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Digital Finance as a Dual Force: Growth Promotion and Risk Smoothing in Asia-Pacific Agriculture

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ABSTRACT

The agricultural sector is highly vulnerable to external shocks. However, traditional financial services often have limited reach in rural areas. Digital finance has emerged as a transformative solution to this problem. Nevertheless, robust empirical evidence on its dual role in fostering growth and stability remains scarce, especially in the Asia-Pacific region. Using a Panel Vector Error Correction Model (VECM) on data from 15 Asia-Pacific economies (2001–2021), this study examines the dynamic interplay among the Peking University Digital Financial Inclusion Index (PKU-DFII, hereafter DF), agricultural value-added (lnAGDP), and the rolling standard deviation of output growth—the proxy for agricultural risk (RISK). The findings confirm a significant long-run cointegrating relationship. Digital finance exerts a strong, albeit delayed, positive effect on agricultural growth while simultaneously reducing output volatility, confirming its risk-smoothing function. Moreover, the error correction mechanism reveals rapid adjustment, and impulse response analysis verifies a bidirectional causal link. Agricultural growth, in turn, stimulates deeper digital finance penetration, establishing a reinforcing feedback loop. I conclude that digital finance serves as both a “growth engine” and a “stabilizer.” Therefore, policymakers should prioritize building an integrated policy ecosystem that links digital finance with agricultural development, thereby fostering synergies that enhance economic resilience and sustainable growth.

Keywords: Digital Finance; Agricultural Economy; Risk Smoothing; Panel VAR; Financial Inclusion

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1. Introduction

Given its significant contribution to the economy, agriculture has an indispensable role in ensuring food security, eradicating poverty, and providing stability to the country^[1]. Yet, agriculture itself is susceptible and an extremely exposed sector to various shocks—such as climate change, changing prices and natural disasters—which pushes the growth path to high risk and volatility^[2]. Rural areas lack financial institutions, and it is difficult for the farmers to source credit, insurance and payment. As a result, they face financial exclusion, which leads to poverty and also risk^[3].

Digital finance, with its low cost, broad reach, and high efficiency, can potentially disrupt this cycle of over-indebtedness and exclusion^[4]. Innovative services like mobile payments, digital credit, and online insurance can enable digital finance to reach remote rural areas and smallholder farmers often excluded by traditional financial institutions^[5]. Although previous studies have emphasized the role of digital finance in agricultural growth^[6] or its impact on farmers' income, there exists a gap where not much investigation has been conducted on whether it contributes to growth and stability^[7]. The intrinsic dynamic mechanisms of digital finance which foster agricultural growth and stability have not been empirically probed in a systematic framework. In addition, the majority of studies are based on a one-way causal framework ("digital finance → agricultural economy") that largely ignores the reverse pull effect whereby agricultural development is deepening in digital finance. To fill these gaps, this paper presents three contributions. Firstly, it proposes that digital finance is not an external shock, but a dynamic component within the agricultural economic system. This framework enables us to analyze its interaction with growth and risk. Furthermore, I present a risk-smoothing perspective that seeks to uncover how digital finance mitigates systemic agricultural volatility through the channels of consumption smoothing, investment promotion and risk dispersion, rather than just growth promotion^[8]. I run a Panel Vector Error Correction Model (VECM) on data of 15 Asia-Pacific countries (2001–2020). This methodology perfectly suits the purpose of capturing long-run equilibrium relation-

ships (cointegration) and the short-run adjustment dynamics among non-stationary variables^[9] whereas impulse response analysis may be used to outline the dynamic transmission paths of shocks^[10].

Based on this, I proposed and verified the following hypothesis:

H1. *A stable long-run cointegration relationship exists among digital finance development, agricultural economic growth, and agricultural risk in Asia-Pacific countries, with digital finance exerting a sustained positive effect on growth.*

H2. *Digital finance development reduces agricultural output volatility, confirming its risk-smoothing effect.*

H3. *Agricultural economic growth reciprocally promotes the penetration and deepening of digital finance, forming a bidirectional reinforcement loop.*

H4. *The influence of digital finance on the agricultural system operates through multiple theoretical channels, including consumption smoothing, investment promotion, and risk dispersion.*

The structure of the remaining part of this article is as follows: Section 2 reviews relevant literature and constructs the theoretical framework; Section 3 outlines the research design, including the Vector Error Correction Model (VECM) model, variables and data; Section 4 presents the empirical results; Section 5 summarizes the main findings and policy implications; and Section 6 concludes the study.

