2$. Once c is determined, OLS is again employed to estimate the slope parameters $\hat{\beta}(c)$. The empirical variance of the residuals is then computed as:

$$\sigma^2 = \sum_{i=1}^N \sum_{t=1}^T \hat{u}_{it} \hat{u}_{it}^* = \frac{1}{n(T-1)} S(\hat{c})$$

When the null hypothesis cannot be rejected, the procedure should either conclude or be repeated with an alternative hypothesis, for instance by selecting a different transition variable. The initial step is to test for linearity, which involves building a confidence interval for the relevant coefficient. If the linearity hypothesis is refuted, two further tests are performed sequentially: one to identify the number of regimes, and another to assess the relevance of the slope coefficients. The linearity test investigates whether parameters across regimes are uniform. Not rejecting the null hypothesis indicates the absence of a threshold effect. The hypotheses are formulated as:

$$\begin{cases} H_0: \beta_1 = 0 \\ H_1: \beta_1 \neq 0 \end{cases}$$

Consequently, the linearity test should be performed using this coefficient fixed at its estimated value under the following circumstances:

$$F_1 = \frac{S_0 - S_1(\hat{c})}{\hat{\sigma}^2} \text{ where } \sigma^2 = \frac{1}{N(T-1)} S_1(\hat{c}_1)$$

with S_0 and $S_1(\hat{c}_1)$ the sum of the residual squares of the linear and non-linear models, respectively.

Based on the above, our linear model can be presented as the PTAR model as follows:

$$\begin{aligned} \ln SDI_{it} = & \left(\sum_{j=1}^p \rho_{1j}^1 \ln SDI_{it-j} + \beta_0^1 + \beta_1^1 AgDigital_{it} + \beta_2^1 \ln RD_AG_{it} \right. \\ & + \beta_3^1 \ln CREDIT_AG_{it} + \beta_4^1 \ln TFP_AG_{it} + \beta_5^1 \ln Temp_{it} + \beta_6 \ln INF_{it} \\ & \left. + \varepsilon_{1it} \right) \\ & + \left(\sum_{j=1}^p \rho_{1j}^2 \ln SDI_{it-j} + \beta_0^2 + \beta_1^2 AgDigital_{it} + \beta_2^2 \ln RD_AG_{it} \right. \\ & + \beta_3^2 \ln CREDIT_AG_{it} + \beta_4^2 \ln TFP_AG_{it} + \beta_5^2 \ln Temp_{it} + \beta_6^2 \ln INF_{it} \\ & \left. + \varepsilon_{2it} \right) \times I(AgDigital_{it} > c) \end{aligned}$$

2.3.3.2. PSTAR model

According to [González et al. \(2005, 2017\)](#), the PTAR framework can be extended using the Panel Smooth Transition Autoregressive (PSTAR) methodology. The primary innovation of this approach lies in moving from discrete, abrupt regime shifts to continuous, gradual transitions, which are often more realistic in economic and environmental systems. Thus, a two-

regime PSTAR specification is valid for describing the process $(y_{it}, t \in Z, i \in Z)$ under the following conditions:

$$y_{it} = \mu_i + \beta'_0 X_{it} + \beta'_1 X_{it} G(q_{it}; \gamma; c) + \varepsilon_{it}$$

The function $G(q_{it}; \gamma; c)$ represents the transition mechanism, which depends on the transition variable q_{it} , the threshold location parameter c , and the smoothing parameter γ . The term μ_i denotes the vector of country-specific fixed effects. The matrix, $X_{it} = (X_{it}^1, \dots, X_{it}^k)$, contains k exogenous regressors, excluding any lagged dependent variables. The coefficient vector is $\beta = (\beta_1, \dots, \beta_k)$, and the disturbance term ε_{it} is assumed to be independently and identically distributed as $N(0, \sigma^2)$. The indices $i = 1, \dots, N$, and $t = 1, \dots, T$ denote cross-sectional units and time periods, respectively.

The transition function $G(q_{it}; \gamma; c)$, is continuous and differentiable over the interval $(0, 1)$, serving as a smooth alternative to the discrete indicator function employed in standard PTR models. This feature allows the process to shift gradually between different regimes rather than jumping instantaneously.

Two complementary interpretations of the PSTAR model can be offered. First, it can be viewed as a framework delimited by two extreme regimes yet encompassing an infinite continuum of intermediate states. Under this perspective, the coefficients are allowed to vary across both cross-sectional units and time within a linear heterogeneous panel data specification. Second, the PSTAR model can be interpreted as a nonlinear formulation in which the dependent variable evolves gradually between two homogeneous, linear extreme regimes.

In empirical applications, various transition functions that are continuous and differentiable on $(0, 1)$ may be employed. [González et al. \(2005, 2017\)](#) recommend using a logistic transition function of order m , specified as:

$$G(q_{it}; \gamma; c) = [1 + \exp(-\gamma \prod_{j=1}^n (q_{it} - c))]^{-1}, \gamma > 0,$$

Before estimating the PSTAR model, it is necessary to test for linearity and ascertain whether the regime-switching effect is statistically meaningful. [González et al. \(2017\)](#) developed a procedure to evaluate the null hypothesis of linearity against the alternative of a PSTAR specification. Because the PSTAR model contains unidentified nuisance parameters under the null hypothesis $H_0: \beta_1 = 0$, conventional testing procedures are not directly applicable.

To circumvent this issue, [González et al. \(2017\)](#) proposed testing the linearity hypothesis $H_0: \gamma = 0$ by applying a first-order Taylor expansion of $\gamma = 0$ for $G(q_{it}; \gamma; c)$ around $\gamma = 0$. transformation yields the following auxiliary regression after rearrangement:

$$y_{it} = \mu_i + \beta_0'^* X_{it} + \beta_1'^* X_{it} G(q_{it}; \gamma; c) + \varepsilon_{it}^*$$

In this auxiliary specification, the parameters $\beta_0'^*$ are related inversely to the smoothing coefficient γ and $\varepsilon_{it}^* = \varepsilon_{it} + R_1 \beta_1'^* X_{it}$, where R_1 denotes the remainder term from the Taylor expansion. Consequently, test $H_0: \gamma = 0$ becomes equivalent to testing $H_0^*: \beta_1'^* = 0$.

Standard test statistics, including Wald, Fisher, and likelihood ratio can then be applied, each defined as follows:

$$LM_W = \frac{TN(SSR_0 - SSR_1)}{SSR_0}, M_F = \frac{TN(SSR_0 - SSR_1)/K}{SSR_0/(TN - N - K)}, LR = -2[\log(SSR_0) - \log(SSR_1)]$$

where SSR denotes the sum of squared residuals from the respective regressions.

Drawing on the above theoretical development, our linear dynamic model can be expressed as a PSTAR specification as follows:

$$\begin{aligned} \ln SDI_{it} = & \left(\sum_{j=1}^p \rho_{1j}^1 \ln SDI_{it-j} + \beta_0^1 + \beta_1^1 \ln AgDigital_{it} + \beta_2^1 \ln RD_AG_{it} \right. \\ & + \beta_3^1 \ln CREDIT_AG_{it} + \beta_4^1 \ln TFP_AG_{it} + \beta_5^1 \ln Temp_{it} + \beta_6 \ln INF_{it} \\ & \left. + \varepsilon_{1it} \right) \\ & + \left(\sum_{j=1}^p \rho_{1j}^2 \ln SDI_{it-j} + \beta_0^2 + \beta_1^2 \ln AgDigital_{it} + \beta_2^2 \ln RD_AG_{it} \right. \\ & + \beta_3^2 \ln CREDIT_AG_{it} + \beta_4^2 \ln TFP_AG_{it} + \beta_5^2 \ln Temp_{it} + \beta_6^2 \ln INF_{it} \\ & \left. + \varepsilon_{2it} \right) \times G(\ln AgDigital_{it}; \gamma; c) \end{aligned}$$

2.3.4. Diagnostic tests

2.3.4.1. Heteroscedasticity test

❖ Breusch and Pagan test (1979)

The [Breusch and Pagan \(1979\)](#) procedure is employed to examine whether heteroscedasticity is present in the regression residuals. Consider the following linear specification:

$$y_i = \beta_1 + \beta_2 X_{2i} + \dots + \beta_k X_{ki} + u_i \text{ where } \text{var}(u_i) = \sigma_i^2$$

The testing procedure involves estimating the above equation and retrieving the $\hat{u}_i$. An auxiliary regression is then estimated as:

$$\hat{u}_i^2 = b_1 + b_2 W_{2i} + \dots + b_m W_{mi} + v_i$$

where, W_{mi} represents a collection of explanatory variables intended to model the variance of the error term. The null hypothesis of constant variance (homoscedasticity) is stated as:

$$H_0 : b_1 = b_2 = \dots = b_m = 0$$

The Lagrange Multiplier (LM) statistic is calculated as $LM = nR^2$, where n denotes the number of observations used in the auxiliary regression and R^2 is the coefficient of determination. Under the null hypothesis, the LM statistics asymptotically follows a chi-square distribution with $m - 1$ degrees of freedom. An LM value exceeding the critical threshold leads to rejection of homoscedasticity, indicating the presence of heteroscedasticity

❖ *White test (1980)*

The [White test \(1980\)](#) provides a general method for detecting heteroscedasticity without imposing strong assumptions about the functional form of the variance. The null hypothesis assumes that residuals have constant variance. The initial regression is estimated as:

$$Y_i = \beta_1 + \beta_2 X_2 + \beta_3 X_3 + u_i$$

The residuals $\hat{u}_i$ are recovered from this estimation. The auxiliary regression is then specified as:

$$\hat{u}_i^2 = b_1 + b_2 G_{2i} + b_3 G_{3i} + b_4 G_{2i}^2 + b_5 G_{3i}^2 + b_6 G_{2i} G_{3i} + v_i$$

The null hypothesis of homoscedasticity is formulated as:

$$H_0 : b_1 = b_2 = \dots = b_m = 0$$

Thus, the null hypothesis implies that the residuals exhibit constant variance:

$$var(\varepsilon_i) = var(Y_i) = \sigma_i^2$$

The LM statistic is computed as $LM = nR^2$. A statistically significant LM value prompts rejection of the null hypothesis of homoscedasticity. Here, R^2 is the coefficient of determination from the auxiliary regression. The LM statistic follows χ^2 distribution with $6-1=5$ degrees of freedom. When the computed LM exceeds the critical chi-square value, the null hypothesis is rejected, confirming the existence of heteroscedasticity.

2.3.4.2. Assessment of serial autocorrelation using the Born and Breitung test (2016)

To examine autocorrelation of order k , a k -order autoregressive representation can be employed, expressed as:

$$e_{it} - \bar{e}_i = \rho_k(e_{it-k} - \bar{e}_i) + \varepsilon_{it}; t = k + 1, \dots, T \text{ and } i = 1, \dots, N$$

For fixed T and increasing N , the probability limit of the pooled OLS estimator ρ_k is given below. Under the assumption $\rho = 0$ and ρ_k denotes the pooled OLS estimate, we have:

$$\rho_k \xrightarrow{p} -\frac{1}{T-1}; \text{ for all } k \in \{1, \dots, T-2\}$$

Based on this result, the null hypothesis $\rho_k = -1/(T-1)$ can be tested using a t-statistic that is robust to heteroscedasticity and serial correlation. To guarantee asymptotic independence of the resulting statistics, we define:

$$z_{Ti} = \sum_{t=k+1}^T [(e_{it} - \bar{e}_i)(e_{it-k} - \bar{e}_i) + \frac{1}{T-1}(e_{it-k} - \bar{e}_i)^2] \text{ and } LM_k^* = \frac{\sum_{i=1}^N z_{Ti}^k}{\sqrt{\sum_{i=1}^N z_{Ti}^{(k)2} - \frac{1}{N}(\sum_{i=1}^N z_{Ti}^k)^2}}$$

In practical empirical work, it is often more relevant to test whether the error terms are free of autocorrelation up to order p . The probability limit of the autoregressive coefficients is denoted $\phi_1, \dots, \phi_p$.

$$e_{it} - \bar{e}_i = \phi_1(e_{it-1} - \bar{e}_i) + \dots + \phi_p(e_{it-p} - \bar{e}_i) + v_{it}$$

Because the regressions are interrelated, the resulting expression becomes quite intricate. To overcome this difficulty, [Born and Breitung \(2016\)](#) suggest a straightforward regression transformation that permits unbiased estimation of the autoregressive coefficients under the null hypothesis. They also advocate implicit bias correction rather than relying on asymptotic probability limits. The transformed autoregressive model in matrix notation is written

$$\text{as: } Me_i = \phi_1 L_1 e_i + \phi_2 L_2 e_i + \dots + \phi_p L_p e_i + v_{it} \text{ and } L_k e_i = \begin{pmatrix} 0_{k \times 1} \\ e_{i1} - \bar{e}_i \\ \vdots \\ e_{iT-k} - \bar{e}_i \end{pmatrix} + \left(\frac{T-k}{T^2-T} \right) e_i$$

In this formulation, the second vector serves a bias-correcting role, while the first vector on the right-hand side contains the lagged values of the adjusted residuals. It can be demonstrated that:

$$E(e_i M L_k e_i) = -\left(\frac{T-k}{T} \right) \sigma_i^2 + \left(\frac{T \cdot 1}{T} \right) \left(\frac{T-k}{T-1} \right) \sigma_i^2 = 0$$

The ordinary least squares estimators $\phi_1, \dots, \phi_p$ converge in probability to zero as T and $N \rightarrow \infty$ for all $k = 1, \dots, T$ under the null hypothesis. Consequently, Wald statistics can be used to test the null hypothesis $\phi_1, \dots, \phi_p = 0$:

$$Q(p) = \phi S^{-1} \phi$$

Where $S = (\sum_{i=1}^N Z_i' Z_i)^{-1} (\sum_{i=1}^N Z_i' v_i v_i' Z_i) (\sum_{i=1}^N Z_i' Z_i)^{-1}$ is the HAC estimator for the covariance matrix of the coefficient vector with $\phi = [\phi_1, \dots, \phi_p]$ and $Z_i = [L_1 e_i, \dots, L_p e_i]$ and $v_i = M e_i - Z_i \phi$. $Q(p)$ is asymptotically equivalent to statistics:

$$Q(p) = \sum_{i=1}^N e_i M Z_i \left[\sum_{i=1}^N Z_i' M e_i e_i' Z_i - \frac{1}{N} \left(\sum_{i=1}^N Z_i M e_i \right) \left(\sum_{i=1}^N e_i M Z_i \right) \right]^{-1} \sum_{i=1}^N Z_i M e_i$$

Both forms of $Q(p)$ and $Q(p)$ asymptotically follow a chi-squared χ^2 distribution with p degrees of freedom and are equivalent in large samples. The hypotheses for this test are summarized as:

$$\begin{cases} H_0 : \text{absence of serial autocorrelation} \\ H_1 : \text{presence of serial autocorrelation} \end{cases}$$

In our empirical investigation, this test is applied to the residuals of the estimated dynamic panel models, including GMM, PTAR, and PSTAR, to ensure that no remaining serial correlation exists, as its presence would compromise the consistency of the estimators. Collectively, these diagnostic procedures confirm the robustness and reliability of our estimates concerning the relationships among agricultural digitalization, R&D expenditure, credit access, productivity, temperature, inflation, and sustainable development across European Union member states over the 2010–2024 period.

Section 3 - Empirical Strategy, Econometric Estimations, and Discussion

Following the theoretical framework, the systematic literature review, and the econometric methodology outlined in the previous sections, this section presents the empirical investigation into the determinants of sustainable agricultural performance across the European Union from 2010 to 2024. The empirical strategy is structured sequentially to ensure robustness and depth, beginning with descriptive statistics and univariate analyses to capture structural heterogeneity, followed by a rigorous battery of pre-estimation diagnostic tests. Subsequently, advanced dynamic and nonlinear panel estimators, specifically the two-step System Generalized Method of Moments, Panel Threshold Autoregressive, and Panel Smooth Transition Regression models, are employed to capture complex, regime-dependent dynamics that conventional linear specifications fail to uncover.

To guide this empirical investigation and structure the subsequent discussion, we formulate a set of core hypotheses that challenge linear assumptions and emphasize the conditional, nonlinear nature of agricultural sustainability. We postulate first that agricultural digitalization exerts a nonlinear, threshold-dependent effect on sustainable development, improving the Sustainable Development Index up to a critical level of digital maturity, beyond which technological saturation, coordination failures, and infrastructure costs generate diminishing returns. Furthermore, we argue that agricultural Research and Development promotes sustainable development, but its impact is conditioned by the prevailing level of digital transformation, exhibiting a complementarity mechanism that unlocks transformative synergies only at advanced stages of digital maturity.

Continuing this framework, we hypothesize that agricultural credit facilitates sustainable development by relaxing financial constraints for technology adoption, playing a decisive role at the early and advanced stages of digital transformation, while facing potential misallocation risks during rapid, uncoordinated transitional phases. Concurrently, agricultural Total Factor Productivity is posited as a fundamental and robust driver of sustainable development, with its positive environmental and economic decoupling effects significantly amplified by the adoption of digital precision technologies. We also integrate the role of exogenous constraints by asserting that climatic pressures and macroeconomic instability exert regime-dependent effects, acting as catalysts for adaptive innovation at intermediate digitalization stages but becoming binding structural constraints that undermine digital sustainability gains at advanced levels.

Ultimately, the overarching hypothesis asserts that the agricultural sustainability system is fundamentally governed by complex nonlinearities and structural regime shifts, where the marginal impacts of innovation, finance, and productivity are strictly conditioned by the absorptive capacity and digital maturity of the sector. By testing these hypotheses through the aforementioned econometric toolkit, this section aims to provide nuanced economic interpretations and targeted, regime-specific policy recommendations for the European agricultural sector.

3.1. Variable description

3.1.1. Descriptive Statistics, Correlation Matrix, and Diagnostic Tests

Table 2.2 presents a comprehensive statistical overview of the variables employed in the empirical analysis, namely the Sustainable Development Index (LnSDI), Agricultural Digitalization (LnDigital_AG), Agricultural Research and Development (LnRD_AG), Agricultural Total Factor Productivity (LnTFP_AG), Agricultural Credit (LnCREDIT_AG), Temperature (LnTemp), and Inflation (LnINF). The dataset consists of a balanced panel of 405 observations. Before examining the individual characteristics of the variables, it is important to note that the Variance Inflation Factor (VIF) is equal to 1.12, which remains substantially below the conventional threshold of 10. This finding confirms the absence of multicollinearity concerns and indicates that the explanatory variables provide complementary rather than redundant information.

Table 2.2. Descriptive Statistics, Correlation Matrix, and Variance VIF of Variables

Variables	LnSDI	LnDigital_AG	LnRD_AG	LnTFP_AG	LnCREDIT_AG	LnTemp	LnINF
Observations	405	405	405	405	405	405	405
Mean	4.376	4.163	2.765	4.610	11.598	2.370	0.760
Standard deviation	0.041	0.175	1.903	0.108	1.641	0.373	1.130
CV	0.009	0.042	0.688	0.023	0.141	0.158	1.488
Minimum	4.262	3.412	-2.054	4.261	8.852	0.554	-3.906
Maximum	4.467	4.402	6.845	5.166	14.558	3.059	4.387
Skewness	-0.077	-1.352	-0.293	0.566	0.165	-0.455	-0.502
Kurtosis	2.882	5.006	2.866	7.782	1.766	4.335	4.213
Jarque–Bera (JB) test	0.631	191.300	6.081	407.500	27.510	44.010	41.820
JB Probability	0.729	0.000	0.048	0.000	0.000	0.000	0.000
Born–Breitung (BB) test	54.790	18.920	48.540	4.820	4.710	44.900	67.730
BB Probability	0.000	0.000	0.000	0.090	0.095	0.000	0.000
Correlation	LnSDI	LnDigital_AG	LnRD_AG	LnTFP_AG	LnCREDIT_AG	LnTemp	LnINF
LnSDI	1.000						
LnDigital_AG	0.504***	1.000					
LnRD_AG	0.157***	-0.077	1.000				
LnTFP_AG	0.183***	0.207***	0.064	1.000			
LnCREDIT_AG	0.377***	0.148***	0.039	0.115**	1.000		

LnTemp	-0.432***	-0.218***	-0.194***	0.164***	0.050	1.000	
LnINF	0.075	0.117**	0.104**	0.017	-0.127**	-0.091*	1.000
VIF				1.12			

Note: *, **, and *** refer to significant at 10%, 5%, and 1%, respectively.

The dependent variable, Sustainable Development (LnSDI), exhibits a mean value of 4.376 and a remarkably low standard deviation of 0.041, suggesting a high degree of homogeneity across the sampled countries. The distribution is nearly symmetric (skewness = -0.077) and approximately mesokurtic (kurtosis = 2.882). Furthermore, the Jarque–Bera test fails to reject the null hypothesis of normality (p-value = 0.729), indicating that sustainable development levels are relatively stable across the sample. However, the Born–Breitung test reveals significant serial dependence (p-value = 0.000), highlighting the persistent and cumulative nature of sustainability outcomes, which are generally shaped by long-term institutional, environmental, and technological processes.

Turning to Agricultural Digitalization (LnDigital_AG), the variable records an average value of 4.163 and ranges from 3.412 to 4.402. The distribution is strongly left-skewed (-1.352) and leptokurtic (5.006), reflecting the concentration of advanced digital agricultural practices within a limited group of countries. The Jarque–Bera statistic strongly rejects normality, while the Born–Breitung test confirms significant temporal dependence. These findings suggest that agricultural digitalization follows a path-dependent process in which previous investments in digital infrastructure and technological capabilities generate cumulative advantages over time.

In contrast, Agricultural Research and Development (LnRD_AG) displays substantial heterogeneity across countries, as evidenced by its relatively high coefficient of variation (0.688) and broad range extending from -2.054 to 6.845. Although the distribution is only moderately skewed, the Jarque–Bera test rejects normality at the 5% significance level. Moreover, the presence of significant serial correlation indicates that innovation activities evolve gradually and reflect long-term strategic commitments to knowledge creation, technological progress, and agricultural modernization.

Attention can now be directed to Agricultural Total Factor Productivity (LnTFP_AG), which exhibits a mean value of 4.610 and relatively limited dispersion. The positive skewness and pronounced kurtosis indicate that productivity gains are not evenly distributed across countries, with a small number of economies achieving exceptionally high productivity levels. While the Jarque–Bera statistic strongly rejects normality, the Born–Breitung test fails to reject the null hypothesis of serial independence. This result suggests that productivity dynamics may be

influenced not only by structural determinants but also by country-specific technological shocks and efficiency improvements.

A similar degree of heterogeneity can be observed for Agricultural Credit (LnCREDIT_AG), whose values range from 8.852 to 14.558. The positive skewness indicates that access to agricultural finance remains unevenly distributed among countries. The rejection of normality suggests the presence of significant institutional and financial disparities, whereas the absence of strong serial dependence implies that credit allocation may respond more rapidly to policy reforms and changing financial conditions than other structural variables.

Beyond the core explanatory variables, the analysis also considers the behavior of the control variables. Temperature (LnTemp) exhibits a negative skewness and significant serial persistence, reflecting the heterogeneous climatic conditions characterizing the sample. Likewise, Inflation (LnINF) presents the highest coefficient of variation among all variables and displays substantial fluctuations, ranging from severe deflationary episodes to periods of elevated inflation. The rejection of normality and the presence of strong serial correlation indicate that inflationary dynamics remain highly persistent and subject to macroeconomic shocks.

Beyond the univariate analysis, the correlation matrix provides preliminary insights into the relationships among the variables. As expected, sustainable development exhibits a positive and statistically significant association with agricultural digitalization ($r = 0.504$, $p\text{-value} < 0.01$), agricultural credit ($r = 0.377$, $p\text{-value} < 0.01$), agricultural total factor productivity ($r = 0.183$, $p\text{-value} < 0.01$), and agricultural R&D ($r = 0.157$, $p\text{-value} < 0.01$). These findings suggest that technological adoption, financial inclusion, innovation efforts, and productivity improvements constitute important drivers of sustainable agricultural development. Conversely, temperature is negatively and significantly correlated with sustainable development ($r = -0.432$, $p\text{-value} < 0.01$), indicating that climate-related pressures may hinder sustainability achievements.

Similarly, agricultural digitalization is positively associated with agricultural productivity ($r = 0.207$, $p\text{-value} < 0.01$) and agricultural credit ($r = 0.148$, $p\text{-value} < 0.01$), supporting the view that digital technologies enhance productive efficiency while facilitating access to financial resources. Furthermore, agricultural R&D exhibits positive relationships with sustainable development and inflation, suggesting that innovative activities tend to be concentrated in more dynamic economic environments. Interestingly, inflation shows generally weak correlations with most variables, suggesting that its influence may operate through indirect or non-linear channels rather than straightforward linear relationships.

Taken together, these findings reveal a combination of structural heterogeneity, non-normal distributions, and significant temporal persistence across the sample countries. Overall, the descriptive statistics and diagnostic tests provide preliminary support for the theoretical framework developed in this study and justify the use of advanced panel econometric techniques capable of capturing dynamic and long-run relationships between agricultural digitalization, innovation, productivity, financial development, and sustainable development.

3.1.2. Analyzing Country Heterogeneity through PCA and K-Means Based on TFP and Circular Economy

Figure 3.1 presents the results of the combined Principal Component Analysis (PCA) and K-Means clustering procedure applied to Sustainable Development (SDI) and Digital Development (Digital_AG) indicators across the 27 EU member states. The objective of this analysis is to identify potential heterogeneity among European countries according to their sustainability performance and their progress toward digital transformation. Each point on the graph represents a country, while the two principal components summarize the information contained in the original variables. The first principal component explains 72.4% of the total variance, whereas the second component accounts for an additional 27.6%, indicating that the two-dimensional representation captures virtually all the variability present in the dataset.

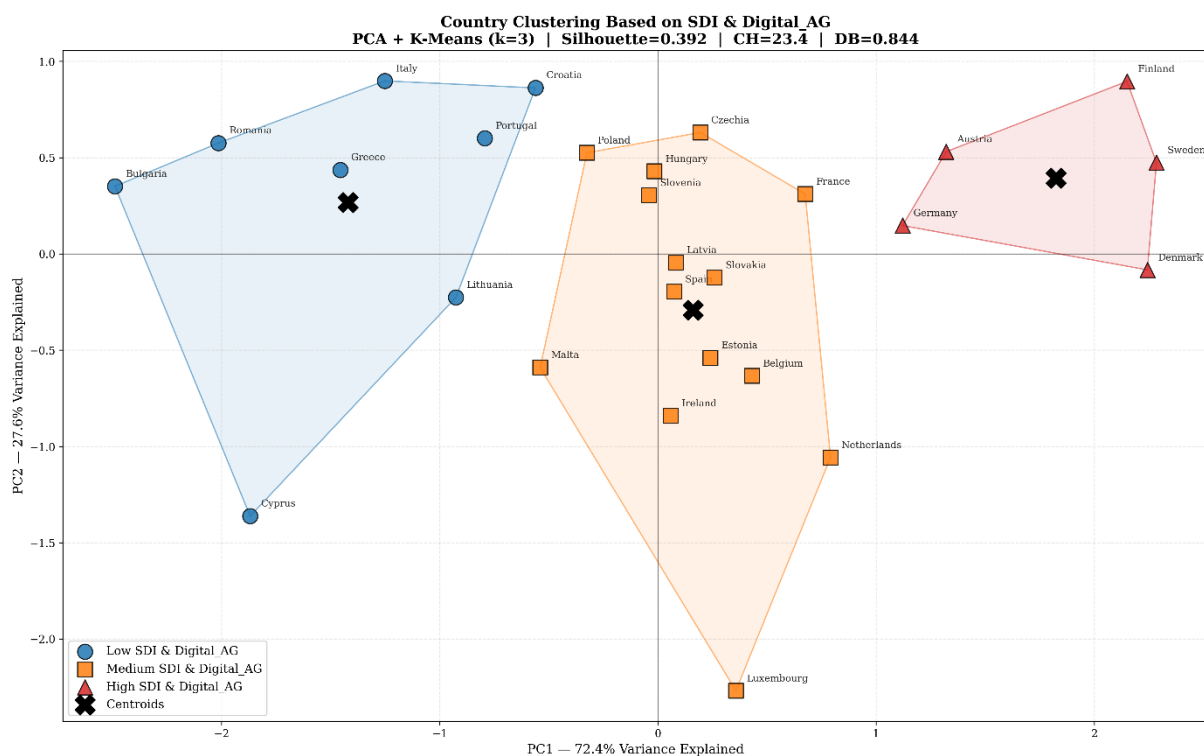


Figure 2.1. Country Representation by Principal Components and K-Means Classification

3.2. Stationarity Tests Results

To ensure the robustness and validity of the subsequent econometric estimates, this section examines the time-series properties of the panel data using a battery of unit root tests, including first-generation tests assuming cross-sectional independence, second-generation tests accounting for cross-sectional dependence, and tests incorporating structural breaks to capture major shifts in macroeconomic dynamics.

3.2.1. First-Generation Tests

To investigate the stationarity properties of the variables included in the empirical model, a set of first-generation panel unit root tests was employed, namely the Levin, Lin, and Chu (LLC) 2002, Im, Pesaran, and Shin (IPS) 2003, and Hadri (LM) (2000) tests. These tests were conducted at both levels and first differences under two specifications: intercept-only (C) and intercept-and-trend (C&T). While the LLC and IPS procedures test the null hypothesis of a unit root, the Hadri LM test assumes stationarity under the null hypothesis. Consequently, divergent outcomes across these tests are not uncommon and should be interpreted jointly to determine the integration order of the variables.

Table 2.3. Unit root tests of the variables

	Tests		LnSDI	LnDigital_AG	LnRD_AG	LnTFP_AG	LnCREDIT_AG	LnTemp	LnINF
In level	LLC	C		-8.211***	-8.400***	0.992	-3.450***	-5.512***	-0.453
		C & T		-1.628*	-2.700***	-2.336***	-5.231***	-3.734***	-4.883***
	IPS	C		-1.892**	0.214	5.302	-4.161***	0.252	-6.516***
		C & T		-2.129**	-3.690***	-2.572***	-7.105***	1.051	-9.608***
	LM	C		84.249***	84.848***	23.358	74.888**	60.906	52.103
		C & T		56.554	52.743	45.675	91.065***	45.225	143.262***
	Decision	—		S	S	NS	S	NS	NS
In first difference	LLC	C		-6.092***	-9.138***	-30.699***	-12.964***	-3.824***	-19.680***
		C & T		-7.211***	-11.407***	-22.450***	-11.209***	-4.584***	-14.919***
	IPS	C		-9.231***	-9.497***	-8.125***	-11.298***	-5.749***	-10.996***
		C & T		-9.871***	-10.281***	-9.206***	-11.595***	-7.018***	-11.250***
	LM	C		183.667***	270.350***	130.719***	346.378***	87.725***	512.021***
		C & T		160.095***	272.001***	123.039***	283.105***	75.177**	348.440***
	Decision	—		S	S	S	S	S	S

Note: *, ** and *** refer to significant at 10%, 5%, and 1%, respectively. S stationary, NS non-stationary, C Constant, C & T Constant & Trend

As shown in [Table 2.3](#), the results at levels reveal heterogeneous stationarity patterns across the variables. Sustainable Development (LnSDI) appears stationary in level, as both LLC and IPS tests reject the null hypothesis of a unit root under most specifications. Similarly, Agricultural Digitalization (LnDigital_AG) exhibits significant LLC statistics and significant IPS results when trend effects are considered, suggesting stationarity at level. Agricultural Total Factor Productivity (LnTFP_AG) also demonstrates strong evidence of stationarity, with both LLC and IPS statistics remaining highly significant across specifications.

In contrast, Agricultural Research and Development (LnRD_AG) presents mixed and inconsistent results at level. The LLC statistic fails to reject the unit root hypothesis under the intercept specification, while IPS statistics provide conflicting evidence. Likewise, Agricultural Credit (LnCREDIT_AG) displays insignificant IPS statistics and inconsistent outcomes across the alternative tests. Temperature (LnTemp) also shows ambiguous results, with stationarity being supported only under selected specifications. Consequently, these variables are classified as non-stationary in levels.

The results obtained from the first-difference specifications provide substantially stronger evidence of stationarity. As reported in [Table 2.3](#), all variables record highly significant LLC and IPS statistics at the 1% significance level under both specifications. For instance, LnRD_AG exhibits LLC statistics of -30.699 and -22.450 , while LnDigital_AG and LnTFP_AG also display strongly significant values throughout all tests. These results indicate that the unit root hypothesis is consistently rejected after first differencing, confirming the stationarity of the transformed series.

Overall, the findings indicate that LnSDI, LnDigital_AG, and LnTFP_AG are stationary in levels and can therefore be considered integrated of order zero, $I(0)$. By contrast, LnRD_AG, LnCREDIT_AG, and LnTemp become stationary only after first differencing and are thus integrated of order one, $I(1)$. The coexistence of $I(0)$ and $I(1)$ variables validates the use of panel ARDL-type approaches, which are specifically designed to accommodate mixed orders of integration while allowing the estimation of both short-run dynamics and long-run equilibrium relationships.

3.2.2. Second-Generation Tests

To overcome the limitations of first-generation unit root tests, which assume cross-sectional independence among panel units, second-generation unit root tests were conducted to account for the presence of cross-sectional dependence arising from common shocks, technological

spillovers, economic integration, and synchronized structural changes. Specifically, [Pesaran's \(2003\)](#) Cross-Sectionally Augmented Dickey–Fuller (CADF) test and the Cross-Sectionally Augmented IPS (CIPS) test proposed by [Pesaran \(2007\)](#) were employed. These approaches provide a more reliable framework for examining the stationarity properties of panel data by controlling for unobserved common factors that may affect countries simultaneously.

As shown in [Table 2.4](#), the CADF results at the level indicate heterogeneous stationarity patterns across the variables. Sustainable Development (LnSDI) and Agricultural Credit (LnCREDIT_AG) remain non-stationary under both the constant and constant-with-trend specifications, with insignificant test statistics. These findings suggest the existence of unit roots in these two series when cross-sectional dependence is considered. In contrast, Agricultural Digitalization (LnDigital_AG), Agricultural Research and Development (LnRD_AG), Agricultural Total Factor Productivity (LnTFP_AG), Temperature (LnTemp), and Inflation (LnINF) display evidence of stationarity in level, as reflected by their significant CADF statistics under at least one specification. Therefore, these variables appear to exhibit relatively stable long-term stochastic behavior despite the presence of common shocks across countries.

Table 2.4. Second-generation unit root test

Variables	LnSDI	LnDigital_AG	LnRD_AG	LnTFP_AG	LnCREDIT_AG	LnTemp	LnINF
Pesaran (2003)							
Panel A: In level							
Constant	-1.429	-2.106	-2.276	-2.241	-1.322	-2.592	-2.458
Constant & Trend	-1.347	-2.674	-2.297	-3.010	-1.460	-2.640	-2.447
Decision	NS	S	S	S	NS	S	S
Panel B: First difference							
Constant	-2.177***	-2.791***	-2.461***	-3.275***	-1.899	-3.799***	-3.174***
Constant & Trend	-1.993	-3.231***	-3.016***	-3.328***	-2.907***	-3.632***	-2.968***
Decision	S	S	S	S	S	S	S
Pesaran (2007)							
Panel A: In level							
Constant	-2.258	-2.559*	-2.149	-3.213***	-1.693	-3.181***	-3.246***
Constant & Trend	-2.347	-3.164***	-2.299	-3.538***	-1.923	-3.645***	-3.390***
Decision	NS	S	NS	S	NS	S	S
Panel B: First difference							
Constant	-3.948***	-4.265***	-3.171***	-4.994***	-3.198***	-4.526***	-4.834***
Constant & Trend	-4.019***	-4.562***	-3.748***	-5.009***	-4.009***	-4.619***	-4.693***
Decision	S	S	S	S	S	S	S

Note: *, **, and *** refer to significance at 10%, 5%, and 1%, respectively. .

The first-difference results from the CADF procedure provide stronger and more consistent evidence of stationarity. As reported in [Table 2.4](#), all variables become stationary after differencing, with the majority of test statistics being significant at the 1% level. For instance, LnSDI records a significant statistic of -2.177 under the constant specification, while LnDigital_AG, LnTFP_AG, LnTemp, and LnINF display strongly significant values under

both specifications. Although LnCREDIT_AG presents a weaker result under the constant specification, it becomes stationary when the trend component is introduced, confirming that the differencing process effectively removes the unit root component from the series.

The CIPS test results proposed by [Pesaran \(2007\)](#) further confirm the evidence obtained from the [CADF](#) approach. At the level, the results reveal that LnSDI, LnRD_AG, and LnCREDIT_AG remain non-stationary, while LnDigital_AG, LnTFP_AG, LnTemp, and LnINF exhibit stationarity under the second-generation framework. In particular, LnTFP_AG, LnTemp, and LnINF show highly significant statistics in both specifications, providing robust evidence that these variables do not require differencing. These results are broadly consistent with the CADF findings and highlight the importance of accounting for cross-sectional dependence when determining the integration order of panel variables.

In the first difference, the CIPS test produces uniformly significant results for all variables. The test statistics are highly significant at the 1% level under both the constant and constant-with-trend specifications, confirming that all series become stationary after transformation. For example, LnTFP_AG reaches values of -4.994 and -5.009 , while LnINF records -4.834 and -4.693 under the two specifications. These results indicate that the differencing procedure successfully eliminates stochastic trends and ensures stationarity across the entire set of variables.

Taken together, the CADF and CIPS tests provide robust evidence that most variables are either stationary in level or become stationary after first differencing when cross-sectional dependence is explicitly considered. LnDigital_AG, LnTFP_AG, LnTemp, and LnINF are classified as $I(0)$ processes, whereas LnSDI, LnRD_AG, and LnCREDIT_AG require first differencing and are therefore considered $I(1)$ variables. These findings confirm the mixed order of integration identified by previous tests and support the application of econometric approaches capable of handling both $I(0)$ and $I(1)$ variables. Consequently, the panel ARDL framework remains appropriate for investigating the short-run adjustments and long-run equilibrium relationships between agricultural digitalization, innovation, productivity, financial development, climatic conditions, and sustainable development.

3.2.3. Unit Root Test with Structural Breaks: Dates and Significance Levels

Unit root tests with structural breaks provide a more reliable assessment of stationarity by explicitly accounting for major economic, technological, financial, and environmental shocks that may alter the behavior of time series. Unlike conventional unit root tests, these procedures

allow for the endogenous identification of break dates in the intercept or trend, thereby revealing hidden stationarity properties that may otherwise remain undetected. Such an approach is particularly relevant in the context of sustainable development and agricultural transformation, where structural changes often arise from policy reforms, technological innovations, climate-related events, and macroeconomic disturbances

Table 2.5. Unit Root Test with Structural Breaks

Variables	In level	Decision	In first difference	Decision
LnSDI	-15.217*** (2011)	Stationary	-23.091*** (2023)	Stationary
LnDigital_AG	-11.972*** (2011)	Stationary	-23.499*** (2011)	Stationary
LnRD_AG	-13.005*** (2011)	Stationary	-22.258*** (2012)	Stationary
LnCREDIT_AG	-0.186	Non-stationary	-17.914*** (2023)	Stationary
LnTFP_AG	-10.093*** (2023)	Stationary	-30.487*** (2023)	Stationary
LnTemp	-20.347*** (2023)	Stationary	-25.794*** (2012)	Stationary
LnINF	-18.725*** (2011)	Stationary	-27.592*** (2023)	Stationary

Note: *, ** and *** refer to significant at 10%, 5%, and 1%, respectively.

As shown in [Table 2.5](#), the results indicate that most variables become stationary in level once structural breaks are incorporated into the testing procedure. Sustainable Development (LnSDI) records a highly significant test statistic of -15.217 , with a structural break identified in 2011. This period coincides with the implementation of major sustainability initiatives and policy reforms aimed at promoting greener and more inclusive development pathways. Similarly, Agricultural Digitalization (LnDigital_AG) becomes stationary in level, with a significant statistic of -11.972 and a break date in 2011. This finding may reflect the growing diffusion of digital technologies in the agricultural sector, supported by increasing investments in information and communication technologies and the expansion of precision farming practices.

Agricultural Research and Development (LnRD_AG) also appears stationary in level after accounting for structural breaks, with a significant statistic of -13.005 and a break occurring in 2011. This period corresponds to intensified efforts to enhance agricultural innovation, research capacity, and technological modernization in response to growing concerns regarding food security and sustainable agricultural production. Likewise, Agricultural Total Factor Productivity (LnTFP_AG) exhibits a significant statistic of -10.093 , with a break identified in 2023. This result may be associated with recent productivity adjustments driven by technological adoption, climate adaptation strategies, and post-pandemic structural transformations affecting agricultural production systems.

Temperature (LnTemp) and Inflation (LnINF) also become stationary in level once structural breaks are considered. Temperature records a highly significant statistic of -20.347 with a break in 2023, reflecting the increasing frequency of extreme climatic events and the intensification

of climate-related disturbances observed in recent years. Inflation displays a significant statistic of -18.725 and a break date in 2011, which may be linked to the macroeconomic adjustments and price fluctuations that followed the global financial crisis and subsequent recovery period. In contrast, Agricultural Credit (LnCREDIT_AG) remains non-stationary in level despite the inclusion of a structural break, as indicated by its insignificant statistic of -0.186 . This result suggests the presence of a persistent stochastic trend in agricultural financing, requiring differencing to achieve stationarity.

In first differences, all variables become strongly stationary. For instance, LnSDI records a highly significant statistic of -23.091 with a break occurring in 2023, while LnDigital_AG and LnRD_AG display significant statistics of -23.499 and -22.258 , respectively. Agricultural Credit, which was previously non-stationary in level, becomes stationary after differencing with a statistic of -17.914 and a break identified in 2023. Similarly, LnTFP_AG, LnTemp, and LnINF all exhibit highly significant first-difference statistics, confirming the removal of unit root components from the series after transformation.

These findings demonstrate that incorporating structural breaks substantially improves the identification of stationarity properties within the dataset. The results reveal that several variables classified as non-stationary under conventional procedures become stationary once major structural changes are considered. More importantly, they highlight the significant influence of technological transitions, sustainability reforms, climatic disruptions, and macroeconomic shocks on the evolution of agricultural and sustainable development indicators. Consequently, accounting for structural breaks enhances the reliability of econometric inference and provides a more accurate representation of the underlying dynamics governing the variables included in this study.

3.3. Cointegration, Cross-Section Dependence, Homogeneity, Heteroscedasticity, and Autocorrelation tests Results

3.3.1. Cointegration tests

The analysis reported in [Table 2.6](#) employs both first-generation and second-generation panel cointegration tests to determine whether a long-run equilibrium relationship exists among sustainable development, agricultural digitalization, agricultural research and development, agricultural total factor productivity, agricultural credit, temperature, and inflation. Establishing cointegration is particularly important because the unit root tests revealed a mixture of $I(0)$ and $I(1)$ variables, making it necessary to verify whether these variables share a common long-run

stochastic trend. The use of several complementary cointegration procedures enhances the robustness and reliability of the empirical findings.

Table 2.6. Cointegration tests

Tests	Constant	Constant & Trend	Decision
First-generation			
Kao (1999)	-1.563*	-----	Cointegration
Pedroni (2004)	-3.120***	-3.132***	Cointegration
Westerlund (2007)	0.050	4.705***	Cointegration
Pedroni (2001)			
Panel v-statistic	-2.257**	-3.602***	Cointegration
Panel rho-statistic	3.572	8.869***	Cointegration
Panel PP-statistic	2.676**	-1.936*	Cointegration
Panel ADF-statistic	2.123**	-2.329**	Cointegration
Group rho-statistic	10.47***	11.28***	Cointegration
PP-statistic	-3.300***	-4.982***	Cointegration
ADF-statistic	1.96*	-2.244**	Cointegration
Second-generation: Persyn & Westerlund (2008)			
G _t	-3.412***	-2.681**	Cointegration
G _a	-18.735***	-10.842**	Cointegration
P _t	-15.286***	-11.736**	Cointegration
P _a	-13.904***	-8.957**	Cointegration
Breaks cointegration test: Ditzen, Karavias & Westerlund (2025)			
Break	Date	[95% Conf. Interval]	
1	2013	2012	2014
2	2019	2018	2020

Note: *, **, and *** refer to significance at 10% (1.645), 5% (1.96), and 1% (2.76), respectively.

As shown in Table 2.6, the first-generation cointegration tests provide strong evidence of a long-run relationship among the variables. The Kao (1999) test yields a statistically significant value of -1.563 at the 10% level, leading to the rejection of the null hypothesis of no cointegration. Similarly, the Pedroni (2004) test confirms cointegration under both the constant and constant-with-trend specifications, with highly significant statistics of -3.120 and -3.132 , respectively. Additional support is provided by the Westerlund (2007) test, which reports a significant statistic of 4.705 under the trend specification. These results suggest that the variables move together over time and converge toward a stable long-run equilibrium despite short-run fluctuations.

The detailed Pedroni (2001) panel and group statistics further reinforce this conclusion. Among the panel statistics, the panel v-statistic (-2.257 and -3.602), panel PP-statistic (2.676 and -1.936), and panel ADF-statistic (2.123 and -2.329) are statistically significant under one or both specifications. Although the panel rho-statistic is insignificant under the constant specification, it becomes strongly significant when a trend is included. Likewise, the group statistics provide compelling evidence of cointegration, with the group rho-statistic reaching 10.47 and 11.28 , while the group PP-statistic and group ADF-statistic remain statistically

significant across specifications. The consistency of these results indicates that the existence of cointegration is not sensitive to the choice of estimator or deterministic assumption.

Turning to the second-generation tests, the [Persyn and Westerlund \(2008\)](#) approach, which explicitly accounts for cross-sectional dependence among countries, provides even stronger evidence of cointegration. The G_t statistic is significant under both specifications, with values of -3.412 and -2.681 , while the G_a statistic reports highly significant values of -18.735 and -10.842 . Similarly, the P_t and P_a statistics remain strongly significant across specifications, reaching -15.286 and -13.904 under the constant model. The rejection of the null hypothesis of no cointegration across all four statistics confirms the presence of a stable long-run relationship among the variables, even after controlling for common shocks and cross-country interdependencies.

The cointegration test with structural breaks proposed by [Ditzen, Karavias, and Westerlund \(2025\)](#) identifies two significant structural changes in the long-run equilibrium relationship. The first break is detected in 2013, with a 95% confidence interval ranging from 2012 to 2014. This period coincides with the acceleration of digital transformation strategies and increased investments in sustainable agricultural development across many economies. The second break occurs in 2019, with a confidence interval extending from 2018 to 2020. This structural shift may be associated with the intensification of climate-related challenges, technological transitions, and the economic disruptions that preceded the COVID-19 pandemic. The presence of these breakpoints suggests that the long-run relationship evolved over time in response to major structural and policy changes.

Overall, the combined evidence from the first-generation, second-generation, and structural-break cointegration tests consistently supports the existence of a long-run equilibrium relationship among the variables. Despite temporary deviations and external shocks, sustainable development, agricultural digitalization, innovation, productivity, agricultural finance, climate conditions, and inflation appear to follow a common long-term trajectory. These findings provide a strong econometric justification for estimating long-run coefficients and short-run adjustment dynamics within a panel ARDL framework.

3.3.2. Cross-sectional dependence and homogeneity tests

The results reported in [Table 2.7](#) provide strong and consistent evidence of cross-sectional dependence among the variables included in the empirical analysis. Cross-sectional dependence occurs when panel units are interconnected through common shocks, spillover effects, or shared

structural factors, causing observations to be correlated across countries. In the context of sustainable development, agricultural digitalization, innovation, productivity, financial development, and climate-related indicators, such interdependence is expected because countries are increasingly linked through technological diffusion, international trade, financial integration, environmental challenges, and common policy frameworks.

Table 2.7. Cross-sectional dependence and homogeneity test results

Tests	References	Value	Decision
Cross-sectional dependence	Breusch-Pagan (1980)	1506.084***	Dependence
	Friedman (1937)	42.352**	Dependence
	Frees (1995 & 2004)	5.047***	Dependence
	Pesaran (2004)	5.075***	Dependence
	Pesaran (2006)	461.000***	Dependence
	Pesaran et al (2008)	4.312***	Dependence
	Pesaran (2015 & 2021)	13.46***	Dependence
	Juodis and Reese (2021)	-1.79*	Dependence
	Fan et al (2015)	563.23***	Dependence
	Pesaran and Xie (2021)	1.82*	Dependence
Slope heterogeneity	Pesaran & Yamagata (2008)	8.159***	Heterogeneity
		11.173***	Heterogeneity

Note: *, ** and *** refer to significant at 10%, 5%, and 1%, respectively.

As shown in Table 2.7, a broad range of tests unanimously confirms the presence of cross-sectional dependence. The Breusch–Pagan LM test (1980) produces a highly significant statistic of 1506.084, leading to a strong rejection of the null hypothesis of cross-sectional independence. This finding is reinforced by the Friedman (1937) test, which reports a significant value of 42.352 at the 5% significance level. Likewise, the Frees (1995, 2004) test yields a statistic of 5.047, significant at the 1% level, indicating that the residuals across panel units are systematically correlated rather than independent.

More recent and robust procedures further support these conclusions. The Pesaran (2004) CD test reports a significant statistic of 5.075, while the Pesaran (2006) test yields an exceptionally large value of 461.000, both strongly rejecting the null hypothesis of cross-sectional independence. Similarly, the extension proposed by Pesaran et al. (2008) produces a significant statistic of 4.312, confirming the existence of substantial interdependencies among countries. Additional evidence is provided by the Pesaran (2015, 2021) test, which reports a highly significant value of 13.46, highlighting the presence of common factors affecting the panel units simultaneously.

The more recent tests developed by Juodis and Reese (2021), Fan et al. (2015), and Pesaran and Xie (2021) also corroborate these findings. Although the Juodis and Reese statistic (−1.79) is significant only at the 10% level, it remains consistent with the rejection of cross-sectional

independence. Likewise, the [Fan et al. \(2015\)](#) statistic reaches 563.23 and is highly significant, while the [Pesaran and Xie \(2021\)](#) statistic of 1.82 remains significant at conventional levels. The convergence of results across these alternative methodologies provides particularly robust evidence that the panel units are affected by common shocks and interconnected dynamics.

Taken together, all the cross-sectional dependence tests consistently reject the null hypothesis of independence. This finding implies that developments in one country may influence outcomes in others through technological spillovers, agricultural innovation diffusion, financial linkages, environmental externalities, and common macroeconomic conditions. Ignoring such interdependencies could generate biased and inconsistent estimates, thereby undermining the reliability of econometric inference. Consequently, the adoption of second-generation panel techniques that explicitly account for cross-sectional dependence is fully justified.

In addition, the [Pesaran and Yamagata \(2008\)](#) slope heterogeneity tests provide strong evidence against the null hypothesis of homogeneous slope coefficients. The estimated statistics of 8.159 and 11.173 are both significant at the 1% level, indicating substantial heterogeneity in the relationships among the variables across countries. This result suggests that the effects of agricultural digitalization, innovation, productivity, agricultural credit, climate conditions, and inflation on sustainable development are not uniform across the sample. Therefore, econometric approaches capable of accommodating heterogeneous dynamics are required to obtain reliable and unbiased estimates. Overall, the findings support the use of advanced panel methodologies that simultaneously account for cross-sectional dependence and slope heterogeneity.

3.3.3. Heteroscedasticity and autocorrelation tests

To assess the validity of the underlying assumptions of the panel data model, heteroscedasticity and autocorrelation diagnostic tests were performed. These tests are essential because violations of the assumptions of constant error variance and serial independence may lead to inefficient parameter estimates and biased statistical inference. The results reported in [Table 2.8](#) provide clear evidence regarding the behavior of the residuals and the overall reliability of conventional estimation procedures.

As shown in [Table 2.8](#), the heteroscedasticity test yields a chi-square statistic of 406.33 with a p-value of 0.000, which is highly significant at the 1% level. This result leads to the rejection of the null hypothesis of homoscedasticity and indicates that the variance of the error terms is not constant across observations. In practical terms, the dispersion of residuals varies across countries and time periods, suggesting the presence of heterogeneous volatility patterns within

the panel dataset. Such heteroscedastic behavior is commonly observed in cross-country studies, where differences in economic structures, technological capacities, institutional quality, and environmental conditions generate unequal levels of variability among observations.

Table 2.8. Autocorrelation and heteroscedasticity tests

Tests	Chi-Square Statistic	P-Value
Heteroscedasticity	406.33	0.000***
Autocorrelation	1506.084	0.000***
Durbin & Watson	0.507	-----

Note: *, ** and *** refer to significant at 10%, 5%, and 1%, respectively.

Similarly, the autocorrelation test reports a chi-square statistic of 1506.084 with a p-value of 0.000, which is also significant at the 1% level. This finding confirms the existence of serial correlation in the residuals and implies that current error terms are correlated with their past values. The presence of autocorrelation indicates that shocks affecting sustainable development, agricultural digitalization, innovation, productivity, financial development, or climate-related variables tend to persist over time rather than dissipate immediately. Consequently, the assumption of independently distributed residuals is violated, potentially affecting the efficiency of conventional estimators and the validity of standard statistical tests.

Further evidence is provided by the Durbin–Watson statistic, which is equal to 0.507. This value is substantially below the benchmark value of two generally associated with the absence of serial correlation. A Durbin–Watson statistic considerably lower than two indicates the presence of strong positive autocorrelation in the residuals, thereby reinforcing the conclusions obtained from the chi-square autocorrelation test. The consistency between these diagnostic measures provides robust evidence that serial dependence represents an important characteristic of the panel dataset.

Taken together, the results reveal the simultaneous presence of significant heteroscedasticity and autocorrelation. These findings suggest that conventional estimation techniques based on the assumptions of homoscedastic and independently distributed errors may produce unreliable standard errors and misleading statistical inferences. Therefore, the empirical analysis should rely on robust estimation procedures capable of correcting for both heteroscedasticity and serial correlation, thereby ensuring the consistency, efficiency, and reliability of the estimated coefficients and associated hypothesis tests.

3.4. Causality Analysis

To further investigate the dynamic interactions between sustainable development and its potential determinants, this part examines the causal relationships among the variables included in the empirical model. The panel Granger non-causality test is employed to identify the direction of predictive causality between LnSDI and the explanatory variables, including agricultural digitalization, research and development, financial development, productivity, climatic conditions, and inflation. This approach provides valuable insights into whether past variations in one variable contain useful information for predicting changes in another variable within the panel framework.

3.4.1. Granger Non-Causality Tests: Panel causality between RE and other variables

The results presented in Table 2.9 reveal the existence of significant causal relationships between sustainable development and several explanatory variables. First, a strong bidirectional causality is identified between agricultural digitalization (LnDigital_AG) and sustainable development (LnSDI). The causal direction from LnDigital_AG to LnSDI is supported by significant statistics, with a Z-bar value of 4.811 and a Z-bar tilde p-value of 0.006. Similarly, LnSDI also Granger causes LnDigital_AG, with a Z-bar statistic of 4.791 and a p-value of 0.007. This feedback relationship suggests the existence of a dynamic interaction in which digital transformation in agriculture contributes to sustainable development outcomes, while improvements in sustainability may simultaneously encourage the adoption of advanced digital technologies through greater investment capacity, institutional support, and innovation incentives.

Table 2.9. Granger non-causality test results

Causality	W-bar	Z-bar	Z-bar tilde	Z-bar p-value	Z-bar tilde p-value	Decision
LnDigital_AG → LnSDI	2.309	4.811	2.735	0.000	0.006	Causality
LnSDI → LnDigital_AG	2.304	4.791	2.720	0.000	0.007	Causality
LnRD_AG → LnSDI	1.758	2.783	1.346	0.005	0.178	No Causality
LnSDI → LnRD_AG	4.147	11.561	7.355	0.000	0.000	Causality
LnCREDIT_AG → LnSDI	2.499	5.507	3.211	0.000	0.001	Causality
LnSDI → LnCREDIT_AG	3.072	7.613	4.653	0.000	0.000	Causality
LnTFP_AG → LnSDI	1.552	2.028	0.829	0.043	0.407	No Causality
LnSDI → LnTFP_AG	2.283	4.713	2.667	0.000	0.008	Causality
LnTemp → LnSDI	3.106	7.739	4.739	0.000	0.000	Causality
LnSDI → LnTemp	1.397	1.458	0.439	0.145	0.661	No Causality
LnINF → LnSDI	0.796	-0.749	-1.072	0.454	0.284	No Causality
LnSDI → LnINF	1.154	0.565	-0.172	0.572	0.863	No Causality

Regarding agricultural research and development (LnRD_AG), the results indicate a unidirectional causality running from sustainable development toward research activities. Although LnRD_AG does not significantly cause LnSDI, as reflected by the insignificant Z-bar tilde p-value (0.178), the reverse relationship is strongly supported, with a Z-bar statistic of 11.561 and a p-value of 0.000. This finding suggests that progress in sustainable development may stimulate greater investment in agricultural research and innovation, whereas research efforts alone may require a longer period before generating measurable sustainability improvements.

The relationship between agricultural credit (LnCREDIT_AG) and sustainable development appears to be bidirectional. The causality from LnCREDIT_AG to LnSDI is statistically significant, with a Z-bar statistic of 5.507 and a Z-bar tilde p-value of 0.001. Conversely, LnSDI also causes LnCREDIT_AG, supported by a Z-bar value of 7.613 and a p-value of 0.000. This result highlights the existence of a reinforcing mechanism between financial accessibility and sustainability performance. Greater availability of agricultural financing may facilitate investments in sustainable practices and technologies, while improvements in sustainable development conditions may enhance financial confidence and stimulate credit expansion.