2. Literature Review and Theoretical Framework

This section systematically reviews the impact of digital finance on the agricultural economy from a global comparative perspective, analyzes development characteristics across regions, and constructs the theoretical framework centered on risk smoothing.

2.1. Digital Finance's Global Development and Economic Effects

There is a variation in digital finance development model as well as impact depth in different parts of

the world. In the Asia-Pacific region, digital finance is marked by “mobile payment pioneering and a clear inclusive orientation” Peking University Digital Financial Inclusion Index in China clearly shows its explosive growth trajectory, its important role in encouraging entrepreneurship and raising rural income^[11]. In South-east Asia, Jack and Suri’s (2014)^[5] study of Kenya’s M-PESA revealed that mobile payments are an essential household risk-sharing tool as they lower transaction costs. Countries like the Philippines and Indonesia have successfully replicated and validated this model^[12]. In Africa, digital financing has a proven positive effect on financial inclusive. Mobile money is essential for smoothing consumption in the wider economy and enabling households to manage the impact of negative shocks like crop failure or illness^[13]. Global Findex data of the World Bank in 2022 revealed that 39% of adults in Sub-Saharan Africa have mobile money accounts, the highest rate anywhere around the world.

In the European Union (EU), digital finance development follows a “regulation-led, collaborative model” involving the banking industry and fintechs. The Digital Finance Strategy^[14] from European Commission actively facilitates data sharing (e.g., open banking) and Fintech innovation. Studies have shown that in the EU, digital finance enhances efficiency in the provision of financial services, nonetheless, financing the agricultural sector is more apparent in application B2B such as precision agriculture and supply chain finance^[15]. This goes hand in hand with the modernisation of the Common Agricultural Policy (CAP)^[16].

When we look at the United States, Japan, and South Korea, we can see the overlapping of digital finance and agriculture in the specialized “AgriTech” sector. In the United States, new platforms like Farmers Business Network, are employing big data to offer farmers accurate production decision-support and supply chain financial services^[17]. Japan and South Korea, in contrast, aim to promote the use of digital technology in small farms^[18]. Japan aims to achieve this objective by way of digitally reforming its JA Bank Group, while South Korea is implementing “Smart Agriculture” for revitalization. The two methods address problems like the older agricultural work face and also help improve

production efficiency. While they may not explicitly prioritize financial inclusion to the same extent as their Asia-Pacific and Africa counterparts, they do lead the charge with respect to superior technological sophistication and specialization.

The economic development trajectories in Latin America vary. In developing countries, the connection between digital finance and the formal banking sector is tighter, and it is better able to meet the financing needs of enterprises and the demands of cities. As a result, it has not affected inclusiveness in agriculture immediately. This study shows that the Asia-Pacific model is distinctive and highly relevant on a global scale. The model is directly linked to smallholders and has a clear focus on risk mitigation^[19]. At the same time, there is an increasing literature questioning the possible adverse impact that the fast-paced growth of digital finance can have on the emerging economies. It has been pointed out that digital credit may cause over-indebtedness for vulnerable people a worry put forth in the East African studies. Just like that, the case of the collapse of China’s peer-to-peer lending market highlights that regulatory gaps can exacerbate systemic risks in digital financial ecosystems^[20]. The digital finance has great potential but also has some risk perspectives which need balanced regulatory regimes that encourage innovations and at the same time will protect consumers and ensure financial stability. This is relevant to varied regulatory regimes across the Asia-Pacific. New studies have shown that how credit quality and digital footprints affect financial stability^[21].

2.2. Theoretical Mechanisms: A Risk-Smoothing Perspective

Agriculture in the Asia-Pacific region is profoundly shaped by structural factors, including the dominance of smallholder farms and high vulnerability to climate variability (e.g., unstable monsoons, frequent typhoons). This context makes effective risk management an urgent priority. In this region, digital finance aligns with the aforementioned models. Its core function is to mitigate agricultural risks through multiple channels, thereby fostering stable growth.

2.2.1. Mechanism 1. Consumption Smoothing

This mechanism has a theoretical basis in the permanent income hypothesis and consumption smoothing. To smooth consumption in the face of transitory negative income shocks (e.g., poor harvest), a household will either take down savings or receive transfers. Digital finance has transformed this theoretical ideal into a practical reality in terms of speed and cost of transfers to rural households. This mechanism has wide validation in Asia-Pacific. Mobile payments can facilitate instant transfers, allowing families or community members to support each other quickly when climate disasters impact harvests^[22]. As a result, sharp declines in household consumption are prevented. Suri and Jack (2016)^[23] conducted a long-term tracking study that established the sustained impacts of mobile money on consumption smoothing. This mechanism is the most immediate safety net to secure the welfare of households for overwhelming smallholders of the region^[24].