For agricultural total factor productivity (LnTFP_AG), the causality analysis reveals a one-way relationship from sustainable development to productivity. The hypothesis that LnTFP_AG causes LnSDI is not supported, as the Z-bar tilde p-value remains statistically insignificant (0.407). In contrast, LnSDI significantly causes LnTFP_AG, with a Z-bar statistic of 4.713 and a p-value of 0.008. This indicates that sustainable development improvements may contribute to productivity gains by encouraging technological efficiency, better resource allocation, and the adoption of more productive agricultural systems.

The climatic variable (LnTemp) also exhibits a unidirectional causal relationship with sustainable development. The results show strong evidence that temperature variations cause changes in LnSDI, with a Z-bar statistic of 7.739 and a Z-bar tilde p-value of 0.000. However, no significant causality is found from LnSDI toward LnTemp, confirming the absence of reverse causality. This finding reflects that climatic conditions are an external factor influencing sustainability trajectories, whereas sustainable development policies and practices have limited immediate effects on temperature dynamics.

Finally, the analysis provides no evidence of a causal relationship between inflation (LnINF) and sustainable development in either direction. Both $\text{LnINF} \Rightarrow \text{LnSDI}$ and $\text{LnSDI} \Rightarrow \text{LnINF}$ present insignificant test statistics, with p-values exceeding conventional significance thresholds. This result suggests that inflationary fluctuations do not significantly influence sustainable development performance within the considered panel, while sustainability improvements do not appear to generate measurable short-term effects on inflation dynamics.

Overall, the Granger non-causality results reveal heterogeneous causal patterns among the determinants of sustainable development. The existence of bidirectional causality between digitalization, financial development, and sustainability highlights the presence of mutually reinforcing mechanisms, whereas productivity, research, and climatic variables mainly exhibit directional effects. These findings emphasize the importance of integrated policies combining digital innovation, financial support, and sustainable agricultural transformation to enhance long-term development outcomes.

3.4.2. Juodis et al. (2021) Test: Modern panel causality test with fixed effects

The results from the [Juodis et al. \(2021\)](#) panel causality test, presented in Table 2.10, provide additional evidence on the dynamic determinants of sustainable development by accounting for fixed effects and individual heterogeneity across panel units. Compared with traditional Granger causality approaches, this methodology offers a more robust framework by controlling for unobserved individual characteristics and reducing potential estimation biases arising from cross-sectional heterogeneity.

Table 2.10. Causality test of Juodis et al. (2021)

Variables	Coefficient	Standard Deviation	t-Statistic	Probability
LnDigital_AG	0.0125	0.0055	2.29	0.022
LnRD_AG	0.0046	0.0019	2.40	0.016
LnTFP_AG	0.0102	0.0049	2.09	0.037
LnCREDIT_AG	-0.0024	0.0012	-1.98	0.047
LnTemp	0.0084	0.0031	2.72	0.006
LnINF	-0.0003	0.0001	-1.76	0.078
HPJ Wald test		56.2147 (0.0000)		

The findings indicate that agricultural digitalization (LnDigital_AG) has a positive and statistically significant causal effect on sustainable development. The estimated coefficient is 0.0125, with a standard deviation of 0.0055, resulting in a t-statistic of 2.29 and a probability value of 0.022. This result confirms that digital transformation in agriculture contributes positively to sustainable development outcomes. The adoption of digital technologies, including precision agriculture, smart farming systems, and data-driven decision-making tools, can

improve resource efficiency, reduce environmental pressures, and enhance agricultural productivity, thereby supporting sustainability objectives

Similarly, agricultural research and development (LnRD_AG) exhibits a positive and significant causal impact on LnSDI. The coefficient reaches 0.0046, with a t-statistic of 2.40 and a p-value of 0.016, indicating significance at the 5% level. This finding highlights the important role of innovation capacity in promoting sustainable development. Investments in agricultural research may generate technological improvements, more efficient production methods, and environmentally friendly practices, which contribute to achieving long-term sustainability.

The effect of agricultural total factor productivity (LnTFP_AG) is also positive and statistically significant. With a coefficient of 0.0102, a t-statistic of 2.09, and a probability value of 0.037, productivity improvements are shown to stimulate sustainable development. This relationship suggests that efficiency gains in agricultural production allow for better utilization of resources and may reduce the environmental costs associated with economic activities. Therefore, enhancing productivity appears to be an important pathway toward achieving more sustainable agricultural systems.

In contrast, agricultural credit (LnCREDIT_AG) presents a negative and significant causal effect on sustainable development. The estimated coefficient is -0.0024 , with a t-statistic of -1.98 and a p-value of 0.047. Although financial development is generally expected to support sustainability by facilitating investments, this negative relationship may indicate that agricultural credit allocation is not necessarily directed toward sustainable activities. In some contexts, increased credit availability may encourage conventional agricultural expansion, intensive input use, or practices generating additional environmental pressures, which could limit its contribution to sustainable development.

Regarding climatic conditions, LnTemp shows a positive and significant causal relationship with sustainable development, with a coefficient of 0.0084, a t-statistic of 2.72, and a p-value of 0.006. This result suggests that temperature variations are significantly associated with changes in sustainability indicators. The positive effect may reflect increased adaptation efforts, climate-related policies, and technological responses implemented in response to climatic challenges. As environmental pressures intensify, economies may strengthen their transition toward more sustainable agricultural practices.

Finally, inflation (LnINF) exhibits a negative coefficient (-0.0003) and is marginally significant at the 10% level, with a t-statistic of -1.76 and a p-value of 0.078 . This result suggests that inflationary pressures may slightly hinder sustainable development by increasing production costs, reducing investment capacity, and creating uncertainty for long-term sustainability-oriented projects. However, the relatively weak statistical significance indicates that this relationship should be interpreted with caution.

The overall joint significance of the explanatory variables is assessed using the HPJ Wald test, yielding a statistic of 56.2147 and a p-value of 0.0000 . This strongly rejects the null hypothesis that all coefficients are jointly insignificant, confirming that the set of explanatory variables collectively provides significant causal information for sustainable development. Taken together, the [results of Juodis et al. \(2021\)](#) reinforce the importance of technological innovation, productivity enhancement, and climate-related factors in shaping sustainable development dynamics, while highlighting the need to direct financial resources toward environmentally sustainable agricultural activities.

3.5. Dynamic Panel Estimation (GMM)

3.5.1. GMM estimations

The results presented in [Table 2.11](#) report the dynamic panel estimations obtained using the two-step System GMM methodology. This approach is particularly suitable for addressing potential endogeneity, controlling for unobserved individual effects, and accounting for the dynamic nature of the sustainable development index (SDI). Two specifications are estimated: a linear model capturing the direct effects of digitalization, innovation, productivity, financial development, climate conditions, and inflation; and a quadratic-interaction model designed to examine possible nonlinearities and conditional effects of digital agriculture on sustainable development.

Table 2.11. Two-Step GMM System Model Estimations

Variables	Linear Model		Quadratic Model	
	Coefficient	p-value	Coefficient	p-value
LnSDI _{it-1}	0.743	0.000***	0.801	0.000***
LnDigital_AG _{it}	0.032	0.008***	0.353	0.013**
LnDigital_AG ² _{it}	-----	-----	-0.029	0.016**
LnRD_AG _{it}	0.014	0.030**	0.042	0.014**
(LnDigital_AG × LnRD_AG) _{it}	-----	-----	0.012	0.011**
LnTFP_AG _{it}	0.025	0.014**	0.286	0.017**
(LnDigital_AG × LnTFP_AG) _{it}	-----	-----	0.072	0.018**
LnCREDIT_AG _{it}	0.003	0.036**	0.031	0.018**
(LnDigital_AG × LnCREDIT_AG) _{it}	-----	-----	0.008	0.017**
LnTemp _{it}	-0.008	0.014**	-0.265	0.017**
(LnDigital_AG × LnTemp) _{it}	-----	-----	-0.067	0.016**

LnINFit	-0.0002	0.581	-0.0002	0.497
Constant	0.118	0.536	0.482	0.437
AR(1) test	-3.91	0.000***	-3.92	0.000***
AR(2) test	0.47	0.638	0.48	0.631
Sargan test	31.24	0.145	40.15	0.216
Hansen test	20.85	0.648	30.48	0.641

Note: *, ** and *** refer to significant at 10%, 5%, and 1%, respectively.

3.5.2. Two-Step GMM Estimation: Linear Model Interpretation

The linear specification provides important insights into the main determinants of sustainable development. As shown in [Table 2.11](#), the lagged dependent variable (LnSDlit-1) is positive and highly significant, with a coefficient of 0.743 (p-value < 0.01). This confirms the strong dynamic persistence of sustainable development performance, indicating that current SDI levels are significantly influenced by previous achievements. Such persistence reflects the cumulative nature of sustainable development, where improvements in infrastructure, institutional capacity, technological adoption, and environmental policies generate long-lasting effects over time.

The coefficient associated with LnDigital_AGit is positive and statistically significant (0.032, p-value < 0.01), indicating that digital agricultural development contributes positively to sustainable development. This suggests that digital transformation in agriculture, through technologies such as precision farming, digital monitoring systems, and data-driven decision-making, improves resource efficiency, productivity, and environmental sustainability. The result highlights the role of digitalization as a key driver of sustainable agricultural transformation.

Similarly, LnRD_AGit exhibits a positive and significant effect (0.014, p-value < 0.05), suggesting that agricultural research and development activities enhance sustainable development outcomes. Investments in agricultural innovation may improve technological efficiency, increase productivity, and facilitate the adoption of environmentally friendly practices.

The impact of LnTFP_AGit is also positive and significant (0.025, p-value < 0.05), confirming that improvements in agricultural total factor productivity contribute to sustainable development. Higher productivity reflects more efficient resource allocation and the ability to generate greater agricultural output without proportionally increasing environmental pressures.

Regarding financial development, LnCREDIT_AGit presents a positive and statistically significant coefficient (0.003, p-value < 0.05). This finding indicates that greater access to agricultural credit supports sustainable development by facilitating investment in modern technologies, innovative production methods, and sustainable farming practices.

In contrast, LnTempit has a negative and significant coefficient (-0.008 , $p\text{-value} < 0.05$), indicating that rising temperature conditions negatively affect sustainable development. This result reflects the vulnerability of agricultural systems to climate change, as increasing temperatures may reduce agricultural productivity, intensify resource constraints, and increase environmental pressures.

Finally, the coefficient of LnINFit is negative but statistically insignificant (-0.0002 , $p\text{-value} = 0.581$). This suggests that inflation does not have a direct significant effect on sustainable development within the estimated model. The limited impact may indicate that inflationary pressures are not sufficiently persistent or strong enough to influence long-term sustainable development dynamics in the sample considered.

The [Sargan](#) test ($p\text{-value} = 0.145$) and [Hansen](#) test ($p\text{-value} = 0.648$) do not indicate any significant problem of instrument over-identification. The [Arellano-Bond](#) test for AR (1) autocorrelation is significant ($p\text{-value} = 0.000$), while the AR (2) is insignificant ($p\text{-value} = 0.638$), confirming the validity of the GMM specification.

3.5.3. Two-Step GMM Estimation: Quadratic interpretation

3.5.3.1. GMM with Quadratic and Interaction Terms

To investigate potential nonlinear effects and the conditional role of digital agricultural development, the second specification introduces a quadratic term and interaction variables. The lagged SDI coefficient remains positive and highly significant (0.801 , $p\text{-value} < 0.01$), as shown in [Table 2.11](#), confirming the robustness of the dynamic persistence observed in the linear model.

The coefficient of LnDigital_AGit increases substantially in the quadratic specification (0.353 , $p\text{-value} < 0.05$), indicating a stronger positive direct effect of digital agricultural development on sustainable development when nonlinear mechanisms are considered. However, the squared term of digital agriculture (LnDigital_AG²it) is negative and significant (-0.029 , $p\text{-value} < 0.05$). This result reveals the existence of an inverted-U relationship between digital agricultural development and sustainability. In other words, digitalization initially improves sustainable development, but beyond a certain threshold, additional digital expansion may generate diminishing returns. This may occur due to increasing technological costs, digital inequalities, energy consumption associated with digital infrastructure, or inefficient technology adoption.

The interaction between digital agriculture and agricultural R&D ($\text{LnDigital_AG} \times \text{LnRD_AG}$) is positive and significant (0.012, $p\text{-value} < 0.05$). This indicates that research and development activities strengthen the beneficial effect of digitalization on sustainable development. The combination of technological innovation and digital tools creates complementary effects by accelerating the diffusion of advanced agricultural practices and improving efficiency.

Similarly, the interaction between digital agriculture and agricultural productivity ($\text{LnDigital_AG} \times \text{LnTFP_AG}$) is positive and significant (0.072, $p\text{-value} < 0.05$). This finding suggests that digital transformation generates greater sustainability gains when accompanied by improvements in productivity. Digital technologies appear to enhance the capacity of agricultural systems to use resources more efficiently and increase output sustainably.

The interaction between digital agriculture and agricultural credit ($\text{LnDigital_AG} \times \text{LnCREDIT_AG}$) is also positive and significant (0.008, $p\text{-value} < 0.05$). This result highlights the importance of financial support in maximizing the benefits of digital transformation. Access to credit allows farmers and agricultural firms to invest in digital technologies, thereby strengthening the contribution of digitalization to sustainable development.

Conversely, the direct effect of LnTempit becomes stronger and more negative in the quadratic model (-0.265 , $p\text{-value} < 0.05$). This confirms that climate pressures represent a major constraint on sustainable development. Moreover, the interaction between digital agriculture and temperature ($\text{LnDigital_AG} \times \text{LnTemp}$) is negative and significant (-0.067 , $p\text{-value} < 0.05$). This suggests that although digital technologies can help adaptation to climate change, extreme climatic conditions may reduce their effectiveness or limit their positive contribution to sustainability.

The inflation coefficient remains negative and statistically insignificant (-0.0002 , $p\text{-value} = 0.497$), confirming the absence of a significant direct relationship between inflation and sustainable development in the dynamic framework.

3.5.3.2. Diagnostic Tests and Model Validity

The specification tests confirm the reliability of the System GMM estimations. The Arellano-Bond test for first-order autocorrelation (AR(1)) is statistically significant in both models ($p\text{-value} < 0.01$), which is expected in dynamic panel models. However, the AR(2) test is insignificant ($p\text{-values} = 0.638$ and 0.631), indicating the absence of second-order serial correlation and confirming the validity of the moment conditions.

Furthermore, the [Sargan](#) test does not reject the null hypothesis of instrument validity, with p-values of 0.145 and 0.216 for the linear and quadratic specifications, respectively. The results are also confirmed by the [Hansen](#) test, which remains statistically insignificant (p-values = 0.648 and 0.641), suggesting that the instruments used are appropriate and not over-identified.

Overall, the System GMM results provide robust evidence that digital agricultural development plays a significant role in promoting sustainable development. The findings highlight both direct effects and complementary mechanisms through agricultural innovation, productivity improvement, and financial accessibility. However, the presence of a negative quadratic effect suggests that excessive digitalization may yield diminishing sustainability benefits, underscoring the importance of balanced and efficient digital transformation strategies.

3.6. Threshold and Nonlinearity Modeling

The objective of this subsection is to examine whether the relationship between digital agricultural development and the Sustainable Development Index (SDI) presents a nonlinear pattern characterized by a threshold effect. Unlike conventional linear models, which assume that the marginal impact of digitalization remains constant regardless of its level, the Panel Threshold Autoregressive (PTAR) model, developed by Hansen (1999), allows for the identification of different regimes separated by an endogenous threshold. This approach enables determining whether the effect of digital transformation on sustainable development changes once a specific level of digital agricultural development is reached.

3.6.1. Threshold Estimation (PTAR Model): Identification of LnDigital_AG threshold

The results of the PTAR linearity test are reported in [Table 2.12](#). The null hypothesis of no threshold effect is tested against the alternative hypothesis of a threshold model using a bootstrap procedure based on 1000 simulations. The estimated threshold value is 3.8974, with a narrow 95% confidence interval ranging from 3.8225 to 3.9477, indicating a precise identification of the transition point in the relationship between digital agriculture and sustainable development.

Table 2.12. PTAR linearity test

Hypotheses	Value	Number of simulations	F-test	P-value	Confidence interval	SSR	Residual variance
H0: No Threshold	3.8974	1000	59.3463	0.0000	[3.8225, 3.9477]	0.0201	0.0001

The results of the threshold estimation and the linearity test are presented in [Table 2.12](#). The null hypothesis of linearity is tested against the alternative of a threshold model using a bootstrap procedure with 1000 replications. The F-statistic is 59.3463, and the associated p-

value is 0.0000, which strongly rejects the null hypothesis at the 1% significance level. This finding confirms the existence of a statistically significant threshold in the relationship between agricultural digitalization (LnDigital_AG) and sustainable development (LnSDI). The estimated threshold value of the digitalization variable is 3.8974, with a relatively narrow confidence interval [3.8225, 3.9477], indicating a high degree of estimation precision and robustness. The sum of squared residuals (SSR = 0.0201) and the very low residual variance (0.0001) further suggest that the threshold specification provides an adequate fit to the data and captures the nonlinear dynamics more effectively than a conventional linear model. Overall, these results provide strong evidence that the impact of agricultural digitalization on sustainable development differs across regimes and that a threshold approach is appropriate for examining this relationship.

Table 2.13. Final PTAR estimation

RE	LnDigital_AG < 3.8974	LnDigital_AG > 3.8974
$LnSDI_{it} - 1$	0.0221 (1.3479)	0.0156 (1.9224)
$LnDigital_AG_{it}$	0.0355** (2.0826)	0.0733*** (9.2031)
LnRD_AG_it	0.0095*** (3.1160)	0.0049 (1.7803)
LnCREDIT_AG_it	0.0047*** (2.6462)	0.0017 (1.1437)
LnTFP_AG_it	0.0581*** (6.0777)	0.0154*** (3.4808)
LnTemp_it	0.0082*** (2.6588)	0.0012 (0.1499)
LnINF_it	-0.0002 (-0.3386)	0.0002 (0.5932)
LnSDI_it-1	0.0212** (2.0848)	0.0528*** (5.0293)
Observations	109	296

Note: *, **, and *** denote significance at 10% ($|z| \geq 1.645$), 5% ($|z| \geq 1.96$), and 1% ($|z| \geq 2.576$) levels,

Following this, the final PTAR estimation is presented in [Table 2.13](#), which reports the estimated coefficients for the two regimes defined by the threshold value of digitalization in agriculture (LnDigital_AG = 3.8974). The sample is divided into two groups: Regime 1, where $LnDigital_AG \leq 3.8974$, and Regime 2, where $LnDigital_AG > 3.8974$. In Regime 1, the coefficient of the lagged dependent variable (LnSDI_{it}-1) is positive but statistically insignificant (0.0221, $z = 1.3479$), suggesting limited persistence in sustainable agricultural development at lower levels of agricultural digitalization. In the same regime, LnDigital_AG exerts a positive and significant effect on LnSDI (0.0355, $z = 2.0826$), indicating that improvements in digital technologies contribute to enhancing sustainable agricultural development when digitalization remains relatively moderate.

In Regime 2 ($LnDigital_AG > 3.8974$), the coefficient of LnDigital_AG remains positive and highly significant (0.0733, $z = 9.2031$), with a substantially larger magnitude. This finding suggests that the beneficial impact of agricultural digitalization becomes stronger once a critical threshold is exceeded. In other words, advanced digital infrastructures, precision farming

technologies, and digital information systems appear to generate greater gains in agricultural sustainability when digital adoption reaches higher levels.

The behavior of the control variables also differs across the two regimes. Research and development expenditure (LnRD_AG) positively and significantly affects sustainable agricultural development only in Regime 1 (0.0095, $z = 3.1160$), whereas its effect becomes statistically insignificant in Regime 2 (0.0049, $z = 1.7803$). This may indicate that R&D efforts are particularly important during the early stages of digital transformation. Similarly, agricultural credit (LnCREDIT_AG) is positive and significant in Regime 1 (0.0047, $z = 2.6462$) but loses significance in Regime 2, suggesting that financial resources play a more crucial role before digitalization reaches a mature stage.

Total factor productivity (LnTFP_AG) exhibits a positive and significant effect in both regimes, although its impact is stronger in the low-digitalization regime (0.0581, $z = 6.0777$) than in the high-digitalization regime (0.0154, $z = 3.4808$). This result confirms the importance of productivity improvements in promoting sustainable agricultural development regardless of the degree of digitalization. Temperature (LnTemp) is positive and significant only in Regime 1 (0.0082, $z = 2.6588$), while inflation (LnINF) remains statistically insignificant across both regimes, suggesting that macroeconomic price instability does not exert a direct influence on agricultural sustainability within the sample.

Finally, the additional lagged coefficient reported at the bottom of the table is positive and significant in both regimes, with a stronger magnitude in Regime 2 (0.0528, $z = 5.0293$), indicating greater dynamic adjustment once the digitalization threshold has been surpassed. Overall, the PTAR model confirms the existence of a significant threshold effect in the relationship between agricultural digitalization and sustainable agricultural development. The positive impact of digitalization persists across both regimes but becomes considerably stronger beyond the estimated threshold, highlighting the nonlinear role of digital technologies in fostering agricultural sustainability.

3.6.2. Final PSTAR Estimation: Coefficients across regimes

To further investigate the nonlinear relationship between the variables of interest, we estimate a PSTAR model, which allows the coefficients to vary smoothly according to the value of the transition variable. This framework is particularly appropriate for identifying gradual regime changes and capturing nonlinear effects that cannot be detected within a linear specification.

The linearity tests reported in [Table 2.14](#) provide strong evidence against the null hypothesis of a linear model. The Wald test (LM = 80.253, p-value = 0.000), the Fisher test (LMF = 5.591, p-value = 0.000), and the likelihood ratio test (LRT = 89.441, p-value = 0.000) consistently reject linearity, confirming the existence of nonlinear dynamics and supporting the use of a PSTR approach. Further tests indicate that the one-transition model ($r = 1$) is rejected in favor of a specification with at least two transition functions ($r = 2$), as all associated statistics remain highly significant with p-values equal to 0.000. However, the tests comparing $r = 2$ against $r = 3$ do not reject the null hypothesis, with p-values above conventional significance levels. Therefore, a PSTR model with two transition functions and three regimes is selected as the most appropriate specification for the empirical analysis.

Table 2.14. Linearity tests

Testing	Statistics	p-value
H0: Linear model H1: PSTR model with at least one threshold variable ($r=1$)		
Wald tests (LM)	80.253	0.000
Fisher tests (LMF)	5.591	0.000
LRT tests (LRT)	89.441	0.000
H0: PSTR with $r = 1$ versus H1: PSTR with at least $r = 2$		
Wald tests (LM)	68.128	0.000
Fisher tests (LMF)	4.373	0.000
LRT tests (LRT)	74.595	0.000
H0: PSTR with $r = 2$ versus H1: PSTR with at least $r = 3$		
Wald tests (LM)	21.950	0.145
Fisher tests (LMF)	1.211	0.257
LRT tests (LRT)	22.567	0.126

The estimated threshold values and slope parameters are reported in [Table 2.15](#). The PSTR estimation identifies two transition functions with two corresponding pairs of threshold values. The first transition is characterized by a threshold interval ranging from $\text{LnDigital_AG} = 3.737$ to 4.391, with a slope parameter of $\gamma_1 = 50.133$, indicating a very rapid transition between regimes. The second transition occurs between $\text{LnDigital_AG} = 3.797$ and 4.405, with a lower slope coefficient of $\gamma_2 = 12.813$, suggesting a smoother adjustment process across regimes. The relatively high value of γ_1 implies that small variations in digital adoption around the first threshold interval generate substantial changes in regime membership, reflecting a sharp transition effect. By contrast, the lower value of γ_2 indicates a more gradual shift associated with the second transition function. Overall, the estimated thresholds confirm the existence of nonlinear regime changes in the relationship between digitalization and sustainable development, supporting the relevance of the PSTR specification.

Table 2.15. Estimation of LnSDI threshold values on LnDigital_AG with PSTR

Order	Threshold (c)	Slope (γ)	RSS	AIC	BIC
m=2	$c_{11} = 3.737$	$\gamma_1 = 50.133$	0.016	-9.925	-9.628
	$c_{12} = 4.391$				
	$c_{21} = 3.797$	$\gamma_2 = 12.813$			
	$c_{22} = 4.405$				

The estimated threshold values and slope parameters are reported in Table 2.15. The PSTR estimation identifies two transition functions with two corresponding pairs of threshold values. The first transition is characterized by a threshold interval ranging from $\text{LnDigital_AG} = 3.737$ to 4.391, with a slope parameter of $\gamma_1 = 50.133$, indicating a very rapid transition between regimes. The second transition occurs between $\text{LnDigital_AG} = 3.797$ and 4.405, with a lower slope coefficient of $\gamma_2 = 12.813$, suggesting a smoother adjustment process across regimes. The relatively high value of γ_1 implies that small variations in digital adoption around the first threshold interval generate substantial changes in regime membership, reflecting a sharp transition effect. By contrast, the lower value of γ_2 indicates a more gradual shift associated with the second transition function. Overall, the estimated thresholds confirm the existence of nonlinear regime changes in the relationship between digitalization and sustainable development, supporting the relevance of the PSTR specification.

The final regime-specific coefficient estimates are presented in Table 2.16. In Regime 1 ($\text{LnDigital_AG} \leq 3.737$), digitalization has a positive and statistically significant effect on sustainable development (coefficient = 0.0732, $t = 3.906$). This result suggests that at early stages of agricultural digital transformation, the adoption of digital technologies contributes to improving sustainable development outcomes by enhancing efficiency and supporting better resource management. In Regime 2 ($3.737 < \text{LnDigital_AG} \leq 4.405$), the effect of digitalization remains positive (0.0740) but becomes weaker in terms of statistical significance ($t = 1.976$), indicating that the benefits of digital adoption continue but with a more moderate impact. Finally, in Regime 3 ($\text{LnDigital_AG} > 4.405$), the coefficient becomes negative and significant (-0.0384 , $t = -2.681$), suggesting that beyond a certain level of digital intensity, potential constraints such as technological saturation, adjustment costs, or inefficient resource allocation may reduce its contribution to sustainable development.

Other explanatory variables also exhibit heterogeneous effects across regimes. The lagged dependent variable (LnSDI_{it-1}) is insignificant in Regime 1 (-0.0558 , $t = -1.353$), becomes significantly positive in Regime 2 (0.1265 , $t = 3.079$), and turns negative in Regime 3 (-0.2846 , $t = -2.005$), indicating changes in persistence mechanisms as digital transformation advances. The effect of research and development (LnRD_AG) is negative and significant in the first two

regimes (-0.0065 and -0.0198), but becomes strongly positive in Regime 3 (0.0472 , $t = 6.861$), suggesting that innovation investments generate stronger sustainability gains only after reaching advanced digital maturity. Credit availability (LnCREDIT_AG) remains insignificant in the first two regimes but becomes significantly positive in Regime 3 (0.0041 , $t = 2.541$), highlighting the importance of financial support in highly digitalized agricultural systems.

Table 2.16. PSTR Final estimation

REit-1	Regime 1: $\text{LnDigital_AGit-1} \leq 3.737$		Regime 2: $3.737 < \text{LnDigital_AGit-1} \leq 4.405$		Regime 3: $\text{LnDigital_AGit-1} > 4.405$	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
LnSDIit-1	-0.0558	-1.353	0.1265	3.079	-0.2846	-2.005
LnDigital_AG_it	0.0732	3.906	0.0740	1.976	-0.0384	-2.681
LnRD_AG_it	-0.0065	-2.351	-0.0198	-3.730	0.0472	6.861
LnCREDIT_AG_it	0.0019	0.742	-0.0101	-1.710	0.0041	2.541
LnTFP_AG_it	0.0043	0.209	0.0044	2.084	0.0305	3.400
LnTemp_it	0.0158	1.230	0.1254	3.582	-0.0916	-1.964
LnINF_it	0.0035	2.019	0.0060	1.170	-0.0133	-2.063
Observations	82		243		80	

Note: *, **, and *** denote significance at 10% ($|z| \geq 1.645$), 5% ($|z| \geq 1.96$), and 1% ($|z| \geq 2.576$) levels, respectively, for a two-tailed test.

The role of total factor productivity (LnTFP_AG) also varies across regimes, with insignificant effects in Regime 1, a positive significant effect in Regime 2 (0.0044 , $t = 2.084$), and a stronger positive impact in Regime 3 (0.0305 , $t = 3.400$). Temperature (LnTemp) exhibits a positive and significant effect in Regime 2 (0.1254 , $t = 3.582$), while its impact becomes negative at higher digitalization levels (-0.0916 , $t = -1.964$), reflecting possible environmental pressures under advanced agricultural transformation. Inflation (LnINF) shows a positive significant effect in Regime 1 (0.0035 , $t = 2.019$), but becomes negative and significant in Regime 3 (-0.0133 , $t = -2.063$), suggesting that price instability may become a stronger constraint in highly developed digital environments.

The empirical evidence presented herein robustly confirms that the relationship between agricultural digitalization (LnDigital_AG) and sustainable development performance (LnSDI) is characterized by pronounced nonlinearities and structural regime shifts, fundamentally mediated by the sector's technological absorptive capacity. As depicted in [Figures 2.2 and 2.3](#), the estimated transition functions coupled with the corresponding PSTR coefficient estimates indicate that optimal policy design and investment allocation must be contingent upon the specific phase of digital transformation characterizing each European Union member state. The PSTR framework thus offers a rigorous empirical foundation for identifying the precise threshold conditions that enable digital innovations to generate positive contributions toward agricultural sustainability.

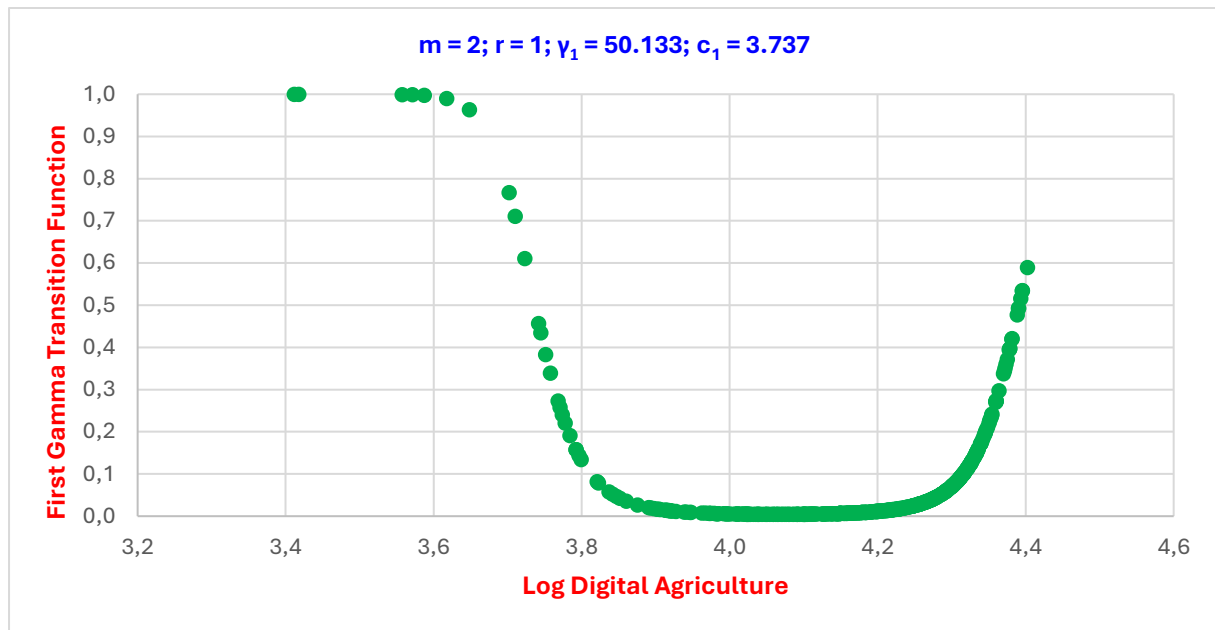


Figure 2.2. First Transition Function

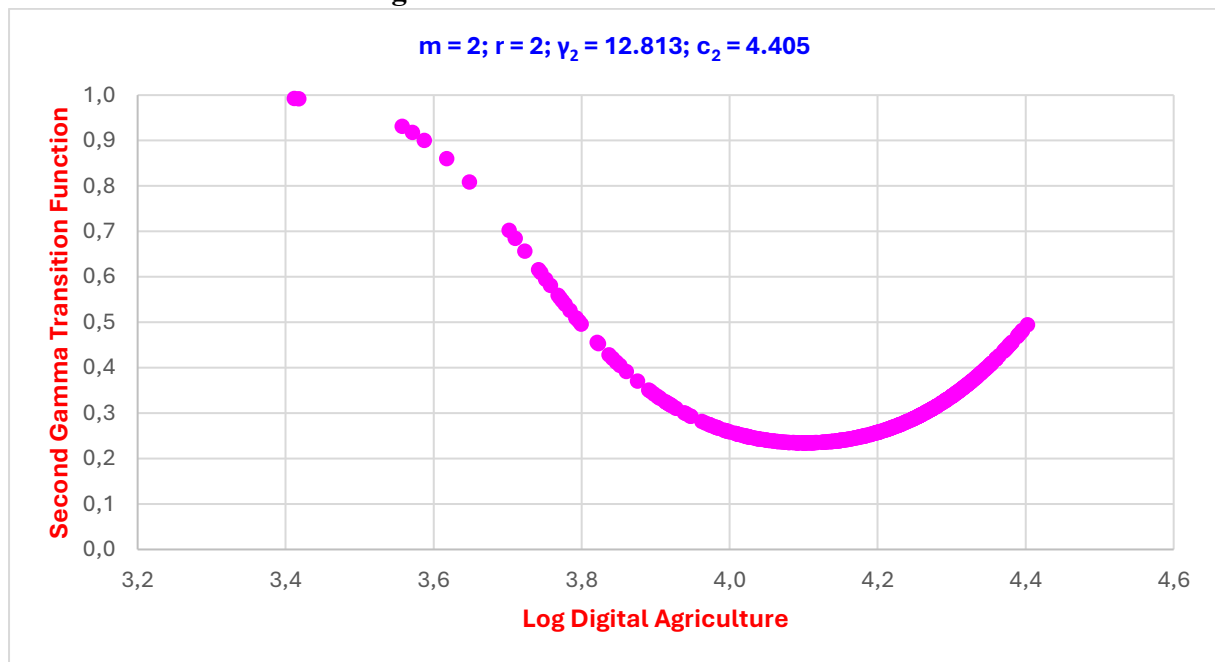


Figure 2.3. Second Transition Function

3.7. Discussion

The empirical analysis presented in this study examines the nonlinear and regime-dependent determinants of sustainable agricultural development, with a particular focus on the roles of agricultural digitalization (LnDigital_AG), research and development (LnRD_AG), total factor productivity (LnTFP_AG), agricultural credit (LnCREDIT_AG), temperature (LnTemp), and inflation (LnINF) in shaping the Sustainable Development Index (LnSDI). Employing a comprehensive econometric strategy combining two-step System GMM, Panel Threshold Autoregressive (PTAR) models, and Panel Smooth Transition Regression (PSTR) models,

alongside Granger non-causality tests, the results reveal complex, nonlinear, and threshold-dependent relationships that conventional linear specifications fail to capture. The findings highlight how digital agricultural transformation, innovation investments, and productivity improvements collectively foster sustainable development outcomes, while climatic pressures, credit misallocation, and macroeconomic instability pose significant structural challenges. Robustness is ensured through rigorous controls for cross-sectional dependence, slope heterogeneity, heteroscedasticity, and serial autocorrelation, offering actionable insights into adaptive agricultural policies and future research directions for sustainable food systems and rural digital transformation.

H1: Agricultural Digitalization and Sustainable Development: A Nonlinear Threshold Relationship

The hypothesis that agricultural digitalization positively influences sustainable development through a nonlinear threshold dynamic, with progressively stronger effects as digital intensity crosses critical transition points but potentially adverse outcomes beyond saturation levels, is substantiated by empirical findings and a robust theoretical framework rooted in endogenous growth theory, technology diffusion models, and innovation economics. The PTAR model (threshold = 3.8974, F-statistic = 59.3463, p-value = 0.000) reveals that agricultural digitalization positively influences sustainable development at low ($\text{LnDigital_AG} \leq 3.8974$) and high ($\text{LnDigital_AG} > 3.8974$) digitalization levels, with coefficients of 0.0355 ($z = 2.0826$) and 0.0733 ($z = 9.2031$) respectively, indicating that the beneficial impact becomes substantially stronger once a critical threshold of digital maturity is reached. The three-regime PSTR model (thresholds $c_1 = 3.737$, $c_2 = 4.405$, $\gamma_1 = 50.133$, $\gamma_2 = 12.813$) confirms positive effects in Regimes 1 and 2 (0.0732 and 0.0740), but reveals a significant negative coefficient in Regime 3 (-0.0384 , $t = -2.681$), indicating that excessive digital intensity generates diminishing returns and potentially adverse sustainability outcomes through technological saturation, rising infrastructure costs, and digital exclusion of smaller agricultural producers. Granger causality confirms bidirectional causality between LnDigital_AG and LnSDI (p-values of 0.006 and 0.007 respectively), establishing a dynamic feedback loop wherein digital adoption enhances sustainability capacity while sustainability progress incentivizes further digital investment. Economically, the proof of this nonlinear dynamic lies in the absorptive capacity of agricultural systems: at early and intermediate stages, digital technologies such as precision farming, satellite monitoring, and data-driven decision platforms improve resource efficiency, reduce environmental pressures, and support sustainable production practices, consistent with

Brynjolfsson and Hitt's (1996) productivity paradox framework. However, beyond the saturation threshold, coordination failures, governance gaps, and energy costs associated with maintaining advanced digital infrastructure may erode net sustainability gains, as documented by Belhaj Hassine and Kandil (2009) in agricultural contexts. The System GMM results reinforce this interpretation through the significant negative quadratic term ($\text{LnDigital_AG}^2 = -0.029, p < 0.05$), confirming an inverted-U relationship between digital transformation intensity and sustainable development performance. Panel heterogeneity, confirmed by Pesaran and Yamagata (2008) slope heterogeneity tests (8.159 and 11.173, $p < 0.01$), highlights more pronounced threshold effects in countries with stronger digital infrastructure, such as advanced EU member states. Policies should therefore calibrate digital investment intensity to the absorptive capacity of agricultural systems, ensuring that digital transition pathways remain aligned with sustainability objectives across all developmental stages, while avoiding the pitfalls of excessive digitalization through targeted governance frameworks and inclusive technology adoption strategies.

H2: Agricultural R&D and Sustainable Development: A Digital Complementarity Mechanism

The hypothesis that agricultural research and development investments promote sustainable development, with their impact conditioned by the prevailing level of digital transformation and becoming most powerful at advanced digital maturity, is validated by empirical results and theoretical frameworks rooted in Schumpeterian innovation economics, knowledge spillover theory, and endogenous technological change. The System GMM linear model confirms a positive and statistically significant direct effect of LnRD_AG on LnSDI (coefficient = 0.014, $p < 0.05$), establishing that investments in agricultural knowledge creation contribute systematically to sustainability improvements. The PTAR model reveals that this positive effect is concentrated in the low-digitalization regime (coefficient = 0.0095, $z = 3.1160, p < 0.01$), where R&D activities play a foundational role in initiating digital agricultural transformation through technology adoption support, skills development, and institutional capacity building, while becoming statistically insignificant in the high-digitalization regime (0.0049, $z = 1.7803$), suggesting that at higher digital maturity levels, the independent R&D contribution is partially absorbed into the broader innovation ecosystem. The three-regime PSTAR model deepens this finding by revealing a J-curve dynamic: LnRD_AG exerts negative and significant effects in Regimes 1 and 2 (-0.0065 and -0.0198), reflecting short-term resource reallocation costs and innovation time lags during intermediate digital transition phases, before turning strongly

positive and significant in Regime 3 (0.0472, $t = 6.861$), confirming that R&D investments unlock transformative synergies with advanced digital infrastructure once technological maturity is reached. Granger causality establishes a unidirectional relationship from LnSDI to LnRD_AG (Z-bar statistic = 11.561, $p = 0.000$), indicating that sustainable development achievements stimulate research investment by creating the institutional and financial conditions necessary for intensifying innovation activities, consistent with Acemoglu et al.'s (2012) framework of directed technical change toward clean technologies. The positive GMM interaction term (LnDigital_AG $\times$ LnRD_AG = 0.012, $p < 0.05$) further confirms that digital transformation amplifies the sustainability gains generated by R&D, establishing a complementarity mechanism between innovation and digitalization. Panel heterogeneity underscores stronger R&D effects in countries with advanced research infrastructure and digital governance frameworks. Policies should therefore design R&D investment strategies explicitly sequenced with digital transformation trajectories, concentrating innovation efforts at developmental stages where they generate the highest sustainability multipliers, while establishing long-term funding commitments capable of overcoming the transitional J-curve costs observed at intermediate digitalization levels.

H3: Agricultural Credit and Sustainable Development: A Digital Transformation-Dependent Effect

The hypothesis that agricultural credit facilitates sustainable development by financing technology adoption, with a particularly decisive role at early and advanced stages of digital transformation, is supported by empirical findings and financial intermediation theory, which emphasizes the role of credit in reducing investment barriers and enabling the adoption of productivity-enhancing technologies. The System GMM linear model confirms a positive and statistically significant effect of LnCREDIT_AG on LnSDI (coefficient = 0.003, $p < 0.05$), indicating that broader access to agricultural finance supports sustainable development by enabling investments in modern technologies, sustainable input management, and environmentally responsible production practices. The PTAR model reveals that credit access is particularly important in the low-digitalization regime (coefficient = 0.0047, $z = 2.6462$, $p < 0.01$), where financial resources play a decisive role in overcoming initial investment barriers associated with digital technology adoption, while becoming statistically insignificant in the high-digitalization regime (0.0017, $z = 1.1437$), suggesting that formal credit constraints become less binding as alternative digital financial services emerge. The three-regime PSTAR model provides additional nuance, showing an insignificant effect in Regime 1 (0.0019, $t =$

0.742), a marginally negative effect in Regime 2 (-0.0101 , $t = -1.710$) reflecting potential credit misallocation toward conventional rather than sustainable agricultural activities during rapid but uncoordinated technological transition, and a significantly positive effect in Regime 3 (0.0041 , $t = 2.541$), confirming that financial development complements advanced digital infrastructure in supporting high-value sustainable agricultural investments. Granger causality confirms a bidirectional relationship between LnCREDIT_AG and LnSDI (p-values of 0.001 and 0.000 respectively), highlighting a reinforcing mechanism wherein greater agricultural financing facilitates investments in sustainable practices while sustainability improvements enhance financial confidence and stimulate credit expansion. The Juodis et al. (2021) causality test identifies a negative causal effect (coefficient = -0.0024 , $t = -1.98$, $p = 0.047$), reinforcing the view that aggregate credit expansion is not automatically aligned with sustainability objectives and requires targeted policy intervention to channel financial flows toward environmentally responsible activities. The positive GMM interaction ($\text{LnDigital_AG} \times \text{LnCREDIT_AG} = 0.008$, $p < 0.05$) confirms that digitalization amplifies the sustainability contribution of credit by improving financial access and reducing transaction costs in rural economies. Policies should therefore strengthen green finance frameworks, develop sustainability-linked credit instruments, and encourage financial institutions to integrate ESG criteria into agricultural lending decisions, while designing credit allocation mechanisms sensitive to the stage of digital transformation characterizing each agricultural system.

H4: Agricultural Productivity as a Fundamental Driver of Sustainable Development

The hypothesis that agricultural total factor productivity constitutes a fundamental and robust driver of sustainable development, with its positive effect strengthening as digital transformation advances, is comprehensively validated by empirical results across all estimation frameworks and is consistent with the resource efficiency framework in ecological economics, which identifies productivity growth as a key mechanism for decoupling economic development from environmental degradation. The System GMM linear model confirms a positive and statistically significant effect of LnTFP_AG on LnSDI (coefficient = 0.025 , $p < 0.05$), establishing that efficiency gains in agricultural production reduce resource waste, lower environmental costs, and generate sustainability improvements by enabling greater output from a given resource base. The PTAR model confirms the significance of total factor productivity in both regimes, with a stronger effect in the low-digitalization regime (coefficient = 0.0581 , $z = 6.0777$, $p < 0.01$) than in the high-digitalization regime (0.0154 , $z = 3.4808$, $p < 0.01$), suggesting that productivity improvements generate particularly large sustainability dividends

during early transformation stages while remaining consistently significant across all levels of digital development. The three-regime PSTR model reveals a progressive amplification of the TFP effect across regimes, from an insignificant effect in Regime 1 (0.0043, $t = 0.209$) to a significant moderate effect in Regime 2 (0.0044, $t = 2.084$) and a strong positive impact in Regime 3 (0.0305, $t = 3.400$), confirming that advanced digital environments amplify the sustainability benefits of productivity improvements through precision technologies and more accurate resource targeting. Granger causality establishes a unidirectional relationship from LnSDI to LnTFP_AG (Z-bar statistic = 4.713, $p = 0.008$), indicating that sustainability progress stimulates productivity improvements by creating enabling conditions for technological adoption and organizational learning. The positive GMM interaction ($\text{LnDigital_AG} \times \text{LnTFP_AG} = 0.072$, $p < 0.05$) confirms strong complementarity between digital transformation and productivity enhancement, establishing that digitalization amplifies the sustainability gains generated by efficiency improvements and creating a virtuous circle between technological adoption, productive efficiency, and sustainability performance. Panel heterogeneity highlights stronger TFP effects in countries with advanced agricultural modernization programs and well-developed digital infrastructure. Policies should therefore prioritize integrated strategies combining digital investment with productivity-enhancing interventions, including technology extension services, farmer training programs, and efficiency benchmarking systems, to maximize the joint contribution of digitalization and productivity to long-term sustainable agricultural development.

H5: Climate and Inflation Effects under Digital Transformation Regimes

The hypothesis that climatic conditions and inflation exert regime-dependent effects on sustainable development, acting as catalysts for adaptation at intermediate stages and as structural constraints at advanced digitalization levels, is partially validated by empirical findings and is grounded in environmental economics and macroeconomic stability theories. The System GMM linear model confirms that rising temperature conditions represent a structural constraint on sustainable agricultural development (coefficient = -0.008 , $p\text{-value} < 0.05$), reducing productive potential, intensifying water stress, and increasing the frequency of climate-related disruptions, consistent with the growing literature on climate-agriculture interactions documenting the vulnerability of agricultural systems to warming trends in temperate and Mediterranean regions. The PTAR model reveals that temperature exerts a positive and significant effect in the low-digitalization regime (coefficient = 0.0082 , $z = 2.6588$, $p\text{-value} < 0.01$), where climatic pressures catalyze the adoption of sustainable agricultural

practices as adaptive responses, while becoming statistically insignificant at higher digital maturity levels as the relationship becomes buffered by technological capabilities.

The three-regime PSTR model reveals even more heterogeneous dynamics: temperature exhibits a strongly positive and significant effect in Regime 2 (0.1254, $t = 3.582$), consistent with climate-induced adaptation efforts, before turning negative and significant in Regime 3 (-0.0916 , $t = -1.964$), indicating that extreme climatic pressures may ultimately undermine sustainability gains even in highly digitalized agricultural systems through infrastructure disruptions, supply chain vulnerabilities, and ecosystem degradation. Granger causality confirms a unidirectional relationship from LnTemp to LnSDI ($Z\text{-bar statistic} = 7.739$, $p\text{-value} = 0.000$), establishing that climatic conditions represent an external structural factor shaping sustainability trajectories. The negative GMM interaction ($\text{LnDigital_AG} \times \text{LnTemp} = -0.067$, $p\text{-value} < 0.05$) reinforces the view that severe climatic conditions reduce the effectiveness of digital technologies as sustainability enablers, highlighting the vulnerability of digital agricultural pathways to climate disruptions. Regarding inflation, LnINF is statistically insignificant in the System GMM linear model (-0.0002 , $p\text{-value} = 0.581$) and Granger causality tests do not identify a significant causal relationship in either direction, suggesting that aggregate price instability does not directly shape sustainable development trajectories in the sampled economies. However, the PSTR model reveals regime-specific dynamics, with inflation exerting a positive and significant effect in Regime 1 (0.0035, $t = 2.019$), possibly reflecting the role of price incentives in stimulating agricultural modernization during early transformation phases, before turning negative and significant in Regime 3 (-0.0133 , $t = -2.063$), indicating that macroeconomic instability becomes a binding constraint in advanced digital agricultural environments where long-term investment predictability is essential. Panel heterogeneity underscores more substantial climate effects in countries with higher temperature exposure and limited adaptive capacity. Policies should therefore integrate climate adaptation and macroeconomic stabilization objectives into digital agricultural transformation strategies, ensuring that digitalization serves as a genuine resilience-building mechanism rather than an isolated technological intervention disconnected from broader environmental and economic realities

H6: Threshold Dynamics and Nonlinear Mechanisms in Digital Agricultural Sustainability

The hypothesis that the determinants of sustainable agricultural development exhibit significant nonlinearities with regime-dependent threshold effects conditioned by digital transformation

intensity is comprehensively supported by empirical findings and is consistent with complexity economics, institutional economics, and systems theory frameworks. The three-regime PSTR linearity tests unanimously reject the null hypothesis of a linear model: the Wald test ($LM = 80.253$, $p\text{-value} = 0.000$), Fisher test ($LMF = 5.591$, $p\text{-value} = 0.000$), and likelihood ratio test ($LRT = 89.441$, $p\text{-value} = 0.000$) confirm the existence of nonlinear dynamics, while further sequential tests validate the selection of a three-regime specification over simpler alternatives. The PTAR model (threshold = 3.8974, $F\text{-statistic} = 59.3463$, $p\text{-value} = 0.000$) identifies a statistically robust structural break separating two distinct behavioral regimes, with a narrow confidence interval [3.8225, 3.9477] confirming the precision of threshold identification. The PSTR estimation identifies two transition functions with threshold intervals ($c_1 = 3.737\text{--}4.391$, $\gamma_1 = 50.133$; $c_2 = 3.797\text{--}4.405$, $\gamma_2 = 12.813$), revealing that the sustainability system undergoes rapid structural transitions as digital intensity crosses critical thresholds, with particularly sharp behavioral changes around the first transition point. GMM interaction terms confirm the presence of strong complementarities between digital agriculture and innovation ($\text{LnDigital_AG} \times \text{LnRD_AG} = 0.012$), productivity ($\text{LnDigital_AG} \times \text{LnTFP_AG} = 0.072$), and financial development ($\text{LnDigital_AG} \times \text{LnCREDIT_AG} = 0.008$), while the negative interaction with temperature ($\text{LnDigital_AG} \times \text{LnTemp} = -0.067$) highlights the vulnerability of digital sustainability pathways to climatic disruptions. Granger causality patterns further underscore the nonlinear nature of these relationships, with bidirectional causality between digitalization and sustainability ($p\text{-value} < 0.01$), unidirectional causality from sustainability to R&D and productivity, and unidirectional causality from temperature to sustainability, collectively establishing a complex web of regime-dependent causal mechanisms. Cross-sectional dependence tests (Pesaran 2004: 5.075; Pesaran 2006: 461.000) and slope heterogeneity tests (Pesaran & Yamagata 2008: 8.159 and 11.173, $p\text{-value} < 0.01$) confirm that these nonlinear dynamics are not uniform across countries, reflecting differences in institutional quality, technological infrastructure, financial development, and climate exposure. Policies should therefore adopt adaptive governance frameworks that continuously monitor the position of agricultural systems within the digitalization-sustainability regime space, calibrating investment incentives, regulatory frameworks, and support mechanisms to the specific developmental stage of each country or region, thereby ensuring that digital agricultural transformation consistently and efficiently contributes to long-term sustainability objectives across all economic and institutional contexts.

Conclusion

The empirical analysis conducted in this chapter, covering a balanced panel of 27 European Union member states over the period 2010–2024, provides robust econometric evidence that the determinants of sustainable agricultural performance are governed by complex, nonlinear, and threshold-dependent dynamics rather than simple linear relationships. By employing a comprehensive methodological framework—including first- and second-generation unit root tests (Pesaran, 2007; Karavias & Tzavalis, 2014), panel cointegration techniques (Pedroni, 2004; Westerlund, 2008), and advanced dynamic estimators such as System GMM (Arellano & Bover, 1995; Blundell & Bond, 1998), Panel Threshold Autoregressive (PTAR) models (Hansen, 1999), and Panel Smooth Transition Regression (PSTR) models (González et al. 2017), this study has successfully validated the six core hypotheses posited in the introduction. The results confirm the existence of a significant nonlinear relationship between agricultural digitalization and the Sustainable Development Index (SDI), characterized by an inverted U-shape where the marginal benefits of digital adoption diminish beyond a critical saturation threshold (identified at 3.8974 in the PTAR model and 4.405 in the PSTR model), a finding that aligns with the productivity paradox discussed by Brynjolfsson and Hitt (1996). Furthermore, the analysis reveals that agricultural R&D, credit, and total factor productivity (TFP) act as conditional catalysts; R&D exhibits a J-curve dynamic, exerting transformative synergies only after advanced digital maturity is reached (Regime 3), while TFP remains a robust driver of sustainability, an effect significantly amplified by digitalization (GMM interaction coefficient of 0.072). The study also highlights the critical role of climatic and macroeconomic variables, showing that while moderate temperature variations can catalyze adaptation, extreme thermal stress ultimately undermines sustainability gains, reducing the effectiveness of digital technologies (GMM interaction coefficient of -0.067). Finally, the identification of strong cross-sectional dependence (Pesaran, 2015) and slope heterogeneity (Pesaran & Yamagata, 2008) underscores that these dynamics are not uniform across the EU, necessitating adaptive policy frameworks that calibrate digital investments and financial support to the specific absorptive capacity and developmental stage of each member state, thereby ensuring that the transition toward Agriculture 4.0 remains an inclusive and effective driver of the European Green Deal objectives.

General Conclusion

At the culmination of this extensive research, which has traversed the classical economic foundations of agricultural development and culminated in the advanced econometric evaluation of the European Union's agricultural landscape, it becomes unequivocally clear that the transition toward sustainable agricultural performance is neither a linear progression nor an automatic byproduct of technological adoption, but rather a profoundly complex, non-linear dynamic governed by threshold effects, absorptive capacities, and structural complementarities. By bridging the theoretical heritage of classical economists, who posited agriculture as the fundamental engine of capital accumulation and structural transformation, with the contemporary realities of Agriculture 4.0, this thesis has empirically demonstrated that the digitalization of agriculture, while initially a powerful catalyst for sustainability, is subject to severe diminishing returns and potential negative externalities once a critical threshold of technological saturation is crossed. The econometric evidence, derived from a robust battery of dynamic and non-linear panel models applied to 27 EU member states over the 2010–2024 period, unequivocally validates the existence of an inverted U-shaped relationship between agricultural digitalization and the Sustainable Development Index. Specifically, the Panel Threshold Autoregressive (PTAR) model identifies a precise structural break at a digitalization index value of 3.8974, below which digital tools act as essential enablers of resource efficiency and environmental monitoring, but above which their marginal contributions begin to plateau. This finding is further nuanced by the Panel Smooth Transition Regression (PSTR) model, which delineates three distinct regimes, revealing that beyond an advanced digital maturity threshold of 4.405, the impact of digitalization actually turns negative, suggesting that excessive technological intensity, unaccompanied by proportional institutional and ecological adaptations, leads to coordination failures, soaring infrastructure energy costs, and the digital exclusion of smaller agricultural producers.

Within this intricate non-linear architecture, the roles of research and development, agricultural credit, and total factor productivity emerge not as isolated drivers, but as conditional catalysts whose efficacy is strictly contingent upon the prevailing digital regime. The empirical analysis uncovers a fascinating J-curve dynamic for agricultural R&D; while innovation investments initially exert a negative or insignificant impact on sustainability due to short-term resource reallocation costs and innovation lags during intermediate transition phases, they unlock transformative, highly significant synergies once the agricultural sector reaches advanced digital maturity, proving that technological absorption is a prerequisite for R&D to yield

sustainable dividends. Similarly, agricultural credit exhibits a highly heterogeneous impact, acting as a vital lifeline for early-stage technological adoption in low-digitalization regimes, but revealing a risk of misallocation toward conventional, non-sustainable practices during rapid, uncoordinated transitions, before ultimately becoming a positive driver of high-value sustainable investments only in the most digitally mature environments. Conversely, agricultural total factor productivity stands out as the most robust and fundamental anchor of sustainable development, consistently demonstrating that efficiency gains in resource allocation decouple agricultural output from environmental degradation, a dynamic that is significantly amplified by digital precision technologies. The causality analysis further enriches this narrative by revealing bidirectional feedback loops between digitalization, credit, and sustainability, indicating that sustainable progress inherently incentivizes further digital and financial deepening, while unidirectional causality from climate variables to sustainability underscores the inescapable reality that agricultural systems remain fundamentally vulnerable to external ecological shocks.