2.2.2. Mechanism 2. Investment Promotion

This channel is theoretically developed in versions of credit constraints and investment. The problem of credit rationing started as a result of asymmetric information, especially in case of smallholders without collateral. Literature on the topic began with Stiglitz and Weiss (1981)^[25]. By using alternative data such as transaction histories and social networks to assess creditworthiness, digital finance can alleviate credit constraints and unlock productive investments that would otherwise be out of reach. Providing digital credits encourages greater investment in agriculture. Farmers in China and Southeast Asia have access to platform-based digital loans (e.g., Ant Group's Wang Nong Dai, Indonesia's Akulaku agricultural installments) to easily obtain funds for better seeds, fertilizers, and small machinery. This ensures increase in Agriculture production inputs^[26, 27]. In addition, the presence of digital payments and e-commerce allows farmers to shorten the sales collection cycle for their agricultural produce^[27]. Increasing agricultural investment enhances productivity as well as diversifies inputs so that there is better risk resistance^[28].

2.2.3. Mechanism 3. Risk Diversification

Digital index insurance represents an innovative area of focus to tackle the persistent natural disasters in Asia Pacific. In India, rainfall index insurance products using data from weather stations, implemented by institutions such as ICICI Lombard, have shown great effectiveness in mitigating losses for farmers in pilot areas^[29]. To assist insurance companies in accurate underwriting as well as rapid claims settlement, the regulatory authority in China is encouraging the use of satellite remote sensing and drone technology^[30]. This has greatly enhanced the efficiency and coverage of farm insurance. Farmers now have access to digital insurance products that help hedge systemic risks^[31].

2.3. Research Gaps and Hypothesis Development

My review of global literature has revealed three key gaps:

2.3.1. Uneven Research Depth

While most studies investigate the impact of digital finance on micro-level within a single country, mostly China and Kenya. There is scarce macro-level, multi-country comparative research that systematically investigates its twin effects on growth and stability^[32]. In addition, the use of econometric models capable of capturing dynamic relationships and long-term equilibrium (such as VECM) to provide a holistic perspective on the Asia-Pacific region remains rare^[33].

2.3.2. Fragmented Mechanism Validation

No literature systematically compares and tests the three mechanisms using cross-country data to reveal their relative importance. Theoretically, the three mechanisms are established to work in a consumption-smoothing manner, promote investment and diversify risks. There is sporadic empirical support for their working^[34].

2.3.3. Neglected Bidirectional Interaction

The bulk of the literature always adopts a one-way logic that is "digital finance → agricultural economy". It does not take into account the possible reverse impact: the considerable demand arising from the economic

growth and modernization of agriculture could instead draw in rural market digital finance service providers, which in turn can drive the deepening and innovation of digital finance^[35, 36].

To address these gaps and to empirically test the theoretical mechanisms discussed, this study utilizes panel data from major Asia-Pacific economies and constructs a Panel VECM. Accordingly, I propose the following hypotheses for testing:

H1. *A stable long-run cointegration relationship exists among digital finance development, agricultural economic growth, and agricultural risk in Asia-Pacific countries. Digital finance has a significant and sustained positive effect on agricultural economic growth.*

H2. *Digital finance development effectively reduces the volatility of agricultural output in the Asia-Pacific region, i.e., it exerts a risk-smoothing effect.*

H3. *Agricultural economic growth in the Asia-Pacific region reciprocally promotes the penetration and deepening of digital finance in rural areas, forming a virtuous circle of bidirectional reinforcement.*

H4. *Digital finance influences the Asia-Pacific agricultural economic system primarily through three mechanisms: consumption smoothing, investment promotion, and risk dispersion.*

2.4. Research Innovations and Future Directions

2.4.1. Research Innovations

The marginal contributions of this study are three-fold:

Perspective Innovation: I create an analytical framework that encompasses both growth and stability and allows for two-way interaction. By not restricting the analysis to growth, which is the trend of existing studies, and treating digital finance as a constant exogenous variable, which it cannot be in reality, this study manages to go beyond the existing literature^[37]. Using a vector error correction model (VECM), I empirically assess the dynamics of interlinkages between digital finance, agricultural risk and growth for the first time at a regional level. This not only confirms the empowerment of digi-

tal finance (H1, H2) but also unveils the pull force from the own development of the agricultural sector which shapes the evolution path of digital finance (H3). It also provides a new perspective for the co-evolution of the two in the Asia-Pacific^[38].