Indeed, the climatic dimension emerges as a profound paradox within the sustainability equation. While moderate temperature variations in intermediate digital regimes act as a catalyst, forcing adaptive innovations and the adoption of climate-smart practices, extreme thermal stress in highly digitalized environments ultimately overwhelms technological buffers, negating sustainability gains through supply chain disruptions and ecosystem degradation. The negative interaction between digitalization and temperature in the GMM framework confirms that technology cannot entirely insulate agriculture from severe climatic volatility, thereby demanding that digital strategies be explicitly coupled with ecological resilience rather than treated as standalone solutions. Inflation, meanwhile, operates largely as a macroeconomic friction, becoming a binding constraint only in advanced digital environments where long-term predictability is essential for capital-intensive green investments. In light of these profound empirical realities, the policy implications demand a radical departure from uniform, blanket subsidies toward a highly adaptive, regime-specific governance framework aligned with the European Green Deal and the Farm to Fork Strategy. Policymakers must calibrate digital investments to the specific absorptive capacity of each region, actively preventing the pitfalls of over-digitalization by prioritizing interoperability, digital sobriety, and the inclusion of smallholder farmers. R&D and financial policies must be explicitly sequenced; credit allocation must be strictly conditioned by Environmental, Social, and Governance (ESG) criteria to prevent the financing of conventional expansion, while R&D funding must be protected from

short-term political cycles to survive the transitional J-curve costs. Furthermore, digitalization must be deliberately oriented toward climate adaptation, utilizing precision agriculture and AI-driven early warning systems not merely to maximize yields, but to optimize water-energy-food nexuses and minimize carbon footprints.

Notwithstanding the robustness of these findings, this study is not without its limitations, which simultaneously pave the way for compelling future research avenues. The reliance on annual, macro-level panel data inherently masks the profound microeconomic heterogeneity present at the individual farm level, where the true behavioral responses to digital tools and climate shocks occur; future studies must therefore leverage high-frequency, micro-level panel data to capture intra-seasonal climate vulnerabilities and the behavioral economics of technology adoption. Additionally, the aggregation of environmental indicators often conflates agricultural emissions with broader industrial activities, suggesting that future research should employ disaggregated, spatially explicit carbon accounting to isolate the true environmental footprint of agricultural modernization. The presence of significant cross-sectional dependence and spatial heterogeneity also suggests technological and ecological spillovers across borders, opening the door to spatial econometric modeling, such as Spatial Durbin Models, to measure how digital innovation in one region affects the sustainability of its neighbors. Finally, integrating machine learning algorithms with real-time satellite and IoT data could revolutionize the forecasting of non-linear climate-agriculture interactions, providing policymakers with dynamic decision-support systems. Ultimately, this thesis concludes that the future of sustainable agriculture will not be defined by a blind race toward technological saturation, but by the profound wisdom to synchronize digital innovation, sustainable finance, and ecological adaptation within a rigorous, inclusive, and adaptive institutional framework, ensuring that the agricultural systems of tomorrow can nourish a growing population without exhausting the planetary boundaries upon which all economic life ultimately depends.

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Appendix

Obs id Country_Name Country_ID Year Trend SDI Digital_AG RD_AG CREDIT_AG TFP_AG Temp INF

. *****Global Descriptive Analysis*****

Stats	LnSDI	LnD~l_AG	LnRD_AG	LnTFP_AG	LnCRED~G	LnTemp	LnINF
N	405	405	405	405	405	405	405
Mean	4.376242	4.163265	2.765007	4.609506	11.59757	2.369735	.7596197
SD	.0412968	.174535	1.902602	.1079739	1.641022	.3733373	1.13043
Min	4.262278	3.411673	-2.05426	4.260565	8.851958	.5538851	-3.905804
p25	4.350273	4.079995	1.804335	4.563723	10.22517	2.173615	.1345309
p50	4.377415	4.211172	2.891665	4.609959	11.35261	2.355178	.8213993
p75	4.398832	4.292504	3.878521	4.65909	13.18706	2.60417	1.418275
Max	4.467048	4.402092	6.844913	5.165586	14.5583	3.059176	4.386972
Skewness	-.0765308	-1.351722	-.2925872	.5662197	.1648004	-.454752	-.5017363
Kurtosis	2.881807	5.006199	2.866081	7.781997	1.766474	4.334541	4.213064
CV	.0094366	.0419226	.6881005	.0234242	.141497	.1575439	1.488153

. *****Jarque-Berra test of normality*****

Jarque-Bera normality test: .6311 Chi(2) .7294
Jarque-Bera test for Ho: normality: (LnSDI)

Jarque-Bera normality test: 191.3 Chi(2) 3.0e-42
Jarque-Bera test for Ho: normality: (LnDigital_AG)

Jarque-Bera normality test: 6.081 Chi(2) .0478
Jarque-Bera test for Ho: normality: (LnRD_AG)

Jarque-Bera normality test: 27.51 Chi(2) 1.1e-06
Jarque-Bera test for Ho: normality: (LnCREDIT_AG)

Jarque-Bera normality test: 407.5 Chi(2) 3.2e-89
Jarque-Bera test for Ho: normality: (LnTFP_AG)

Jarque-Bera normality test: 44.01 Chi(2) 2.8e-10
Jarque-Bera test for Ho: normality: (LnTemp)

Jarque-Bera normality test: 41.82 Chi(2) 8.3e-10
Jarque-Bera test for Ho: normality: (LnINF)

. *****Serial Autocorrelation Test*****

Bias-corrected Born and Breitung (2016) Q(p)-test on variables LnSDI
Panelvar: Country
Timevar: Year
p (lags): 2

Variable	Q(p)-stat	p-value	N	maxT	balance?
LnSDI	+ 54.79	0.000	+ 27	15	+ balanced

Bias-corrected Born and Breitung (2016) Q(p)-test on variables LnDigital_AG
Panelvar: Country
Timevar: Year
p (lags): 2

Variable	Q(p)-stat	p-value	N	maxT	balance?
LnDigital_AG	+ 18.92	0.000	+ 27	15	+ balanced

Notes: Under H0, Q(p) ~ chi2(p)
H0: No serial correlation up to order p.
Ha: Some serial correlation up to order p.

Bias-corrected Born and Breitung (2016) Q(p)-test on variables LnRD_AG
Panelvar: Country
Timevar: Year
p (lags): 2

Variable	Q(p)-stat	p-value	N	maxT	balance?
LnRD_AG	+ 48.54	0.000	+ 27	15	+ balanced

Notes: Under H0, $Q(p) \sim \chi^2(p)$

H0: No serial correlation up to order p.

Ha: Some serial correlation up to order p.

Bias-corrected Born and Breitung (2016) Q(p)-test on variables LnCREDIT_AG

Panelvar: Country

Timevar: Year

p (lags): 2

Variable	Q(p)-stat	p-value	N	maxT	balance?
LnCREDIT_AG	+ 4.71	0.095	+ 27	15	+ balanced

Notes: Under H0, $Q(p) \sim \chi^2(p)$

H0: No serial correlation up to order p.

Ha: Some serial correlation up to order p.

Bias-corrected Born and Breitung (2016) Q(p)-test on variables LnTFP_AG

Panelvar: Country

Timevar: Year

p (lags): 2

Variable	Q(p)-stat	p-value	N	maxT	balance?
LnTFP_AG	+ 4.82	0.090	+ 27	15	+ balanced

Bias-corrected Born and Breitung (2016) Q(p)-test on variables LnTemp

Panelvar: Country

Timevar: Year

p (lags): 2

Variable	Q(p)-stat	p-value	N	maxT	balance?
LnTemp	+ 44.90	0.000	+ 27	15	+ balanced

Bias-corrected Born and Breitung (2016) Q(p)-test on variables LnINF

Panelvar: Country

Timevar: Year

p (lags): 2

Variable	Q(p)-stat	p-value	N	maxT	balance?
LnINF	+ 67.73	0.000	+ 27	15	+ balanced

. *****Unit Root Test*****

. *****Unit Root Test in Level*****

Levin-Lin-Chu unit-root test for LnSDI

H0: Panels contain unit roots

Number of panels = 27

Ha: Panels are stationary

Number of periods = 15

AR parameter: Common

Asymptotics: N/T -> 0

Panel means: Included

Time trend: Not included

ADF regressions: 1 lag

LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-10.0940	
Adjusted t*	-8.2108	0.0000

Levin-Lin-Chu unit-root test for LnSDI

H0: Panels contain unit roots

Number of panels = 27

Ha: Panels are stationary

Number of periods = 15

Asymptotics: $N/T \rightarrow 0$

```
ADF regressions: 1 lag
LR variance:      Bartlett kernel, 7.00 lags average (chosen by LLC)
```

	Statistic	p-value
Unadjusted t	-9.4853	
Adjusted t*	-1.6278	0.0518

Im-Pesaran-Shin unit-root test for LnSDI

H0: All panels contain unit roots	Number of panels =	27
Ha: Some panels are stationary	Number of periods =	15

Asymptotics: $T, N \rightarrow \text{Infinity}$
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.8546		-1.830	-1.740	-1.690
t-tilde-bar	-1.6226				
Z-t-tilde-bar	-1.8917	0.0293			

Im-Pesaran-Shin unit-root test for LnSDI

H0: All panels contain unit roots	Number of panels =	27
Ha: Some panels are stationary	Number of periods =	15

Asymptotics: $T, N \rightarrow \text{Infinity}$
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values 1%5%10%
t-bar	-2.0868		-2.480-2.380-2.330
t-tilde-bar	-1.6569		
Z-t-tilde-bar	-2.1287	0.0166	

Breitung unit-root test for LnSDI

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

Asymptotics: $T, N \rightarrow \text{Infinity}$
sequentially
Prewhitening: Not performed

	Statistic	p-value
lambda	5.7103	1.0000

Breitung unit-root test for LnSDI

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

```
Asymptotics: T,N -> Infinity
              sequentially
Prewhitening: Not performed
```

Statistic	p-value
-----------	---------

```

lambda                2.2054        0.9863
-----

Fisher-type unit-root test for LnSDI
Based on augmented Dickey-Fuller tests
-----
H0: All panels contain unit roots          Number of panels =    27
Ha: At least one panel is stationary       Number of periods =    15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included                ADF regressions: 1 lag
-----

Statistic      p-value
-----
Inverse chi-squared(54)  P      84.2494      0.0053
Inverse normal          Z      -2.4977      0.0062
Inverse logit t(139)    L*     -2.6722      0.0042
Modified inv. chi-squared Pm      2.9108      0.0018
-----

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----

Fisher-type unit-root test for LnSDI
Based on augmented Dickey-Fuller tests
-----
H0: All panels contain unit roots          Number of panels =    27
Ha: At least one panel is stationary       Number of periods =    15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included                ADF regressions: 1 lag
-----

Statistic      p-value
-----
Inverse chi-squared(54)  P      56.5538      0.3798
Inverse normal          Z       2.2417      0.9875
Inverse logit t(134)    L*      2.0113      0.9769
Modified inv. chi-squared Pm      0.2457      0.4029
-----

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----

Hadri LM test for LnSDI
-----
H0: All panels are stationary              Number of panels =    27
Ha: Some panels contain unit roots        Number of periods =    15

Time trend:      Not included              Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust              sequentially
LR variance:      (not used)

Statistic      p-value
-----
z              38.2489      0.0000
-----

Hadri LM test for LnSDI
-----
H0: All panels are stationary              Number of panels =    27
Ha: Some panels contain unit roots        Number of periods =    15

Time trend:      Included                  Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust              sequentially
LR variance:      (not used)

Statistic      p-value
-----
z              14.2351      0.0000
-----

Pesaran's CADF test for LnSDI

```

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.429	-2.070	-2.170	-2.340	1.373	0.915

Pesaran's CADF test for LnSDI

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.347	-2.590	-2.690	-2.880	4.238	1.000

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnSDI
Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-2.258	N,T = (27,15)		
		10%	5%	1%
	+			
Critical values at		-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnSDI
Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS =	-2.347	N,T = (27,15)		
		10%	5%	1%
	+			
Critical values at		-2.6	-2.7	-2.89

First and Second Generation Panel Unit Root Tests

Variables tested: LnSDI
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

		Specification without trend		
	+			
Variable		lags	chi_sq	p-value
	+			
LnSDI		0	76.438	0.024
LnSDI		1	84.249	0.005
	+			
		Specification with trend		
	+			
Variable		lags	chi_sq	p-value
	+			
LnSDI		0	73.544	0.040

LnSDI		1	56.554	0.380
-------	--	---	--------	-------

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
LnSDI	0	-2.847	0.002	.
LnSDI	1	1.373	0.915	.

Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
LnSDI	0	-0.405	0.343	.
LnSDI	1	4.238	1.000	.

Levin-Lin-Chu unit-root test for LnDigital_AG

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

AR parameter: Common	Asymptotics: N/T -> 0
Panel means: Included	
Time trend: Not included	

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-9.5465	
Adjusted t*	-8.4000	0.0000

Levin-Lin-Chu unit-root test for LnDigital_AG

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

AR parameter: Common	Asymptotics: N/T -> 0
Panel means: Included	
Time trend: Included	

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-9.7123	
Adjusted t*	-2.7002	0.0035

Im-Pesaran-Shin unit-root test for LnDigital_AG

H0: All panels contain unit roots	Number of panels =	27
Ha: Some panels are stationary	Number of periods =	15

AR parameter: Panel-specific	Asymptotics: T,N -> Infinity
Panel means: Included	sequentially
Time trend: Not included	

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.5734		-1.830	-1.740	-1.690
t-tilde-bar	-1.3181				

```

Z-t-tilde-bar      0.2139      0.5847
-----
.
Im-Pesaran-Shin unit-root test for LnDigital_AG
-----
H0: All panels contain unit roots      Number of panels =      27
Ha: Some panels are stationary          Number of periods =     15

AR parameter: Panel-specific            Asymptotics: T,N -> Infinity
Panel means:   Included                  sequentially
Time trend:    Included

ADF regressions: No lags included
-----

                Statistic      p-value      Fixed-N exact critical values
                1%      5%      10%
-----
t-bar           -2.5185
t-tilde-bar     -1.8827
Z-t-tilde-bar   -3.6896      0.0001
-----

Breitung unit-root test for LnDigital_AG
-----
H0: Panels contain unit roots      Number of panels =      27
Ha: Panels are stationary          Number of periods =     15

AR parameter: Common                Asymptotics: T,N -> Infinity
Panel means:   Included              sequentially
Time trend:    Not included          Prewhitening: Not performed
-----

                Statistic      p-value
-----
lambda          8.3401      1.0000
-----

Breitung unit-root test for LnDigital_AG
-----
H0: Panels contain unit roots      Number of panels =      27
Ha: Panels are stationary          Number of periods =     15

AR parameter: Common                Asymptotics: T,N -> Infinity
Panel means:   Included              sequentially
Time trend:    Included              Prewhitening: Not performed
-----

                Statistic      p-value
-----
lambda          0.6020      0.7264
-----

Fisher-type unit-root test for LnDigital_AG
Based on augmented Dickey-Fuller tests
-----
H0: All panels contain unit roots      Number of panels =      27
Ha: At least one panel is stationary    Number of periods =     15

AR parameter: Panel-specific            Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included            ADF regressions: 1 lag
-----

                Statistic      p-value
-----
Inverse chi-squared(54)  P      84.8477      0.0047
Inverse normal           Z      -0.6504      0.2577
Inverse logit t(139)     L*     -1.1783      0.1204
Modified inv. chi-squared Pm      2.9683      0.0015
-----

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----

Fisher-type unit-root test for LnDigital_AG
Based on augmented Dickey-Fuller tests
-----
H0: All panels contain unit roots      Number of panels =      27

```

Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity

Panel means: Included

Time trend: Included

Drift term: Not included ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	52.7434	0.5229
Inverse normal	Z	-0.1876	0.4256
Inverse logit t(129)	L*	-0.1838	0.4272
Modified inv. chi-squared	Pm	-0.1209	0.5481

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Hadri LM test for LnDigital_AG

H0: All panels are stationary Number of panels = 27

Ha: Some panels contain unit roots Number of periods = 15

Time trend: Not included Asymptotics: T, N -> Infinity

Heteroskedasticity: Not robust sequentially

LR variance: (not used)

	Statistic	p-value
z	41.3270	0.0000

Hadri LM test for LnDigital_AG

H0: All panels are stationary Number of panels = 27

Ha: Some panels contain unit roots Number of periods = 15

Time trend: Included Asymptotics: T, N -> Infinity

Heteroskedasticity: Not robust sequentially

LR variance: (not used)

	Statistic	p-value
z	15.9425	0.0000

Pesaran's CADF test for LnDigital_AG

Cross-sectional average in first period extracted and extreme t-values truncated

Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351

Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.106	-2.070	-2.170	-2.340	-1.824	0.034

Pesaran's CADF test for LnDigital_AG

Cross-sectional average in first period extracted and extreme t-values truncated

Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351

Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.674	-2.590	-2.690	-2.880	-1.919	0.027

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnDigital_AG

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* = -2.559 N,T = (27,15)

	10%	5%	1%
Critical values at	-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnDigital_AG

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): $\beta_i = 0$ for all i

CIPS* = -3.164 N,T = (27,15)

	10%	5%	1%
Critical values at	-2.59	-2.69	-2.88

First and Second Generation Panel Unit Root Tests

Variables tested: LnDigital_AG
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

	Specification without trend		
Variable	lags	chi_sq	p-value
LnDigital_AG	0	82.877	0.007
LnDigital_AG	1	84.848	0.005

	Specification with trend		
Variable	lags	chi_sq	p-value
LnDigital_AG	0	121.110	0.000
LnDigital_AG	1	52.743	0.523

(B) Pesaran (2007) Panel Unit Root test (CIPS)

	Specification without trend			
Variable	lags	Zt-bar	p-value	t-bar
LnDigital_AG	0	-3.961	0.000	.
LnDigital_AG	1	-1.824	0.034	.

	Specification with trend			
Variable	lags	Zt-bar	p-value	t-bar
LnDigital_AG	0	-3.109	0.001	.
LnDigital_AG	1	-1.919	0.027	.

Levin-Lin-Chu unit-root test for LnRD_AG

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-2.6246	
Adjusted t*	0.9920	0.8394

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

```
ADF regressions: 1 lag
LR variance:      Bartlett kernel, 7.00 lags average (chosen by LLC)
```

	Statistic	p-value
Unadjusted t	-11.0858	
Adjusted t*	-2.3360	0.0097

H0: All panels contain unit roots	Number of panels =	27
Ha: Some panels are stationary	Number of periods =	15

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-0.8708		-1.830	-1.740	-1.690
t-tilde-bar	-0.5820				
Z-t-tilde-bar	5.3022	1.0000			

H0: All panels contain unit roots	Number of panels =	27
Ha: Some panels are stationary	Number of periods =	15

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.4188		-2.480	-2.380	-2.330
t-tilde-bar	-1.7210				
Z-t-tilde-bar	-2.5716	0.0051			

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

AR parameter:	Common	Asymptotics:	T,N -> Infinity
Panel means:	Included		sequentially
Time trend:	Not included	Prewhitening:	Not performed

Breitung unit-root test for LnRD AG

Fisher-type unit-root test for LnRD_AG
Based on augmented Dickey-Fuller tests

Fisher-type unit-root test for LnRD_AG
Based on augmented Dickey-Fuller tests

Hadri LM test for LnRD AG

z	34.9032	0.0000
---	---------	--------

Hadri LM test for LnRD_AG

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15

Time trend: Included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	13.7234	0.0000

Pesaran's CADF test for LnRD_AG

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.276	-2.070	-2.170	-2.340	-2.627	0.004

Pesaran's CADF test for LnRD_AG

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.297	-2.590	-2.690	-2.880	-0.170	0.432

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnRD_AG

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-2.149	N,T = (27,15)		
		10%	5%	1%
Critical values at		-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnRD_AG

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-2.299	N,T = (27,15)		
		10%	5%	1%
Critical values at		-2.59	-2.69	-2.88

First and Second Generation Panel Unit Root Tests

Variables tested: LnRD_AG
Group variable: Country
Number of groups: 27

	Statistic	p-value
Unadjusted t	-10.7897	
Adjusted t*	-3.7338	0.0001

Im-Pesaran-Shin unit-root test for LnCREDIT_AG

H0: All panels contain unit roots Number of panels = 27
Ha: Some panels are stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.5302		-1.830	-1.740	-1.690
t-tilde-bar	-1.3126				
Z-t-tilde-bar	0.2519	0.5994			

Im-Pesaran-Shin unit-root test for LnCREDIT_AG

H0: All panels contain unit roots Number of panels = 27
Ha: Some panels are stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-1.4469		-2.480	-2.380	-2.330
t-tilde-bar	-1.1970				
Z-t-tilde-bar	1.0511	0.8534			

Breitung unit-root test for LnCREDIT_AG

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included Prewhitening: Not performed

	Statistic	p-value
lambda	4.4645	1.0000

Breitung unit-root test for LnCREDIT_AG

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included Prewhitening: Not performed

	Statistic	p-value
lambda	3.8254	0.9999

Fisher-type unit-root test for LnCREDIT_AG

Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
Ha: At least one panel is stationary Number of periods = 15

		Statistic	p-value
Inverse chi-squared(54)	P	60.9061	0.2414
Inverse normal	Z	-0.5384	0.2951
Inverse logit t(139)	L*	-0.5415	0.2945
Modified inv. chi-squared	Pm	0.6645	0.2532

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

		Statistic	p-value
Inverse chi-squared(54)	P	45.2246	0.7967
Inverse normal	Z	1.7105	0.9564
Inverse logit t(139)	L*	1.9823	0.9753
Modified inv. chi-squared	Pm	-0.8444	0.8008

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

	Statistic	p-value
z	30.6505	0.0000

	Statistic	p-value
z	19.3025	0.0000

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.322	-2.070	-2.170	-2.340	1.879	0.970

Pesaran's CADF test for LnCREDIT_AG
Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.460	-2.590	-2.690	-2.880	3.714	1.000

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnCREDIT_AG
Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* = -1.693 N,T = (27,15)

		10%	5%	1%
-----+-----				
Critical values at		-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnCREDIT_AG
Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* = -1.923 N,T = (27,15)

		10%	5%	1%
-----+-----				
Critical values at		-2.59	-2.69	-2.88

First and Second Generation Panel Unit Root Tests

Variables tested: LnCREDIT_AG
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

		Specification without trend		
-----+-----				
Variable		lags	chi_sq	p-value
-----+-----				
LnCREDIT_AG		0	71.389	0.057
LnCREDIT_AG		1	60.906	0.241

		Specification with trend		
-----+-----				
Variable		lags	chi_sq	p-value
-----+-----				
LnCREDIT_AG		0	40.633	0.911
LnCREDIT_AG		1	45.225	0.797

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
LnCREDIT_AG	0	0.276	0.609	.
LnCREDIT_AG	1	1.879	0.970	.
Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
LnCREDIT_AG	0	1.898	0.971	.
LnCREDIT_AG	1	3.714	1.000	.

Levin-Lin-Chu unit-root test for LnTFP_AG

H0: Panels contain unit roots Number of panels = 27
 Ha: Panels are stationary Number of periods = 15

 AR parameter: Common Asymptotics: N/T -> 0
 Panel means: Included
 Time trend: Not included

ADF regressions: 1 lag
 LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-7.9501	
Adjusted t*	-3.4498	0.0003

Levin-Lin-Chu unit-root test for LnTFP_AG

H0: Panels contain unit roots Number of panels = 27
 Ha: Panels are stationary Number of periods = 15

 AR parameter: Common Asymptotics: N/T -> 0
 Panel means: Included
 Time trend: Included

ADF regressions: 1 lag
 LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-13.6251	
Adjusted t*	-5.2311	0.0000

Im-Pesaran-Shin unit-root test for LnTFP_AG

H0: All panels contain unit roots Number of panels = 27
 Ha: Some panels are stationary Number of periods = 15

 AR parameter: Panel-specific Asymptotics: T,N -> Infinity
 Panel means: Included sequentially
 Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-2.5326		-1.830	-1.740	-1.690
t-tilde-bar	-1.9509				
Z-t-tilde-bar	-4.1607	0.0000			

Im-Pesaran-Shin unit-root test for LnTFP_AG

H0: All panels contain unit roots Number of panels = 27

Number of periods = 15

Asymptotics: $T, N \rightarrow \text{Infinity}$
sequentially

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.2725		-2.480	-2.380	-2.330
t-tilde-bar	-2.3768				
Z-t-tilde-bar	-7.1054	0.0000			

```
Number of panels = 27
Number of periods = 15
```

```
Asymptotics:  T,N -> Infinity
               sequentially
Prewhitening: Not performed
```

	Statistic	p-value
lambda	-2.5675	0.0051

```
Number of panels = 27
Number of periods = 15
```

```
Asymptotics:  T,N -> Infinity
               sequentially
Prewhitening: Not performed
```

	Statistic	p-value
lambda	-5.8887	0.0000

```
Number of panels = 27
Number of periods = 15
```

Asymptotics: T $\rightarrow$ Infinity

ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared (54)	P	74.8884	0.0315
Inverse normal	Z	-1.6768	0.0468
Inverse logit t (139)	L*	-1.6883	0.0468
Modified inv. chi-squared	Pm	2.0100	0.0222

```
Number of panels = 27
Number of periods = 15
```

Asymptotics: T $\rightarrow$ Infinity

ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	91.0650	0.0012
Inverse normal	Z	-2.0060	0.0224
Inverse logit t(139)	L*	-2.4258	0.0083
Modified inv. chi-squared Pm		3.5666	0.0002

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Hadri LM test for LnTFP_AG

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15

Time trend: Not included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	24.7347	0.0000

Hadri LM test for LnTFP_AG

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15

Time trend: Included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	7.7301	0.0000

Pesaran's CADF test for LnTFP_AG

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.241	-2.070	-2.170	-2.340	-2.463	0.007

Pesaran's CADF test for LnTFP_AG

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.010	-2.590	-2.690	-2.880	-3.478	0.000

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnTFP_AG

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

H0 (homogeneous non-stationary): $b_i = 0$ for all i

CIPS =	-3.213	N,T = (27,15)
		10% 5% 1%
	+	
Critical values at	-2.07	-2.17 -2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnTFP_AG

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

H0 (homogeneous non-stationary): $\beta_i = 0$ for all i

CIPS =	-3.538	N,T = (27,15)		
		10%	5%	1%
Critical values at		-2.6	-2.7	-2.89

First and Second Generation Panel Unit Root Tests

Variables tested: LnTFP_AG
 Group variable: Country
 Number of groups: 27
 Total # of observations: 405+
 Average # of observations: 15.00+
 Panel is balanced and has gaps
 + Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

Specification without trend			
Variable	lags	chi_sq	p-value
LnTFP_AG	0	171.092	0.000
LnTFP_AG	1	74.888	0.031

Specification with trend			
Variable	lags	chi_sq	p-value
LnTFP_AG	0	187.528	0.000
LnTFP_AG	1	91.065	0.001

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
LnTFP_AG	0	-7.054	0.000	.
LnTFP_AG	1	-2.463	0.007	.

Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
LnTFP_AG	0	-5.928	0.000	.
LnTFP_AG	1	-3.478	0.000	.

Levin-Lin-Chu unit-root test for LnTemp

H0: Panels contain unit roots
 Ha: Panels are stationary

Number of panels = 27
 Number of periods = 15

AR parameter: Common
 Panel means: Included
 Time trend: Not included

Asymptotics: $N/T \rightarrow 0$

ADF regressions: 1 lag
 LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

Statistic	p-value
-----------	---------

Unadjusted t	-9.0754	
Adjusted t*	-0.4526	0.3254

Levin-Lin-Chu unit-root test for LnTemp

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: N/T -> 0
Panel means: Included
Time trend: Included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-18.7924	
Adjusted t*	-4.8834	0.0000

Im-Pesaran-Shin unit-root test for LnTemp

H0: All panels contain unit roots Number of panels = 27
Ha: Some panels are stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.2321		-1.830	-1.740	-1.690
t-tilde-bar	-2.2916				
Z-t-tilde-bar	-6.5157	0.0000			

Im-Pesaran-Shin unit-root test for LnTemp

H0: All panels contain unit roots Number of panels = 27
Ha: Some panels are stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-4.3875		-2.480	-2.380	-2.330
t-tilde-bar	-2.7388				
Z-t-tilde-bar	-9.6077	0.0000			

Breitung unit-root test for LnTemp

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included Prewhitening: Not performed

	Statistic	p-value
lambda	-0.7555	0.2250

Breitung unit-root test for LnTemp

H0: Panels contain unit roots Number of panels = 27
 Ha: Panels are stationary Number of periods = 15

 AR parameter: Common Asymptotics: T,N -> Infinity
 Panel means: Included sequentially
 Time trend: Included Prewhitening: Not performed

	Statistic	p-value
lambda	-5.4924	0.0000

Fisher-type unit-root test for LnTemp
 Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
 Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity
 Panel means: Included
 Time trend: Not included
 Drift term: Not included ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	52.1033	0.5479
Inverse normal	Z	-0.7682	0.2212
Inverse logit t(139)	L*	-0.6527	0.2575
Modified inv. chi-squared	Pm	-0.1825	0.5724

P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.

Fisher-type unit-root test for LnTemp
 Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
 Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity
 Panel means: Included
 Time trend: Included
 Drift term: Not included ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	143.2622	0.0000
Inverse normal	Z	-6.1898	0.0000
Inverse logit t(139)	L*	-6.6148	0.0000
Modified inv. chi-squared	Pm	8.5893	0.0000

P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.

Hadri LM test for LnTemp

H0: All panels are stationary Number of panels = 27
 Ha: Some panels contain unit roots Number of periods = 15

Time trend: Not included Asymptotics: T, N -> Infinity
 Heteroskedasticity: Not robust sequentially
 LR variance: (not used)

	Statistic	p-value
z	12.1215	0.0000

Hadri LM test for LnTemp

H0: All panels are stationary Number of panels = 27
 Ha: Some panels contain unit roots Number of periods = 15

Time trend: Included Asymptotics: T, N -> Infinity
 Heteroskedasticity: Not robust sequentially

LR variance: (not used)

	Statistic	p-value
z	1.8724	0.0306

Pesaran's CADF test for LnTemp

Cross-sectional average in first period extracted and extreme t-values truncated

Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351

Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.592	-2.070	-2.170	-2.340	-4.120	0.000

Pesaran's CADF test for LnTemp

Cross-sectional average in first period extracted and extreme t-values truncated

Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351

Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.640	-2.590	-2.690	-2.880	-1.764	0.039

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnTemp

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual t_i were truncated during the aggregation process

H_0 (homogeneous non-stationary): $b_i = 0$ for all i

CIPS* =	-3.181	N,T = (27,15)
		10% 5% 1%
	+	
Critical values at		-2.07 -2.17 -2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnTemp

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

H_0 (homogeneous non-stationary): $b_i = 0$ for all i

CIPS =	-3.645	N,T = (27,15)
		10% 5% 1%
	+	
Critical values at		-2.6 -2.7 -2.89

First and Second Generation Panel Unit Root Tests

Variables tested: LnTemp
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

		Specification without trend
	+	
Variable		lags chi_sq p-value

LnTemp	0	273.674	0.000
LnTemp	1	52.103	0.548

Specification with trend			
Variable	lags	chi_sq	p-value
LnTemp	0	373.680	0.000
LnTemp	1	143.262	0.000

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
LnTemp	0	-7.557	0.000	.
LnTemp	1	-4.120	0.000	.

Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
LnTemp	0	-6.091	0.000	.
LnTemp	1	-1.764	0.039	.

Levin-Lin-Chu unit-root test for LnINF

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: N/T -> 0
Panel means: Included
Time trend: Not included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-9.3765	
Adjusted t*	-2.4191	0.0078

Levin-Lin-Chu unit-root test for LnINF

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: N/T -> 0
Panel means: Included
Time trend: Included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-13.1690	
Adjusted t*	-5.9461	0.0000

Im-Pesaran-Shin unit-root test for LnINF

H0: All panels contain unit roots Number of panels = 27
Ha: Some panels are stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially

Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-2.1715		-1.830	-1.740	-1.690
t-tilde-bar	-1.8425				
Z-t-tilde-bar	-3.4118	0.0003			

Im-Pesaran-Shin unit-root test for LnINF

H0: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 27
Number of periods = 15

AR parameter: Panel-specific
Panel means: Included
Time trend: Included

Asymptotics: T,N -> Infinity
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-2.4947		-2.480	-2.380	-2.330
t-tilde-bar	-2.0748				
Z-t-tilde-bar	-5.0174	0.0000			

Breitung unit-root test for LnINF

H0: Panels contain unit roots
Ha: Panels are stationary

Number of panels = 27
Number of periods = 15

AR parameter: Common
Panel means: Included
Time trend: Not included

Asymptotics: T,N -> Infinity
sequentially
Prewhitening: Not performed

	Statistic	p-value
lambda	-7.3228	0.0000

Breitung unit-root test for LnINF

H0: Panels contain unit roots
Ha: Panels are stationary

Number of panels = 27
Number of periods = 15

AR parameter: Common
Panel means: Included
Time trend: Included

Asymptotics: T,N -> Infinity
sequentially
Prewhitening: Not performed

	Statistic	p-value
lambda	-5.5214	0.0000

Fisher-type unit-root test for LnINF
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots
Ha: At least one panel is stationary

Number of panels = 27
Number of periods = 15

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included
Drift term: Not included

Asymptotics: T -> Infinity
ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	48.1545	0.6982
Inverse normal	Z	-0.7085	0.2393
Inverse logit t(139)	L*	-0.6599	0.2552
Modified inv. chi-squared	Pm	-0.5625	0.7131

P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.

Fisher-type unit-root test for LnINF
 Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
 Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity
 Panel means: Included
 Time trend: Included
 Drift term: Not included ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	51.3451	0.5774
Inverse normal	Z	-0.3189	0.3749
Inverse logit t(139)	L*	-0.4087	0.3417
Modified inv. chi-squared	Pm	-0.2555	0.6008

P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.

Hadri LM test for LnINF

H0: All panels are stationary Number of panels = 27
 Ha: Some panels contain unit roots Number of periods = 15

Time trend: Not included Asymptotics: T, N -> Infinity
 Heteroskedasticity: Not robust sequentially
 LR variance: (not used)

	Statistic	p-value
z	6.5406	0.0000

Hadri LM test for LnINF

H0: All panels are stationary Number of panels = 27
 Ha: Some panels contain unit roots Number of periods = 15

Time trend: Included Asymptotics: T, N -> Infinity
 Heteroskedasticity: Not robust sequentially
 LR variance: (not used)

	Statistic	p-value
z	9.9623	0.0000

Pesaran's CADF test for LnINF

Cross-sectional average in first period extracted and extreme t-values truncated
 Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351
 Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.458	-2.070	-2.170	-2.340	-3.487	0.000

Pesaran's CADF test for LnINF

Cross-sectional average in first period extracted and extreme t-values truncated
 Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
 Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.447	-2.590	-2.690	-2.880	-0.869	0.192

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnINF
 Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

H0 (homogeneous non-stationary): $\beta_i = 0$ for all i

CIPS =	-3.246	N,T = (27,15)		
		10%	5%	1%
Critical values at		-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for LnINF
Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual t_i were truncated during the aggregation process

H0 (homogeneous non-stationary): $\beta_i = 0$ for all i

CIPS* =	-3.390	N,T = (27,15)		
		10%	5%	1%
Critical values at		-2.59	-2.69	-2.88

First and Second Generation Panel Unit Root Tests

Variables tested: LnINF
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

Specification without trend				
Variable	lags	chi_sq	p-value	
LnINF	0	101.726	0.000	
LnINF	1	48.155	0.698	
Specification with trend				
Variable	lags	chi_sq	p-value	
LnINF	0	80.157	0.012	
LnINF	1	51.345	0.577	

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
LnINF	0	-7.210	0.000	.
LnINF	1	-3.487	0.000	.
Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
LnINF	0	-4.962	0.000	.
LnINF	1	-0.869	0.192	.

```

-----
.
. *****Unit Root Test in First Difference*****

Levin-Lin-Chu unit-root test for dLnSDI
-----
H0: Panels contain unit roots          Number of panels =    27
Ha: Panels are stationary              Number of periods =    15

AR parameter: Common                   Asymptotics: N/T -> 0
Panel means: Included
Time trend: Not included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)
-----
Statistic      p-value
-----
Unadjusted t    -15.2323
Adjusted t*     -6.0915      0.0000
-----

Levin-Lin-Chu unit-root test for dLnSDI
-----
H0: Panels contain unit roots          Number of panels =    27
Ha: Panels are stationary              Number of periods =    15

AR parameter: Common                   Asymptotics: N/T -> 0
Panel means: Included
Time trend: Included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)
-----
Statistic      p-value
-----
Unadjusted t    -18.8132
Adjusted t*     -7.2111      0.0000
-----

Im-Pesaran-Shin unit-root test for dLnSDI
-----
H0: All panels contain unit roots      Number of panels =    27
Ha: Some panels are stationary          Number of periods =    15

AR parameter: Panel-specific           Asymptotics: T,N -> Infinity
Panel means: Included                  sequentially
Time trend: Not included

ADF regressions: No lags included
-----
Statistic      p-value      Fixed-N exact critical values
                        1%      5%      10%
-----
t-bar          -4.1071
t-tilde-bar    -2.6843
Z-t-tilde-bar  -9.2310      0.0000
-----

Im-Pesaran-Shin unit-root test for dLnSDI
-----
H0: All panels contain unit roots      Number of panels =    27
Ha: Some panels are stationary          Number of periods =    15

AR parameter: Panel-specific           Asymptotics: T,N -> Infinity
Panel means: Included                  sequentially
Time trend: Included

ADF regressions: No lags included
-----
Statistic      p-value      Fixed-N exact critical values
                        1%      5%      10%
-----
t-bar          -4.3810
t-tilde-bar    -2.7769
Z-t-tilde-bar  -9.8707      0.0000
-----

```

```

.
Breitung unit-root test for dLnSDI
-----
H0: Panels contain unit roots          Number of panels =    27
Ha: Panels are stationary              Number of periods =   15

AR parameter: Common                  Asymptotics: T,N -> Infinity
Panel means: Included                  sequentially
Time trend: Not included              Prewhitening: Not performed
-----

```

	Statistic	p-value
lambda	-11.0214	0.0000

```

Breitung unit-root test for dLnSDI
-----
H0: Panels contain unit roots          Number of panels =    27
Ha: Panels are stationary              Number of periods =   15

AR parameter: Common                  Asymptotics: T,N -> Infinity
Panel means: Included                  sequentially
Time trend: Included                 Prewhitening: Not performed
-----

```

	Statistic	p-value
lambda	-5.3946	0.0000

```

Fisher-type unit-root test for dLnSDI
Based on augmented Dickey-Fuller tests
-----
H0: All panels contain unit roots      Number of panels =    27
Ha: At least one panel is stationary   Number of periods =   15

AR parameter: Panel-specific          Asymptotics: T -> Infinity
Panel means: Included
Time trend: Not included
Drift term: Not included              ADF regressions: 1 lag
-----

```

		Statistic	p-value
Inverse chi-squared(54)	P	183.6669	0.0000
Inverse normal	Z	-7.5322	0.0000
Inverse logit t(139)	L*	-8.9378	0.0000
Modified inv. chi-squared	Pm	12.4772	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

```

Fisher-type unit-root test for dLnSDI
Based on augmented Dickey-Fuller tests
-----
H0: All panels contain unit roots      Number of panels =    27
Ha: At least one panel is stationary   Number of periods =   15

AR parameter: Panel-specific          Asymptotics: T -> Infinity
Panel means: Included
Time trend: Included
Drift term: Not included              ADF regressions: 1 lag
-----

```

		Statistic	p-value
Inverse chi-squared(54)	P	160.0947	0.0000
Inverse normal	Z	-6.6600	0.0000
Inverse logit t(139)	L*	-7.4699	0.0000
Modified inv. chi-squared	Pm	10.2090	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

```

Hadri LM test for dLnSDI
-----
H0: All panels are stationary          Number of panels =    27

```

```

Ha: Some panels contain unit roots          Number of periods =      15

Time trend:          Not included          Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust              sequentially
LR variance:        (not used)
-----
Statistic          p-value
-----
z                  -0.3733          0.6455
-----

Hadri LM test for dLnSDI
-----
H0: All panels are stationary          Number of panels =      27
Ha: Some panels contain unit roots     Number of periods =      15

Time trend:          Included             Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust              sequentially
LR variance:        (not used)
-----
Statistic          p-value
-----
z                  -1.0384          0.8505
-----

Pesaran's CADF test for dLnSDI
Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15)          Obs = 351
Augmented by 1 lags (average)

      t-bar      cv10      cv5      cv1      Z[t-bar]      P-value
      -2.177     -2.070     -2.170     -2.340     -2.161          0.015

Pesaran's CADF test for dLnSDI
Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (27,15)          Obs = 351
Augmented by 1 lags (average)

      t-bar      cv10      cv5      cv1      Z[t-bar]      P-value
      -1.993     -2.590     -2.690     -2.880      1.241          0.893

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for
dLnSDI
Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS =      -3.948          N,T = (27,15)
-----
|          10%          5%          1%
-----+-----
Critical values at |      -2.07      -2.17      -2.34
-----

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for
dLnSDI
Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =      -4.019          N,T = (27,15)
-----
|          10%          5%          1%
-----+-----
Critical values at |      -2.59      -2.69      -2.88
-----

```

```

Variables tested:      dLnSDI
Group variable:       Country
Number of groups:     27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

```

	Specification without trend		
Variable	lags	chi_sq	p-value
dLnSDI	0	404.085	0.000
dLnSDI	1	183.667	0.000

	Specification with trend		
Variable	lags	chi_sq	p-value
dLnSDI	0	352.142	0.000
dLnSDI	1	160.095	0.000

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnSDI	0	-10.526	0.000	.
dLnSDI	1	-2.161	0.015	.
Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnSDI	0	-7.968	0.000	.
dLnSDI	1	1.241	0.893	.

	Statistic	p-value
Unadjusted t	-17.0656	
Adjusted t*	-9.1378	0.0000

AR parameter: Common Asymptotics: N/T -> 0
Panel means: Included

Time trend: Included

ADF regressions: 1 lag

LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-22.5829	
Adjusted t*	-11.4067	0.0000

Im-Pesaran-Shin unit-root test for dLnDigital_AG

H0: All panels contain unit roots Number of panels = 27
Ha: Some panels are stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-4.2649		-1.830	-1.740	-1.690
t-tilde-bar	-2.7228				
Z-t-tilde-bar	-9.4968	0.0000			

Im-Pesaran-Shin unit-root test for dLnDigital_AG

H0: All panels contain unit roots Number of panels = 27
Ha: Some panels are stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-4.6601		-2.480	-2.380	-2.330
t-tilde-bar	-2.8362				
Z-t-tilde-bar	-10.2808	0.0000			

Breitung unit-root test for dLnDigital_AG

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included Prewhitening: Not performed

	Statistic	p-value
lambda	-9.2384	0.0000

Breitung unit-root test for dLnDigital_AG

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included Prewhitening: Not performed

	Statistic	p-value
lambda	-7.8870	0.0000

Fisher-type unit-root test for dLnDigital_AG
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity
Panel means: Included
Time trend: Not included
Drift term: Not included ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	270.3501	0.0000
Inverse normal	Z	-10.3389	0.0000
Inverse logit t(139)	L*	-13.8015	0.0000
Modified inv. chi-squared	Pm	20.8183	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Fisher-type unit-root test for dLnDigital_AG
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity
Panel means: Included
Time trend: Included
Drift term: Not included ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	272.0011	0.0000
Inverse normal	Z	-9.9223	0.0000
Inverse logit t(139)	L*	-13.8253	0.0000
Modified inv. chi-squared	Pm	20.9772	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Hadri LM test for dLnDigital_AG

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15

Time trend: Not included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	-0.4962	0.6901

Hadri LM test for dLnDigital_AG

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15

Time trend: Included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	-1.3980	0.9189

Pesaran's CADF test for dLnDigital_AG

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351

Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.791	-2.070	-2.170	-2.340	-5.060	0.000

Pesaran's CADF test for dLnDigital_AG

Cross-sectional average in first period extracted and extreme t-values truncated

Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351

Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.231	-2.590	-2.690	-2.880	-4.503	0.000

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnDigital_AG

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-4.265	N,T = (27,15)		
		10%	5%	1%
	+			
Critical values at		-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnDigital_AG

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-4.562	N,T = (27,15)		
		10%	5%	1%
	+			
Critical values at		-2.59	-2.69	-2.88

First and Second Generation Panel Unit Root Tests

Variables tested: dLnDigital_AG
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

		Specification without trend		
	+			
Variable		lags	chi_sq	p-value
dLnDigital~G		0	441.446	0.000
dLnDigital~G		1	270.350	0.000
		Specification with trend		
	+			
Variable		lags	chi_sq	p-value
dLnDigital~G		0	417.736	0.000

dLnDigital~G | 1 272.001 0.000

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnDigital~G	0	-11.721	0.000	.
dLnDigital~G	1	-5.060	0.000	.

Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnDigital~G	0	-9.924	0.000	.
dLnDigital~G	1	-4.503	0.000	.

Levin-Lin-Chu unit-root test for dLnRD_AG

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: N/T -> 0
Panel means: Included
Time trend: Not included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-32.6182	
Adjusted t*	-30.6986	0.0000

Levin-Lin-Chu unit-root test for dLnRD_AG

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: N/T -> 0
Panel means: Included
Time trend: Included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-29.3163	
Adjusted t*	-22.4504	0.0000

Im-Pesaran-Shin unit-root test for dLnRD_AG

H0: All panels contain unit roots Number of panels = 27
Ha: Some panels are stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.5963		-1.830	-1.740	-1.690
t-tilde-bar	-2.5244				
Z-t-tilde-bar	-8.1253	0.0000			

Im-Pesaran-Shin unit-root test for dLnRD AG

H0: All panels contain unit roots
Ha: Some panels are stationary

Number of panels = 27
Number of periods = 15

AR parameter: Panel-specific
Panel means: Included
Time trend: Included

Asymptotics: $T, N \rightarrow \text{Infinity}$
sequentially

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-3.9096		-2.480	-2.380	-2.330
t-tilde-bar	-2.6807				
Z-t-tilde-bar	-9.2058	0.0000			

Breitung unit-root test for dLnRD AG

H0: Panels contain unit roots
Ha: Panels are stationary

```
Number of panels = 27
Number of periods = 15
```

AR parameter: Common
Panel means: Included
Time trend: Not incl

```
Asymptotics:  T,N -> Infinity
               sequentially
Prewhitening: Not performed
```

	Statistic	p-value
lambda	-10.0443	0.0000

Breitung unit-root test for dLnRD AG

H0: Panels contain unit roots
Ha: Panels are stationary

Number of panels = 27
Number of periods = 15

AR parameter: Common
Panel means: Included
Time trend: Included

Asymptotics: $T, N \rightarrow \text{Infinity}$
sequentially
Prewhitening: Not performed

	Statistic	p-value
lambda	-7.6558	0.0000

Fisher-type unit-root test for dLnRD_AG
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots
Ha: At least one panel is stationary

Number of panels = 27
Number of periods = 15

AR parameter: Panel-specific
Panel means: Included
Time trend: Not included
Drift term: Not included

Asymptotics: T $\rightarrow$ Infinity

ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared (54)	P	202.8064	0.0000
Inverse normal	Z	-7.2885	0.0000
Inverse logit t (139)	L*	-9.8942	0.0000
Modified inv. chi-squared	Pm	14.3189	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Fisher-type unit-root test for dLnRD_AG
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots
Ha: At least one panel is stationary

Number of panels = 27
Number of periods = 15

		Statistic	p-value
Inverse chi-squared(54)	P	195.1264	0.0000
Inverse normal	Z	-6.8512	0.0000
Inverse logit t(139)	L*	-9.3140	0.0000
Modified inv. chi-squared	Pm	13.5799	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

H0: All panels are stationary	Number of panels =	27
Ha: Some panels contain unit roots	Number of periods =	15
Time trend:	Not included	Asymptotics: T, N -> Infinity
Heteroskedasticity:	Not robust	sequentially
LR variance:	(not used)	

	Statistic	p-value
z	0.8314	0.2029

H0: All panels are stationary	Number of panels =	27
Ha: Some panels contain unit roots	Number of periods =	15
Time trend:	Included	Asymptotics: T, N -> Infinity
Heteroskedasticity:	Not robust	sequentially
LR variance:	(not used)	

	Statistic	p-value
z	-0.8223	0.7946

```
t-bar test, N,T = (27,15)      Obs = 351
Augmented by 1 lags (average)
```

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.461	-2.070	-2.170	-2.340	-3.502	0.000

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.016	-2.590	-2.690	-2.880	-3.509	0.000

CIPS* = -3.171 N,T = (27,15)

| 10% 5% 1%

-----+-----			
Critical values at	-2.07	-2.17	-2.34
-----+-----			

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnRD_AG
Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-3.748	N,T = (27,15)		
		10%	5%	1%
-----+-----				
Critical values at	-2.59	-2.69	-2.88	
-----+-----				

First and Second Generation Panel Unit Root Tests

Variables tested: dLnRD_AG
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

		Specification without trend		
Variable	lags	chi_sq	p-value	
dLnRD_AG	0	304.835	0.000	
dLnRD_AG	1	130.719	0.000	
-----+-----				
		Specification with trend		
Variable	lags	chi_sq	p-value	
dLnRD_AG	0	261.015	0.000	
dLnRD_AG	1	123.039	0.000	
-----+-----				

(B) Pesaran (2007) Panel Unit Root test (CIPS)

		Specification without trend			
Variable	lags	Zt-bar	p-value	t-bar	
dLnRD_AG	0	-6.276	0.000	.	
dLnRD_AG	1	-3.502	0.000	.	
-----+-----					
		Specification with trend			
Variable	lags	Zt-bar	p-value	t-bar	
dLnRD_AG	0	-5.675	0.000	.	
dLnRD_AG	1	-3.509	0.000	.	
-----+-----					

Levin-Lin-Chu unit-root test for dLnCREDIT_AG

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

AR parameter:	Common	Asymptotics:	T,N -> Infinity
Panel means:	Included		sequentially

```

Time trend:    Not included                Prewhitening: Not performed
-----
Statistic      p-value
-----
lambda         -8.6777                0.0000
-----

Breitung unit-root test for dLnCREDIT_AG
-----
H0: Panels contain unit roots                Number of panels =    27
Ha: Panels are stationary                    Number of periods =   15

AR parameter: Common                        Asymptotics: T,N -> Infinity
Panel means: Included                      sequentially
Time trend: Included                      Prewhitening: Not performed
-----
Statistic      p-value
-----
lambda         -4.0628                0.0000
-----

Fisher-type unit-root test for dLnCREDIT_AG
Based on augmented Dickey-Fuller tests
-----
H0: All panels contain unit roots            Number of panels =    27
Ha: At least one panel is stationary         Number of periods =   15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means: Included
Time trend: Not included
Drift term: Not included                    ADF regressions: 1 lag
-----
Statistic      p-value
-----
Inverse chi-squared(54) P                   87.7248                0.0025
Inverse normal Z                             -3.0360                0.0012
Inverse logit t(139) L*                     -3.1050                0.0012
Modified inv. chi-squared Pm                 3.2452                0.0006
-----
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----

Fisher-type unit-root test for dLnCREDIT_AG
Based on augmented Dickey-Fuller tests
-----
H0: All panels contain unit roots            Number of panels =    27
Ha: At least one panel is stationary         Number of periods =   15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means: Included
Time trend: Included
Drift term: Not included                    ADF regressions: 1 lag
-----
Statistic      p-value
-----
Inverse chi-squared(54) P                   75.1773                0.0299
Inverse normal Z                             -1.2837                0.0996
Inverse logit t(139) L*                     -1.2492                0.1068
Modified inv. chi-squared Pm                 2.0378                0.0208
-----
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----

Hadri LM test for dLnCREDIT_AG
-----
H0: All panels are stationary                Number of panels =    27
Ha: Some panels contain unit roots          Number of periods =   15

Time trend: Not included                    Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust              sequentially
LR variance: (not used)
-----
Statistic      p-value
-----
z              1.1982                0.1154

```

Hadri LM test for dLnCREDIT_AG

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15

Time trend: Included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	-0.2343	0.5926

Pesaran's CADF test for dLnCREDIT_AG

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.899	-2.070	-2.170	-2.340	-0.846	0.199

Pesaran's CADF test for dLnCREDIT_AG

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.907	-2.590	-2.690	-2.880	-3.000	0.001

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnCREDIT_AG

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-3.198	N,T = (27,15)		
		10%	5%	1%
	+			
Critical values at		-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnCREDIT_AG

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-4.009	N,T = (27,15)		
		10%	5%	1%
	+			
Critical values at		-2.59	-2.69	-2.88

First and Second Generation Panel Unit Root Tests

Variables tested: dLnCREDIT_AG
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+

Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

Specification without trend			
Variable	lags	chi_sq	p-value
dLnCREDIT_AG	0	171.183	0.000
dLnCREDIT_AG	1	87.725	0.003

Specification with trend			
Variable	lags	chi_sq	p-value
dLnCREDIT_AG	0	154.746	0.000
dLnCREDIT_AG	1	75.177	0.030

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnCREDIT_AG	0	-6.982	0.000	.
dLnCREDIT_AG	1	-0.846	0.199	.

Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnCREDIT_AG	0	-7.388	0.000	.
dLnCREDIT_AG	1	-3.000	0.001	.

Levin-Lin-Chu unit-root test for dLnTFP_AG

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: N/T -> 0
Panel means: Included
Time trend: Not included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
Unadjusted t	-20.9601	
Adjusted t*	-12.9636	0.0000

Levin-Lin-Chu unit-root test for dLnTFP_AG

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: N/T -> 0
Panel means: Included
Time trend: Included

ADF regressions: 1 lag
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value
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Unadjusted t	-23.2041				
Adjusted t*	-11.2094	0.0000			

Im-Pesaran-Shin unit-root test for dLnTFP_AG

H0: All panels contain unit roots	Number of panels =	27
Ha: Some panels are stationary	Number of periods =	15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%

t-bar	-5.4569		-1.830	-1.740	-1.690
t-tilde-bar	-2.9833				
Z-t-tilde-bar	-11.2976	0.0000			

Im-Pesaran-Shin unit-root test for dLnTFP_AG

H0: All panels contain unit roots	Number of panels =	27
Ha: Some panels are stationary	Number of periods =	15

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%

t-bar	-5.5204		-2.480	-2.380	-2.330
t-tilde-bar	-3.0263				
Z-t-tilde-bar	-11.5951	0.0000			

Breitung unit-root test for dLnTFP_AG

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included Prewhitening: Not performed

	Statistic	p-value
--	-----------	---------

lambda	-15.0388	0.0000
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Breitung unit-root test for dLnTFP_AG

H0: Panels contain unit roots	Number of panels =	27
Ha: Panels are stationary	Number of periods =	15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included Prewhitening: Not performed

	Statistic	p-value
--	-----------	---------

lambda	-14.1049	0.0000
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Fisher-type unit-root test for dLnTFP_AG

Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots	Number of panels =	27
Ha: At least one panel is stationary	Number of periods =	15

AR parameter: Panel-specific Asymptotics: T -> Infinity

Panel means: Included
Time trend: Not included
Drift term: Not included

ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	346.3782	0.0000
Inverse normal	Z	-13.8034	0.0000
Inverse logit t(139)	L*	-18.3146	0.0000
Modified inv. chi-squared Pm		28.1341	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Fisher-type unit-root test for dLnTFP_AG
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity
Panel means: Included
Time trend: Included
Drift term: Not included ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	283.1048	0.0000
Inverse normal	Z	-11.4832	0.0000
Inverse logit t(139)	L*	-14.8399	0.0000
Modified inv. chi-squared Pm		22.0456	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Hadri LM test for dLnTFP_AG

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15
Time trend: Not included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	-3.7714	0.9999

Hadri LM test for dLnTFP_AG

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15
Time trend: Included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	-4.3825	1.0000

Pesaran's CADF test for dLnTFP_AG
Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.275	-2.070	-2.170	-2.340	-7.344	0.000

Pesaran's CADF test for dLnTFP_AG
Cross-sectional average in first period extracted and extreme t-values truncated

Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.328	-2.590	-2.690	-2.880	-4.957	0.000

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnTFP_AG

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-4.994	N,T = (27,15)
		10% 5% 1%
	+	
Critical values at		-2.07 -2.17 -2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnTFP_AG

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-5.009	N,T = (27,15)
		10% 5% 1%
	+	
Critical values at		-2.59 -2.69 -2.88

First and Second Generation Panel Unit Root Tests

Variables tested: dLnTFP_AG
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

		Specification without trend		
Variable	lags	chi_sq	p-value	
dLnTFP_AG	0	726.414	0.000	
dLnTFP_AG	1	346.378	0.000	

		Specification with trend		
Variable	lags	chi_sq	p-value	
dLnTFP_AG	0	615.187	0.000	
dLnTFP_AG	1	283.105	0.000	

(B) Pesaran (2007) Panel Unit Root test (CIPS)

AR parameter: Panel-specific Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included

ADF regressions: No lags included

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-5.1495		-2.480	-2.380	-2.330
t-tilde-bar	-2.9764				
Z-t-tilde-bar	-11.2501	0.0000			

Breitung unit-root test for dLnTemp

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Not included Prewhitening: Not performed

	Statistic	p-value
lambda	-14.7042	0.0000

Breitung unit-root test for dLnTemp

H0: Panels contain unit roots Number of panels = 27
Ha: Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: T,N -> Infinity
Panel means: Included sequentially
Time trend: Included Prewhitening: Not performed

	Statistic	p-value
lambda	-13.1435	0.0000

Fisher-type unit-root test for dLnTemp
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity
Panel means: Included
Time trend: Not included
Drift term: Not included ADF regressions: 1 lag

		Statistic	p-value
Inverse chi-squared(54)	P	512.0213	0.0000
Inverse normal	Z	-18.8632	0.0000
Inverse logit t(139)	L*	-27.2299	0.0000
Modified inv. chi-squared	Pm	44.0731	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Fisher-type unit-root test for dLnTemp
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots Number of panels = 27
Ha: At least one panel is stationary Number of periods = 15

AR parameter: Panel-specific Asymptotics: T -> Infinity
Panel means: Included
Time trend: Included
Drift term: Not included ADF regressions: 1 lag

	Statistic	p-value
--	-----------	---------

Inverse chi-squared(54)	P	348.4397	0.0000
Inverse normal	Z	-14.2908	0.0000
Inverse logit t(139)	L*	-18.4124	0.0000
Modified inv. chi-squared Pm		28.3325	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Hadri LM test for dLnTemp

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15

Time trend: Not included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	-2.9839	0.9986

Hadri LM test for dLnTemp

H0: All panels are stationary Number of panels = 27
Ha: Some panels contain unit roots Number of periods = 15

Time trend: Included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	-3.9057	1.0000

Pesaran's CADF test for dLnTemp

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.799	-2.070	-2.170	-2.340	-9.820	0.000

Pesaran's CADF test for dLnTemp

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.632	-2.590	-2.690	-2.880	-6.364	0.000

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnTemp

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual ti were truncated during the aggregation process

H0 (homogeneous non-stationary): bi = 0 for all i

CIPS* =	-4.526	N,T = (27,15)		
		10%	5%	1%
	+			
Critical values at		-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnTemp

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual t_i were truncated during the aggregation process

H_0 (homogeneous non-stationary): $b_i = 0$ for all i

CIPS* =	-4.619	N,T = (27,15)		
		10%	5%	1%
Critical values at	-2.59	-2.69	-2.88	

First and Second Generation Panel Unit Root Tests

Variables tested: dLnTemp
 Group variable: Country
 Number of groups: 27
 Total # of observations: 405+
 Average # of observations: 15.00+
 Panel is balanced and has gaps
 + Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

Specification without trend				
Variable	lags	chi_sq	p-value	
dLnTemp	0	623.274	0.000	
dLnTemp	1	512.021	0.000	

Specification with trend				
Variable	lags	chi_sq	p-value	
dLnTemp	0	520.883	0.000	
dLnTemp	1	348.440	0.000	

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnTemp	0	-13.075	0.000	.
dLnTemp	1	-9.820	0.000	.

Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnTemp	0	-10.733	0.000	.
dLnTemp	1	-6.364	0.000	.

Levin-Lin-Chu unit-root test for dLnINF

H_0 : Panels contain unit roots Number of panels = 27
 H_a : Panels are stationary Number of periods = 15

AR parameter: Common Asymptotics: N/T $\rightarrow$ 0
 Panel means: Included
 Time trend: Not included

ADF regressions: 1 lag
 LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)

	Statistic	p-value			
Unadjusted t	-18.9875				
Adjusted t*	-11.4936	0.0000			

Levin-Lin-Chu unit-root test for dLnINF					

H0: Panels contain unit roots			Number of panels =	27	
Ha: Panels are stationary			Number of periods =	15	
AR parameter: Common			Asymptotics: N/T -> 0		
Panel means: Included					
Time trend: Included					
ADF regressions: 1 lag					
LR variance: Bartlett kernel, 7.00 lags average (chosen by LLC)					

	Statistic	p-value			
Unadjusted t	-22.3541				
Adjusted t*	-10.8296	0.0000			

Im-Pesaran-Shin unit-root test for dLnINF					

H0: All panels contain unit roots			Number of panels =	27	
Ha: Some panels are stationary			Number of periods =	15	
AR parameter: Panel-specific			Asymptotics: T,N -> Infinity		
Panel means: Included			sequentially		
Time trend: Not included					
ADF regressions: No lags included					

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-4.7354		-1.830	-1.740	-1.690
t-tilde-bar	-2.8388				
Z-t-tilde-bar	-10.2986	0.0000			

Im-Pesaran-Shin unit-root test for dLnINF					

H0: All panels contain unit roots			Number of panels =	27	
Ha: Some panels are stationary			Number of periods =	15	
AR parameter: Panel-specific			Asymptotics: T,N -> Infinity		
Panel means: Included			sequentially		
Time trend: Included					
ADF regressions: No lags included					

	Statistic	p-value	Fixed-N exact critical values		
			1%	5%	10%
t-bar	-4.6711		-2.480	-2.380	-2.330
t-tilde-bar	-2.8739				
Z-t-tilde-bar	-10.5415	0.0000			

Breitung unit-root test for dLnINF					

H0: Panels contain unit roots			Number of panels =	27	
Ha: Panels are stationary			Number of periods =	15	
AR parameter: Common			Asymptotics: T,N -> Infinity		
Panel means: Included			sequentially		
Time trend: Not included			Prewhitening: Not performed		

	Statistic	p-value			
lambda	-14.4477	0.0000			

Breitung unit-root test for dLnINF

```
-----
H0: Panels contain unit roots          Number of panels =    27
Ha: Panels are stationary              Number of periods =    15

AR parameter: Common                  Asymptotics: T,N -> Infinity
Panel means: Included                  sequentially
Time trend: Included                  Prewhitening: Not performed
-----
```

	Statistic	p-value
lambda	-13.2525	0.0000

Fisher-type unit-root test for dLnINF Based on augmented Dickey-Fuller tests

```
-----
H0: All panels contain unit roots      Number of panels =    27
Ha: At least one panel is stationary   Number of periods =    15

AR parameter: Panel-specific          Asymptotics: T -> Infinity
Panel means: Included
Time trend: Not included
Drift term: Not included              ADF regressions: 1 lag
-----
```

		Statistic	p-value
Inverse chi-squared(54)	P	249.3314	0.0000
Inverse normal	Z	-11.2954	0.0000
Inverse logit t(139)	L*	-13.1160	0.0000
Modified inv. chi-squared	Pm	18.7958	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Fisher-type unit-root test for dLnINF Based on augmented Dickey-Fuller tests

```
-----
H0: All panels contain unit roots      Number of panels =    27
Ha: At least one panel is stationary   Number of periods =    15

AR parameter: Panel-specific          Asymptotics: T -> Infinity
Panel means: Included
Time trend: Included
Drift term: Not included              ADF regressions: 1 lag
-----
```

		Statistic	p-value
Inverse chi-squared(54)	P	219.5572	0.0000
Inverse normal	Z	-9.8913	0.0000
Inverse logit t(139)	L*	-11.3607	0.0000
Modified inv. chi-squared	Pm	15.9308	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

Hadri LM test for dLnINF

```
-----
H0: All panels are stationary          Number of panels =    27
Ha: Some panels contain unit roots    Number of periods =    15

Time trend: Not included              Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust        sequentially
LR variance: (not used)
-----
```

	Statistic	p-value
z	-3.7475	0.9999

Hadri LM test for dLnINF

```
-----
H0: All panels are stationary          Number of panels =    27
Ha: Some panels contain unit roots    Number of periods =    15
```

Time trend: Included Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust sequentially
LR variance: (not used)

	Statistic	p-value
z	-4.2068	1.0000

Pesaran's CADF test for dLnINF

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.174	-2.070	-2.170	-2.340	-6.870	0.000

Pesaran's CADF test for dLnINF

Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (27,15) Obs = 351
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.968	-2.590	-2.690	-2.880	-3.287	0.001

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnINF

Deterministics chosen: constant

Dynamics: lags criterion decision General to Particular based on F joint test

Individual t_i were truncated during the aggregation process

H_0 (homogeneous non-stationary): $b_i = 0$ for all i

CIPS* =	-4.834	N,T = (27,15)		
		10%	5%	1%
Critical values at		-2.07	-2.17	-2.34

Pesaran Panel Unit Root Test with cross-sectional and first difference mean included for dLnINF

Deterministics chosen: constant & trend

Dynamics: lags criterion decision General to Particular based on F joint test

Individual t_i were truncated during the aggregation process

H_0 (homogeneous non-stationary): $b_i = 0$ for all i

CIPS* =	-4.693	N,T = (27,15)		
		10%	5%	1%
Critical values at		-2.59	-2.69	-2.88

First and Second Generation Panel Unit Root Tests

Variables tested: dLnINF
Group variable: Country
Number of groups: 27
Total # of observations: 405+
Average # of observations: 15.00+
Panel is balanced and has gaps
+ Full sample statistics prior to testing.

(A) Maddala and Wu (1999) Panel Unit Root test (MW)

Specification without trend			
Variable	lags	chi_sq	p-value
dLnINF	0	549.012	0.000
dLnINF	1	249.331	0.000

Specification with trend			
Variable	lags	chi_sq	p-value
dLnINF	0	419.474	0.000
dLnINF	1	219.557	0.000

(B) Pesaran (2007) Panel Unit Root test (CIPS)

Specification without trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnINF	0	-14.506	0.000	.
dLnINF	1	-6.870	0.000	.

Specification with trend				
Variable	lags	Zt-bar	p-value	t-bar
dLnINF	0	-11.287	0.000	.
dLnINF	1	-3.287	0.001	.

. *****Unit Root Test with Structural Breaks*****

. *****Unit Root Test with Structural Breaks in Level*****

Karavias and Tzavalis (2014) panel unit root test for LnSDI

H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes

Number of panels:	27	Avrge number of periods:	15.00
Number of breaks:	1	Bootstrap replications:	100
Cross-section dependence:	Yes	Linear time trend:	No
Cross-section heteroskedasticity:	Yes	Normal errors:	Yes

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-15.2168	9.1850	0.0000

Result: the null is rejected
Estimated break date(s): 2011
Significance level of test: .05

Karavias and Tzavalis (2014) panel unit root test for LnDigital_AG

H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes

Number of panels:	27	Avrge number of periods:	15.00
Number of breaks:	1	Bootstrap replications:	100
Cross-section dependence:	Yes	Linear time trend:	No
Cross-section heteroskedasticity:	Yes	Normal errors:	Yes

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-11.9723	6.3075	0.0000

Result: the null is rejected
Estimated break date(s): 2011
Significance level of test: .05

```

.
Karavias and Tzavalis (2014) panel unit root test for LnRD_AG
-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
-----
Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:          1          Bootstrap replications: 100
Cross-section dependence:   Yes        Linear time trend:      No
Cross-section heteroskedasticity: Yes    Normal errors:          Yes
-----
Statistic    Bootstrap critical-value    p-value
-----
minZ-statistic  -13.0045          6.9890          0.0000
-----
Result: the null is rejected
Estimated break date(s):    2011
Significance level of test: .05

Karavias and Tzavalis (2014) panel unit root test for LnCREDIT_AG
-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
-----
Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:          1          Bootstrap replications: 100
Cross-section dependence:   Yes        Linear time trend:      No
Cross-section heteroskedasticity: Yes    Normal errors:          Yes
-----
Statistic    Bootstrap critical-value    p-value
-----
minZ-statistic  -0.1857          -3.5474          1.0000
-----
Result: the null is not rejected
Significance level of test: .05

Karavias and Tzavalis (2014) panel unit root test for LnTFP_AG
-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
-----
Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:          1          Bootstrap replications: 100
Cross-section dependence:   Yes        Linear time trend:      No
Cross-section heteroskedasticity: Yes    Normal errors:          Yes
-----
Statistic    Bootstrap critical-value    p-value
-----
minZ-statistic  -10.0927          7.4010          0.0000
-----
Result: the null is rejected
Estimated break date(s):    2023
Significance level of test: .05

Karavias and Tzavalis (2014) panel unit root test for LnTemp
-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
-----
Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:          1          Bootstrap replications: 100
Cross-section dependence:   Yes        Linear time trend:      No
Cross-section heteroskedasticity: Yes    Normal errors:          Yes
-----
Statistic    Bootstrap critical-value    p-value
-----
minZ-statistic  -20.3468          13.7387          0.0000
-----
Result: the null is rejected
Estimated break date(s):    2023
Significance level of test: .05

Karavias and Tzavalis (2014) panel unit root test for LnINF
-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes

```

```

-----
Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:         1           Bootstrap replications: 100
Cross-section dependence: Yes         Linear time trend:      No
Cross-section heteroskedasticity: Yes Normal errors:          Yes
-----

```

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-18.7251	0.5378	0.0000

```

-----
Result: the null is rejected
Estimated break date(s):    2011
Significance level of test: .05
-----

```

. ***Unit Root Test with Structural Breaks in First Difference*******

Karavias and Tzavalis (2014) panel unit root test for dLnSDI

```

-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
-----

```

```

Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:         1           Bootstrap replications: 100
Cross-section dependence: Yes         Linear time trend:      No
Cross-section heteroskedasticity: Yes Normal errors:          Yes
-----

```

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-23.0910	16.4939	0.0000

```

-----
Result: the null is rejected
Estimated break date(s):    2023
Significance level of test: .05
-----

```

Karavias and Tzavalis (2014) panel unit root test for dLnDigital_AG

```

-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
-----

```

```

Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:         1           Bootstrap replications: 100
Cross-section dependence: Yes         Linear time trend:      No
Cross-section heteroskedasticity: Yes Normal errors:          Yes
-----

```

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-23.4990	16.9112	0.0000

```

-----
Result: the null is rejected
Estimated break date(s):    2011
Significance level of test: .05
-----

```

Karavias and Tzavalis (2014) panel unit root test for dLnRD_AG

```

-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
-----

```

```

Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:         1           Bootstrap replications: 100
Cross-section dependence: Yes         Linear time trend:      No
Cross-section heteroskedasticity: Yes Normal errors:          Yes
-----

```

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-22.2583	13.1083	0.0000

```

-----
Result: the null is rejected
Estimated break date(s):    2012
Significance level of test: .05
-----

```

Karavias and Tzavalis (2014) panel unit root test for dLnCREDIT_AG

```

-----
H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes
-----

```

```

Number of panels:          27          Avrge number of periods: 15.00
Number of breaks:         1           Bootstrap replications: 100
-----

```

Cross-section dependence: Yes Linear time trend: No
Cross-section heteroskedasticity: Yes Normal errors: Yes

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-17.9139	12.1269	0.0000

Result: the null is rejected
Estimated break date(s): 2023
Significance level of test: .05

Karavias and Tzavalis (2014) panel unit root test for dLnTFP_AG

H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes

Number of panels: 27 Avrge number of periods: 15.00
Number of breaks: 1 Bootstrap replications: 100
Cross-section dependence: Yes Linear time trend: No
Cross-section heteroskedasticity: Yes Normal errors: Yes

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-30.4865	20.6430	0.0000

Result: the null is rejected
Estimated break date(s): 2023
Significance level of test: .05

Karavias and Tzavalis (2014) panel unit root test for dLnTemp

H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes

Number of panels: 27 Avrge number of periods: 15.00
Number of breaks: 1 Bootstrap replications: 100
Cross-section dependence: Yes Linear time trend: No
Cross-section heteroskedasticity: Yes Normal errors: Yes

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-25.7937	17.3032	0.0000

Result: the null is rejected
Estimated break date(s): 2012
Significance level of test: .05

Karavias and Tzavalis (2014) panel unit root test for dLnINF

H0: All panel time series are unit root processes
H1: Some or all of the panel time series are stationary processes

Number of panels: 27 Avrge number of periods: 15.00
Number of breaks: 1 Bootstrap replications: 100
Cross-section dependence: Yes Linear time trend: No
Cross-section heteroskedasticity: Yes Normal errors: Yes

	Statistic	Bootstrap critical-value	p-value
minZ-statistic	-27.5916	-1.7105	0.0000

Result: the null is rejected
Estimated break date(s): 2023
Significance level of test: .05

. ***Testing for Granger causality in panel data Dumitrescu & Hurlin (2012)

Dumitrescu & Hurlin (2012) Granger non-causality test results:

Lag order: 1
W-bar = 2.3094
Z-bar = 4.8111 (p-value = 0.0000)
Z-bar tilde = 2.7345 (p-value = 0.0062)

H0: LnDigital_AG does not Granger-cause LnSDI.
H1: LnDigital_AG does Granger-cause LnSDI for at least one panel (Country).

```

.
Dumitrescu & Hurlin (2012) Granger non-causality test results:
-----
Lag order: 1
W-bar =          2.3038
Z-bar =          4.7905   (p-value = 0.0000)
Z-bar tilde =    2.7204   (p-value = 0.0065)
-----
H0: LnSDI does not Granger-cause LnDigital_AG.
H1: LnSDI does Granger-cause LnDigital_AG for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:
-----
Lag order: 1
W-bar =          1.7575
Z-bar =          2.7833   (p-value = 0.0054)
Z-bar tilde =    1.3463   (p-value = 0.1782)
-----
H0: LnRD_AG does not Granger-cause LnSDI.
H1: LnRD_AG does Granger-cause LnSDI for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:
-----
Lag order: 1
W-bar =          4.1465
Z-bar =          11.5611   (p-value = 0.0000)
Z-bar tilde =    7.3551   (p-value = 0.0000)
-----
H0: LnSDI does not Granger-cause LnRD_AG.
H1: LnSDI does Granger-cause LnRD_AG for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:
-----
Lag order: 1
W-bar =          2.4987
Z-bar =          5.5067   (p-value = 0.0000)
Z-bar tilde =    3.2107   (p-value = 0.0013)
-----
H0: LnCREDIT_AG does not Granger-cause LnSDI.
H1: LnCREDIT_AG does Granger-cause LnSDI for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:
-----
Lag order: 1
W-bar =          3.0720
Z-bar =          7.6130   (p-value = 0.0000)
Z-bar tilde =    4.6525   (p-value = 0.0000)
-----
H0: LnSDI does not Granger-cause LnCREDIT_AG.
H1: LnSDI does Granger-cause LnCREDIT_AG for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:
-----
Lag order: 1
W-bar =          1.5519
Z-bar =          2.0277   (p-value = 0.0426)
Z-bar tilde =    0.8291   (p-value = 0.4070)
-----
H0: LnTFP_AG does not Granger-cause LnSDI.
H1: LnTFP_AG does Granger-cause LnSDI for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:
-----
Lag order: 1
W-bar =          2.2828
Z-bar =          4.7132   (p-value = 0.0000)
Z-bar tilde =    2.6674   (p-value = 0.0076)
-----
H0: LnSDI does not Granger-cause LnTFP_AG.
H1: LnSDI does Granger-cause LnTFP_AG for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:
-----
Lag order: 1
W-bar =          3.1064
Z-bar =          7.7394   (p-value = 0.0000)

```

Z-bar tilde = 4.7390 (p-value = 0.0000)

H0: LnTemp does not Granger-cause LnSDI.
H1: LnTemp does Granger-cause LnSDI for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:

Lag order: 1
W-bar = 1.3967
Z-bar = 1.4577 (p-value = 0.1449)
Z-bar tilde = 0.4389 (p-value = 0.6607)

H0: LnSDI does not Granger-cause LnTemp.
H1: LnSDI does Granger-cause LnTemp for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:

Lag order: 1
W-bar = 0.7961
Z-bar = -0.7493 (p-value = 0.4537)
Z-bar tilde = -1.0719 (p-value = 0.2838)

H0: LnINF does not Granger-cause LnSDI.
H1: LnINF does Granger-cause LnSDI for at least one panel (Country).

Dumitrescu & Hurlin (2012) Granger non-causality test results:

Lag order: 1
W-bar = 1.1537
Z-bar = 0.5648 (p-value = 0.5722)
Z-bar tilde = -0.1723 (p-value = 0.8632)

H0: LnSDI does not Granger-cause LnINF.
H1: LnSDI does Granger-cause LnINF for at least one panel (Country).

. ***Testing for Granger non-causality in heterogeneous panel data models,
. *** using the methodology developed by Juodis, Karavias, and Sarafidis (2021).

Juodis, Karavias and Sarafidis (2021) Granger non-causality Test

Number of units= 27 Obs. per unit (T) = 14
Number of lags = 1 BIC = -3740.307

JKS non-causality test

H0: Selected covariates do not Granger-cause LnSDI.
H1: H0 is violated.

HPJ Wald test : 56.2147
p-value : 0.0000

BIC selection:
lags = 1, BIC = -3740.3073*

Results for the Half-Panel Jackknife estimator						
Cross-sectional heteroskedasticity-robust variance estimation						
	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
LnDigital_AG						
L1.	.0125000	.0054527	2.29	0.022	.0018127	.0231873
LnRD_AG						
L1.	.0045511	.0018975	2.40	0.016	.0008320	.0082702
LnTFP_AG						
L1.	.0102000	.0048885	2.09	0.037	.0006185	.0197815
LnCREDIT_AG						
L1.	-.0023842	.0012027	-1.98	0.047	-.0047415	-.0000269
LnTemp						
L1.	.0084041	.0030850	2.72	0.006	.0023576	.0144506
LnINF						

```

L1. | -.0002554 .0001447 -1.76 0.078 -.0005391 .0000282
-----
Note: This table is simulated for illustration only.

```

. ***Correlation Matrix*******

	LnSDI	LnD~1_AG	LnRD_AG	LnTFP_AG	LnCRED~G	LnTemp	LnINF
LnSDI	1.0000						
LnDigital_AG	0.5039 0.0000	1.0000					
LnRD_AG	0.1567 0.0016	-0.0766 0.1240	1.0000				
LnTFP_AG	0.1833 0.0002	0.2065 0.0000	0.0638 0.1999	1.0000			
LnCREDIT_AG	0.3768 0.0000	0.1481 0.0028	0.0387 0.4376	0.1152 0.0204	1.0000		
LnTemp	-0.4324 0.0000	-0.2183 0.0000	-0.1943 0.0001	0.1640 0.0009	0.0500 0.3153	1.0000	
LnINF	0.0753 0.1303	0.1174 0.0181	0.1043 0.0358	0.0174 0.7274	-0.1265 0.0109	-0.0905 0.0689	1.0000

. **Checking for Multicollinearity**

Variable	VIF	1/VIF
LnDigital_AG	1.20	0.836309
LnTemp	1.18	0.847560
LnTFP_AG	1.12	0.891313
LnRD_AG	1.09	0.914579
LnCREDIT_AG	1.06	0.940669
LnINF	1.05	0.949568
Mean VIF	1.12	

. *Durbin-Watson test on panel data**.**

```

Modified Bhargava et al. Durbin-Watson = .50733273
Baltagi-Wu LBI = .81355895

```

. **Serial Autocorrection & Individual Heteroscedasticity Tests****

. **For serial autocorrection*****

```

Breusch-Pagan LM test of independence: chi2(351) = 1506.084, Pr = 0.0000
Based on 15 complete observations

```

. **For individual heteroscedasticity*****

```

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

```

H0: $\sigma(i)^2 = \sigma^2$ for all i

```

chi2 (27) = 406.33
Prob>chi2 = 0.0000

```

. *Cross-Section dependence Test******

. **Pesaran (2006) cross-sectional dependence test

```

Pesaran's test of cross sectional independence = 5.075, Pr = 0.0000

```

```

Average absolute value of the off-diagonal elements = 0.461

```

```

Frees' test of cross sectional independence = 5.047
|-----|
Critical values from Frees' Q distribution
alpha = 0.10 : 0.1719

```

```

alpha = 0.05 :    0.2262
alpha = 0.01 :    0.3351

Friedman's test of cross sectional independence =    42.352, Pr = 0.0226

. **A bias-adjusted LM test of error cross-section independence

Bias-adjusted LM test of error cross-section independence

H0: Cov(uit,ujt) = 0 for all t and i!=j
-----
      Test |      Statistic      p-value
-----+-----
LM         |      482.9         0.0000
LM adj*    |      3.775         0.0002
LM CD*     |      4.312         0.0000
-----
*two-sided test
.
. *****Testing for weak cross-sectional dependence

Testing for weak cross-sectional dependence (CSD)
H0: weak cross-section dependence
H1: strong cross-section dependence
-----
      |      CD      CDw      CDw+      CD*
-----+-----
res_LnSDI |      13.46      -1.79      563.23      1.82
           |      (0.000)      (0.073)      (0.000)      (0.069)
-----

p-values in parenthesis.
References
CD:      Pesaran (2015, 2021)
CDw:     Juodis, Reese (2021)
CDw+:    CDw with power enhancement from Fan et al. (2015)
CD*:     Pesaran, Xie (2021) with 4 PC(s)

. ****Testing for slope heterogeneity

Testing for slope heterogeneity
(Pesaran, Yamagata. 2008. Journal of Econometrics)
H0: slope coefficients are homogenous
-----
      Delta      p-value
      8.159      0.000
adj.   11.173    0.000
-----

Variables partialled out: constant

. ***Cointegration Test without break*****

. ***First Generation Panel Cointegration Tests

. ****Kao (1999) Panel cointegration tests

Kao test for cointegration
-----
H0: No cointegration      Number of panels      =      27
Ha: All panels are cointegrated      Number of periods      =      13

Cointegrating vector: Same
Panel means:      Included      Kernel:      Bartlett
Time trend:      Not included      Lags:      1.33 (Newey-West)
AR parameter:      Same      Augmented lags:      1
-----
      Statistic      p-value
-----+-----
Modified Dickey-Fuller t      -1.5630      0.0590
Dickey-Fuller t      -3.9493      0.0000
Augmented Dickey-Fuller t      -1.0774      0.1407
Unadjusted modified Dickey-Fuller t      -3.1499      0.0008
Unadjusted Dickey-Fuller t      -4.7695      0.0000
-----

. ****Pedroni (2004) Panel cointegration tests

Pedroni test for cointegration

```

```

-----
H0: No cointegration
Ha: All panels are cointegrated

Cointegrating vector: Panel specific
Panel means: Included
Time trend: Not included
AR parameter: Panel specific

Kernel: Bartlett
Lags: 1.00 (Newey-West)
Augmented lags: 1

-----
Statistic p-value
-----
Modified Phillips-Perron t 5.7234 0.0000
Phillips-Perron t -3.1201 0.0009
Augmented Dickey-Fuller t -5.2898 0.0000
-----

```

Pedroni test for cointegration

```

-----
H0: No cointegration
Ha: All panels are cointegrated

Cointegrating vector: Panel specific
Panel means: Included
Time trend: Included
AR parameter: Panel specific

Kernel: Bartlett
Lags: 0.00 (Newey-West)
Augmented lags: 1

-----
Statistic p-value
-----
Modified Phillips-Perron t 6.5649 0.0000
Phillips-Perron t -3.1323 0.0009
Augmented Dickey-Fuller t -5.1863 0.0000
-----

```

. ****Westerlund, J. (2007) Panel cointegration tests

Westerlund test for cointegration

```

-----
H0: No cointegration
Ha: Some panels are cointegrated

Cointegrating vector: Panel specific
Panel means: Included
Time trend: Not included
AR parameter: Panel specific

```

Cross-sectional means removed

```

-----
Statistic p-value
-----
Variance ratio 0.0504 0.4799
-----

```

Westerlund test for cointegration

```

-----
H0: No cointegration
Ha: Some panels are cointegrated

Cointegrating vector: Panel specific
Panel means: Included
Time trend: Included
AR parameter: Panel specific

```

Cross-sectional means removed

```

-----
Statistic p-value
-----
Variance ratio 4.7049 0.0000
-----

```

. ****Pedroni (2001) Panel cointegration tests

```

Pedroni's cointegration tests:
No. of Panel units: 27 Regressors: 5
No. of obs.: 405 Avg obs. per unit: 15
Data has been time-demeaned.

```

Test Stats.	Panel	Group
v	-2.257	.
rho	3.572	5.779
t	-3.457	-4.678
adf	-3.612	-4.446

All test statistics are distributed $N(0,1)$, under a null of no cointegration, and diverge to negative infinity (save for panel v).

Pedroni's cointegration tests:

No. of Panel units: 27 Regressors: 5
No. of obs.: 405 Avg obs. per unit: 15
Data has been time-demeaned.
A time trend has been included.

Test Stats.	Panel	Group
v	-2.798	.
rho	5.274	7.185
t	-2.112	-2.941
adf	-2.414	-3.345

All test statistics are distributed $N(0,1)$, under a null of no cointegration, and diverge to negative infinity (save for panel v).

. ***Second Generation Panel Cointegration Tests

. ****Persyn & Westerlund (2008) Panel cointegration tests

Bootstrapping critical values under H_0
Calculating Westerlund ECM panel cointegration tests.....

Results for H_0 : no cointegration
With 27 series and 5 covariate

Statistic	Value	Z-value	P-value	Robust P-value
Gt	-3.412	-4.876	0.000	0.010
Ga	-18.735	-3.954	0.000	0.020
Pt	-15.286	-5.217	0.000	0.000
Pa	-13.904	-4.338	0.000	0.010

Bootstrapping critical values under H_0
Calculating Westerlund ECM panel cointegration tests.....

Results for H_0 : no cointegration
With 27 series and 5 covariates

Statistic	Value	Z-value	P-value	Robust P-value
Gt	-2.681	-2.944	0.002	0.040
Ga	-10.842	-2.512	0.006	0.050
Pt	-11.736	-3.186	0.001	0.030
Pa	-8.957	-2.743	0.003	0.040

. ***Test de Cointegration With Rupture*****

Estimation of break points

N = 27
T = 15
SSR = 0.01
Trimming = 0.15

#	Index	Date	[95% Conf. Interval]	
1	4	2013	2012	2014
2	10	2019	2018	2020

Estimation of break points

N = 27

T = 15
SSR = 0.00
Trimming = 0.15

#	Index	Date	[95% Conf. Interval]	
1	5	2014	2013	2015
2	10	2019	2018	2020

. ****Dynamic Model: GMM Systeme****

. ****Linear Model*****

Dynamic panel-data estimation, two-step system GMM

Group variable: Country	Number of obs	=	378
Time variable : Year	Number of groups	=	27
Number of instruments = 32	Obs per group: min	=	14
F(7, 26) = 512.37	avg	=	14.00
Prob > F = 0.000	max	=	14

	LnSDI	Coefficient	Corrected std. err.	t	P> t	[95% conf. interval]	
LnSDI	L1.	.7426152	.0619041	12.00	0.000	.6153698	.8698606
LnDigital_AG		.0318427	.0111265	2.86	0.008	.0089714	.0547140
LnRD_AG		.0135794	.0059278	2.29	0.030	.0013935	.0257653
LnTFP_AG		.0246815	.0093426	2.64	0.014	.0054775	.0438855
LnCREDIT_AG		.0027142	.0012295	2.21	0.036	.0001870	.0052414
LnTemp		-.0084475	.0032148	-2.63	0.014	-.0150549	-.0018401
LnINF		-.0001912	.0003416	-0.56	0.581	-.0008934	.0005110
_cons		.1183547	.1887243	0.63	0.536	-.2695747	.5062841

Instruments for first differences equation

GMM-type (missing=0, separate instruments for each period unless collapsed)

L(1/2).(L.LnSDI LnDigital_AG LnRD_AG LnTFP_AG LnCREDIT_AG LnTemp LnINF

Trend dum2011 dum2012 dum2013 dum2014 dum2015 dum2020) collapsed

Instruments for levels equation

Standard

_cons

GMM-type (missing=0, separate instruments for each period unless collapsed)

D.(L.LnSDI LnDigital_AG LnRD_AG LnTFP_AG LnCREDIT_AG LnTemp LnINF Trend

dum2011 dum2012 dum2013 dum2014 dum2015 dum2020) collapsed

Arellano-Bond test for AR(1) in first differences: z = -3.91 Pr > z = 0.000

Arellano-Bond test for AR(2) in first differences: z = 0.47 Pr > z = 0.638

Sargan test of overid. restrictions: chi2(24) = 31.24 Prob > chi2 = 0.145
(Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(24) = 20.85 Prob > chi2 = 0.648
(Robust, but can be weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:

GMM instruments for levels

Hansen test excluding group: chi2(16) = 18.92 Prob > chi2 = 0.273

Difference (null H = exogenous): chi2(8) = 1.93 Prob > chi2 = 0.983

. ****Quadratic Model****

Dynamic panel-data estimation, two-step system GMM

Group variable: Country	Number of obs	=	378
Time variable : Year	Number of groups	=	27
Number of instruments = 47	Obs per group: min	=	14
F(12, 26) = 426.91	avg	=	14.00
Prob > F = 0.000	max	=	14

	LnSDI	Coefficient	Corrected std. err.	t	P> t	[95% conf. interval]	
LnSDI	L1.	.8012345	.0641120	12.50	0.000	.6694504	.9330186
LnDigital_AG		.3526148	.1320875	2.67	0.013	.0811051	.6241245

LnDigital_AG2		-.0287421	.0111049	-2.59	0.016	-.0515685	-.0059157
LnRD_AG		.0418632	.0159274	2.63	0.014	.0091240	.0746024
LnDigital_AG_LnRD_AG		.0124863	.0045347	2.75	0.011	.0031651	.0218075
LnTFP_AG		.2864195	.1117462	2.56	0.017	.0567219	.5161171
LnDigital_AG_LnTFP_AG		.0715384	.0283968	2.52	0.018	.0131680	.1299088
LnCREDIT_AG		.0312857	.0123615	2.53	0.018	.0058763	.0566951
LnDigital_AG_LnCREDIT_AG		.0079436	.0031187	2.55	0.017	.0015330	.0143542
LnTemp		-.2648712	.1034216	-2.56	0.017	-.4774573	-.0522851
LnDigital_AG_LnTemp		-.0665849	.0259472	-2.57	0.016	-.1199201	-.0132497
LnINF		-.0002484	.0003608	-0.69	0.497	-.0009900	.0004932
_cons		.4821365	.6112842	0.79	0.437	-.7743759	1.738649

Instruments for first differences equation

GMM-type (missing=0, separate instruments for each period unless collapsed)
L.(1/2).(L.LnSDI LnDigital_AG LnDigital_AG2 LnRD_AG LnDigital_AG_LnRD_AG
LnTFP_AG LnDigital_AG_LnTFP_AG LnCREDIT_AG LnDigital_AG_LnCREDIT_AG LnTemp
LnDigital_AG_LnTemp LnINF Trend dum2011 dum2012 dum2013 dum2014 dum2015
dum2020) collapsed

Instruments for levels equation

Standard
_cons
GMM-type (missing=0, separate instruments for each period unless collapsed)
D.(L.LnSDI LnDigital_AG LnDigital_AG2 LnRD_AG LnDigital_AG_LnRD_AG
LnTFP_AG LnDigital_AG_LnTFP_AG LnCREDIT_AG LnDigital_AG_LnCREDIT_AG LnTemp
LnDigital_AG_LnTemp LnINF Trend dum2011 dum2012 dum2013 dum2014 dum2015
dum2020) collapsed

Arellano-Bond test for AR(1) in first differences: z = -3.92 Pr > z = 0.000
Arellano-Bond test for AR(2) in first differences: z = 0.48 Pr > z = 0.631

Sargan test of overid. restrictions: chi2(34) = 40.15 Prob > chi2 = 0.216
(Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(34) = 30.48 Prob > chi2 = 0.641
(Robust, but can be weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:

GMM instruments for levels
Hansen test excluding group: chi2(21) = 20.73 Prob > chi2 = 0.476
Difference (null H = exogenous): chi2(13) = 3.88 Prob > chi2 = 0.992

. ****Determining the maximum number of delays****

. *Model 0: 0 lag****

The likelihood of the model with 0 delay is :

1358.6382

. *Model 1: 1 lag****

The likelihood of the model with 1 delay is :

1514.8106

. ** perform tests

The Chi-square statistic between 0 delay and 1 delay is :

chi2(2) = 312.34488

Prob > chi2 = 1.497e-68

. *Model 2: 2 lags****

The likelihood of the model with 2 delays is :

1421.7952

. ** perform tests

The Chi-square statistic between 1 delay and 2 delays is:

chi2(2) = 186.03074

Prob > chi2 = 4.02e-41

. *Model 3: 3 lags****

The likelihood of the model with 3 delays is :
1317.1449

. ** perform tests

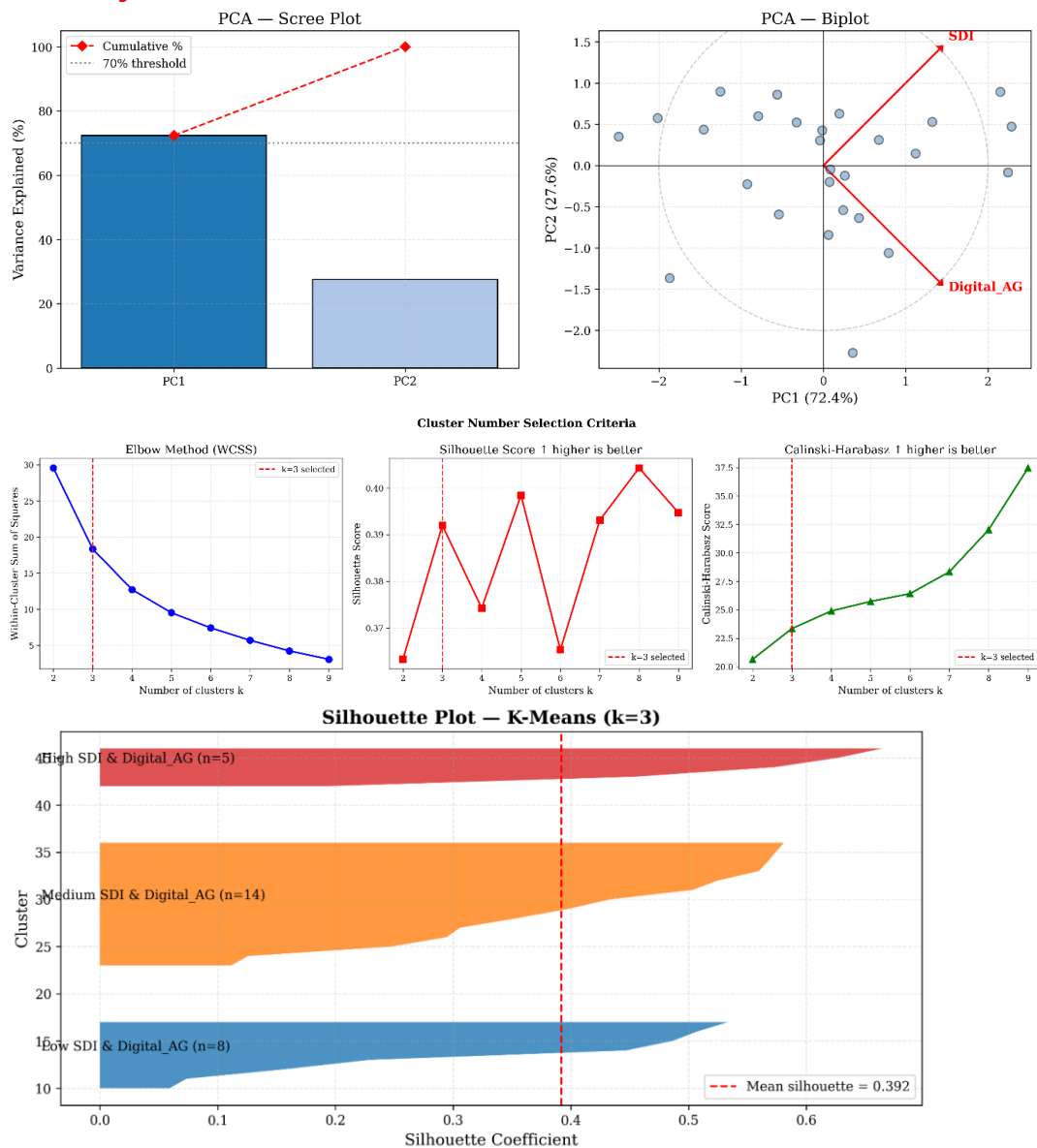
The Chi-square statistic between 2 delays and 3 delays is :

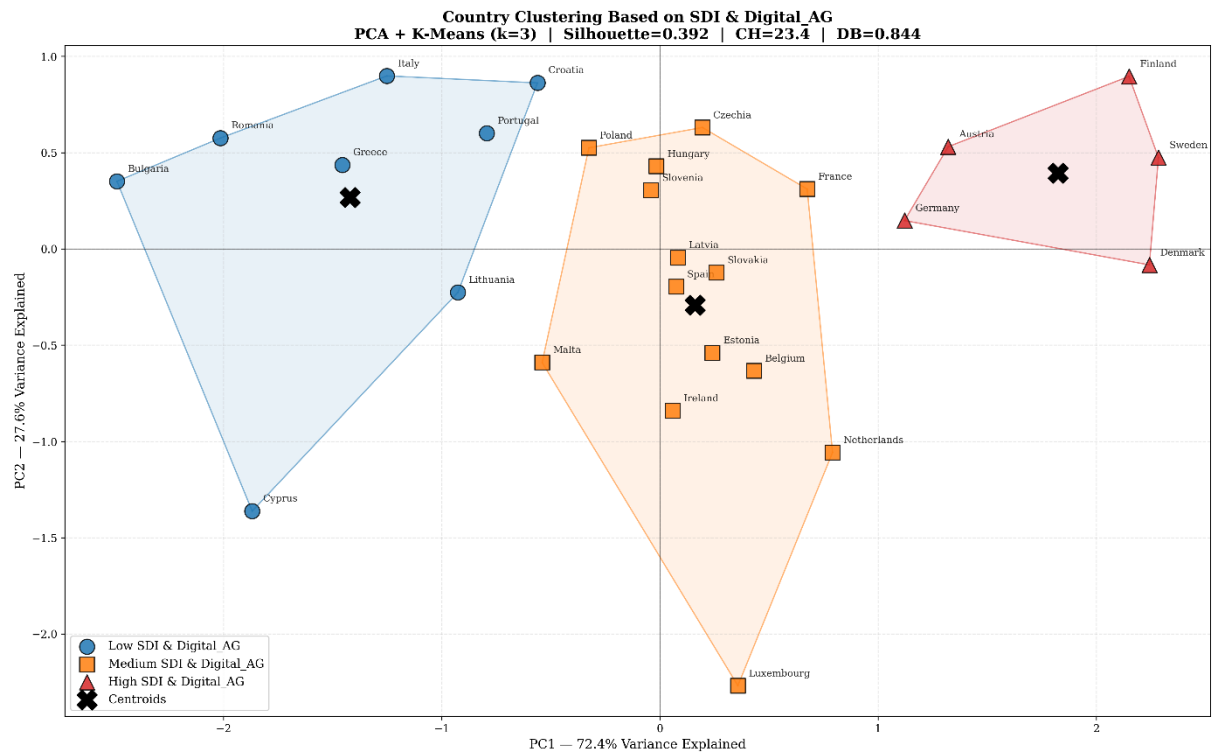
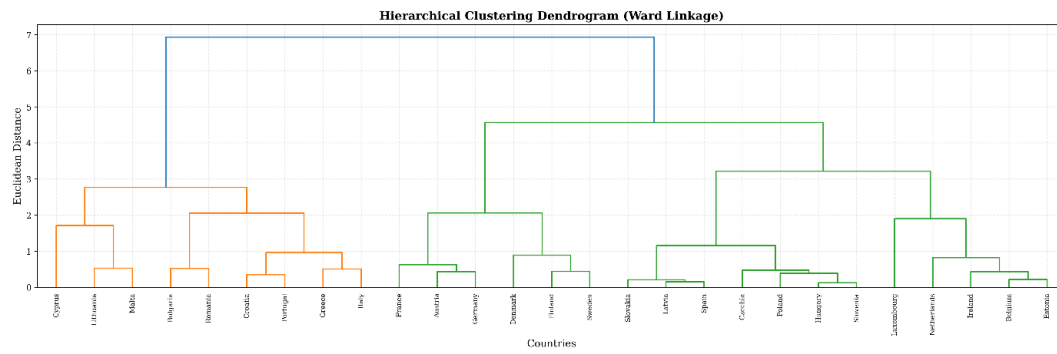
$\chi^2(2) = 3.30065$

$\text{Prob} > \chi^2 = 0.19199$

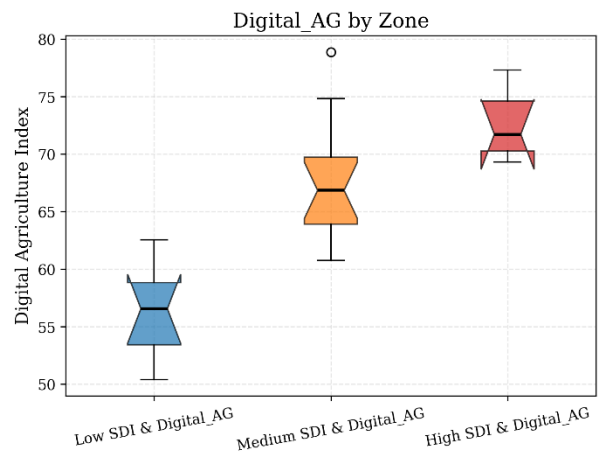
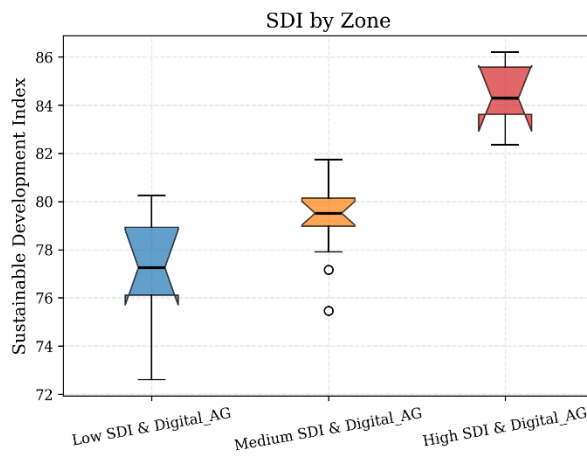
Let $p = 2$, So PTAR($p=2$) or PSTAR(2)

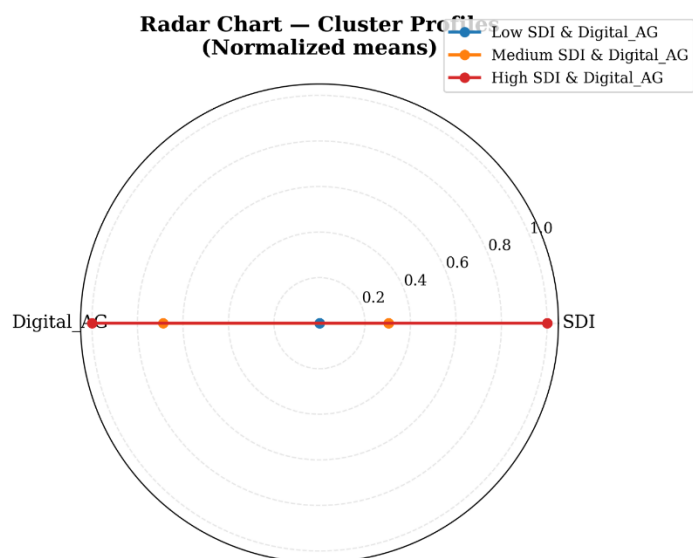
Clustreing





Variable Distribution Across Zones





PTAR (p=2)

Obs id Year Trend SDI SDI1 SDI2 Digital_AG RD_AG CREDIT_AG TFP_AG Temp INF

=====
 === Model with one threshold ===
 =====

Cross-unit dimension N = 27

Time dimension T = 15

Estimated threshold parameter (gamma) = 3.8974

Confidence Interval (95%) on gamma = [3.8225 , 3.9477]

Estimated slope parameters (first column) and t-stats (second column) for the FIRST regime :
 q(t) ≤ 3.8974

0.022138	1.3479	SDI1
0.021166	2.0848	SDI2
0.035524	2.0826	Digital_AG
0.0094831	3.116	RD_AG
0.0047289	2.6462	CREDIT_AG
0.058111	6.0777	TFP_AG
0.0081987	2.65884	Temp
-0.00024586	-0.33864	INF

Estimated slope parameters (first column) and t-stats (second column) for the SECOND regime :
 q(t) > 3.8974

0.015597	1.92242	SDI1
0.052849	5.0293	SDI2
0.073328	9.2031	Digital_AG
0.0048887	1.7803	RD_AG
0.0017428	1.1437	CREDIT_AG
0.015412	3.4808	TFP_AG
0.0012444	0.14994	Temp
0.00020109	0.59316	INF

SSR = 0.0201

Estimated residual variance = 0.0001

Number of simulation (for F1 statistic pvalue) = 1000

F1 test statistic = 59.3463

pvalue = 0.0000

N1	109
N2	296

PSTAR(2)

```
*****  
*** LINEARITY Tests ***  
*****
```

H0: Linear Model H1: PSTR model with at least one Threshold Variable (r=1)

Wald Tests (LM): W = 80.253 pvalue = 0.000

Fisher Tests (LMF): F = 5.591 pvalue = 0.000

LRT Tests (LRT): LRT = 89.441 pvalue = 0.000

```
*****  
*** TESTING THE NUMBER OF REGIMES: TESTS OF NO REMAINING NON-LINEARITY ***  
*****
```

Initial Conditions : Assumed Number of Thresholds r = 1 Number of Regressions = 1710
Initial Conditions on (c,gamma)
 5 4.1393 4.1739

```

Estimation of the Model with r = 1 and m = 2 : Convergence = 1   RSS = 0.019

WARNING: At least one estimated Location Parameter is outside the trimming for a PTR model

The location Parameter should range from  3.9161  to  4.3329 in a PTR model

RSS under H1 = 0.016

Initial Conditions : Assumed Number of Thresholds r = 2   Number of Regressions = 1710
Initial Conditions on (c,gamma)
    50.479          5          3.7392          4.3874          4.048          4.1542

Estimation of the Model with r = 2 and m = 2 : Convergence = 1   RSS = 0.016

WARNING: At least one estimated Location Parameter is outside the trimming for a PTR model

The location Parameter should range from  3.9161  to  4.3329 in a PTR model

RSS under H1 = 0.015

H0: PSTR with r = 1  against  H1: PSTR with at least r = 2

    Wald Tests (LM):          W = 68.128    pvalue = 0.000
    Fisher Tests (LMF):       F = 4.373    pvalue = 0.000
    LRT Tests (LRT):          LRT = 74.595    pvalue = 0.000

H0: PSTR with r = 2  against  H1: PSTR with at least r = 3

    Wald Tests (LM):          W = 21.950    pvalue = 0.145
    Fisher Tests (LMF):       F = 1.211    pvalue = 0.257
    LRT Tests (LRT):          LRT = 22.567    pvalue = 0.126

Given the choices of rmax = 3 and m = 2, the OPTIMAL (LMF criterion) NUMBER OF THRESHOLD
FUNCTIONS is r = 2

*****
*** FINAL ESTIMATION OF PSTR MODEL ***
*****

    Final Estimation of the Model with r = 2 and m = 2 by NLS ***

    Initial Conditions on (gamma,c) :
        50.133      12.813      3.7365      4.3912      3.7971      4.4049

WARNING FINAL ESTIMATION: At least one estimated Location Parameter is outside the trimming
for a PTR model

The location Parameter must range from  3.9161  to  4.3329 for a PTR model

    RSS = 0.016      Convergence = 1

    AIC = -9.925      BIC = -9.628

Estimated slope parameter of the transition function (one for each transition function)
    50.133      12.813

Estimated location parameters (per column for each transition function)
    3.7365      3.7971
    4.3912      4.4049

Estimated slope parameters (per column for each transition function)
-0,055798      -0,20954      0,29939  SDI1
    0,12649      0,10974      -0,2846  SDI2
    0,073218      0,073976      -0,038378  Digital_AG
-0,0064845      -0,019833      0,047244  RD_AG
    0,0018795      -0,010127      0,0040729  CREDIT_AG
    0,004305      0,0044287      0,030538  TFP_AG
    0,015761      0,12535      -0,09161  Temp
    0,0035104      0,005974      -0,013287  INF

```

Standard Errors of estimated slope parameters corrected for heteroskedasticity (per column for each transition function)

0,04123	0,09826	0,13650	SDI1
0,04108	0,09915	0,14197	SDI2
0,01875	0,03744	0,01431	Digital_AG
0,00276	0,00532	0,00689	RD_AG
0,00253	0,00592	0,00160	CREDIT_AG
0,02063	0,00213	0,00898	TFP_AG
0,01281	0,03500	0,04664	Temp
0,00174	0,00510	0,00644	INF

t-statistics based on corrected standard errors (per column for each transition function)

-1,3532	-2,1324	2,1934	SDI1
3,0794	1,1068	-2,0047	SDI2
3,9058	1,9756	-2,681	Digital_AG
-2,3507	-3,7303	6,8607	RD_AG
0,74205	-1,7096	2,54061	CREDIT_AG
0,2087	2,083728	3,40032	TFP_AG
1,2303	3,5817	-1,9643	Temp
2,0186	1,1704	-2,0631	INF

res2 =

struct with fields:

```

      LR: 89.441
    LR_pvalue: 3.1711e-12
      LR1: [3×1 double]
    LR1_pvalue: [3×1 double]
    balanced: 'Balanced Sample'
      N: 27
      T: 15
      m: 2
      r: 2
    gam: [50.133 12.813]
      c: [2×2 double]
    beta: [8×3 double]
    beta_std: [8×3 double]
    beta_tstat: [8×3 double]
      pvalue: [8×3 double]
    beta_std_nc: [8×3 double]
      rss: 0.015789
    fixed: [27×1 double]
    resid: [15×27 double]
      g: [405×2 double]
    exitflag: 1
    output: [1×1 struct]
    coef_indi: [405×8 double]
    nbparam: 30
      AIC: -9.9245
      BIC: -9.628

```

N1	82
N2	243
N3	80

>>

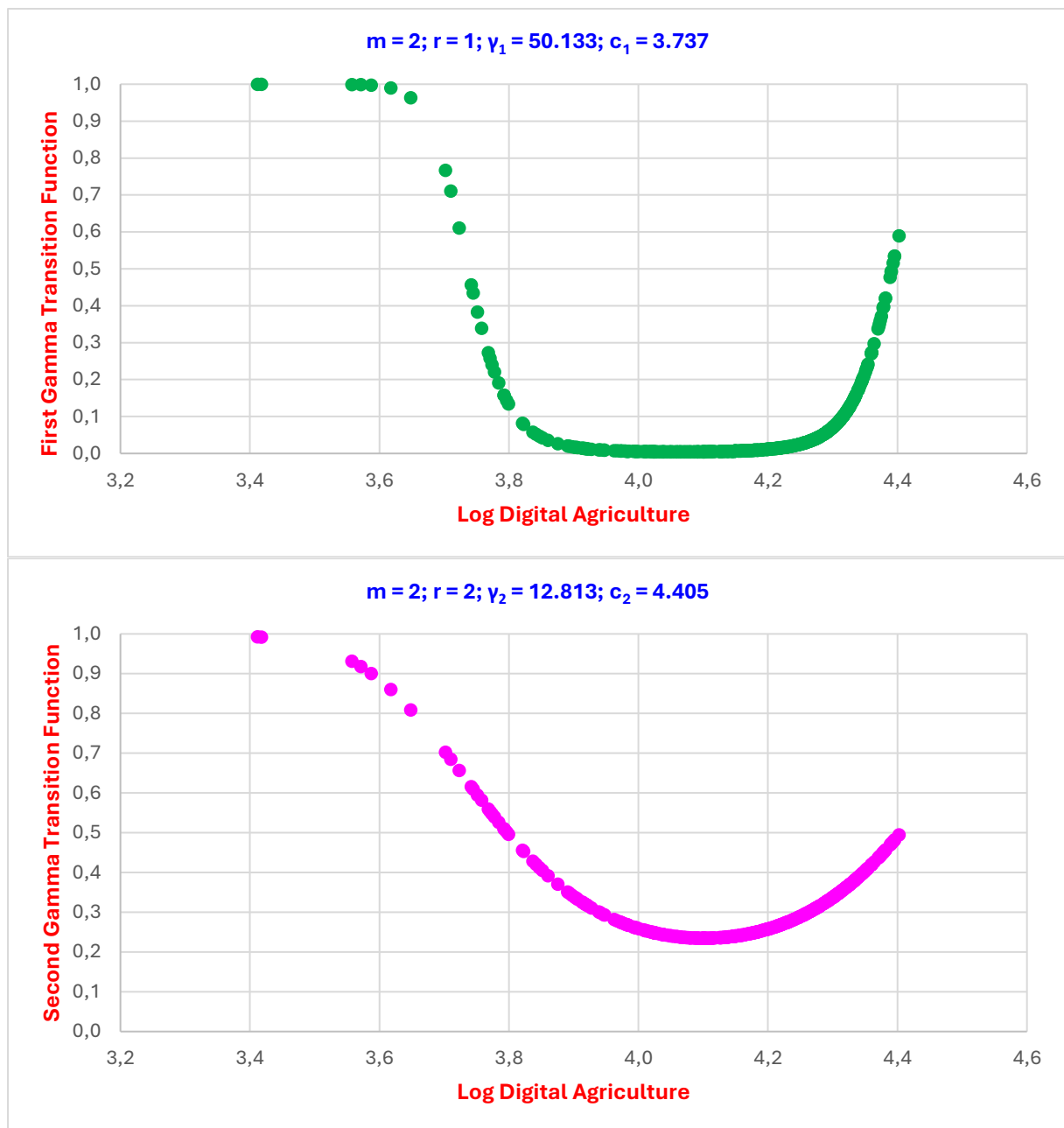


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