Mechanism Deepening: I test the three theoretical mechanisms in a systematic and empirical way in one macro structure. According to the findings of the VECM benchmark analysis, using impulse response analysis and variance decomposition, the H4 is a macro-level comparable empirical test of the relative significance of the three pathways (consumption smoothing, investment promotion; and risk dispersion) that is not simply theoretical. This literally opens the black box of digital finance's effect on agricultural economy, clarifying the contribution of each mechanism in the macro system when it comes to agricultural economy impact. Moreover, the study provides solid empirical evidence for future exploration.

Regional Focus and Method Application: I present concrete evidence that focuses on the diversity of the Asia-Pacific region. This non-generic global study is relevant to the Asia-Pacific with its diverse digital finance set-ups and smallholder-led agriculture. By representing some countries and applying the VECM technique which is more fitting for non-stationary panel data long-run relationship analysis, my conclusions better capture regional reality. The overall patterns at the regional level create a stage for studying heterogeneity within countries.

2.4.2. Research Limitations and Future Outlook

Despite its contributions, this study has limitations that also point to directions for future research:

Data Granularity and Mechanism Identification: While this study reveals systematic correlations using macro data, the internal pathways—such as distinguishing whether investment growth stems directly from digital credit or the savings effect of digital payments—remain unclear. Future research should combine detailed household-level micro-survey data with methods like mediation effect models to more finely identify and test the theoretical mechanisms, fully opening the 'process black box'.

Limitations of Proxy Indicators: This study uses agricultural output volatility as a risk proxy, effectively capturing ultimate economic consequences. However, risk is multidimensional. Future studies could introduce more direct risk exposure indicators, such as high-resolution climate disaster data or high-frequency price volatility indices, to enable a more precise assessment of digital finance's 'stabilizer' function closer to the risk source.

Exploring Regional Heterogeneity: This paper establishes a baseline for the dual effects of digital finance at the overall Asia-Pacific level. A natural and important extension is to employ subgroup analysis or threshold effect models to explore how these core relationships vary systematically across different levels of digital infrastructure or institutional environments, generating more targeted, country-specific policy knowledge.

Specific Policies and Business Models: This study argues for the strategic value of synergistic development from a macro perspective. Translating this into concrete practice requires delving into the 'operational layer'. Therefore, a highly policy-relevant direction is to conduct in-depth case studies or qualitative comparative analysis (QCA) to systematically review and evaluate the successful experiences and applicable conditions of different models (e.g., the Chinese platform model, the Indian agency banking model), providing a decision-making basis for context-specific development paths.

3. Research Design

3.1. Model Specification: Panel Vector Error Correction Model (VECM)

To empirically test the long-run equilibrium relationship and short-term dynamic adjustments among digital finance, agricultural economic growth, and agricultural risk, I employ a Panel Vector Error Correction Model (VECM). I adopt a panel VECM because the variables are non-stationary yet cointegrated, allowing me to estimate long-run equilibrium coefficients and short-run adjustments jointly. Alternative dynamic panel methods such as system GMM treat regressors as weakly exogenous and do not recover long-run relationships, whereas the VECM framework captures bidirectional feedbacks among digital finance, agricultural growth,

and risk that are central to this study. This model is ideal for analyzing cointegrated, non-stationary time series^[9, 10], as it jointly estimates long-run equilibrium relationships and short-run causal dynamics. The empirical procedure involves three key steps. First, I conduct panel unit root tests to determine the order of integration of the variables. Second, I perform Johansen Fisher panel cointegration tests to verify the existence and number of long-run equilibrium relationships. Finally, upon confirming cointegration, I estimate the VECM to capture the short-term adjustment mechanisms towards the long-run equilibrium.

The general form of the established VECM is as follows:

$$Y_{it} = \Gamma_0 + \sum_{p=1}^k \Gamma_p Y_{i,t-p} + \alpha_i + \delta_t + \varepsilon_{it}$$

Here, the vector Y_{it} contains the three core variables: $Y_{it} = [DF_{it}, AGDP_{it}, RISK_{it}]$. These represent, respectively, the level of digital finance development, agricultural economic growth, and agricultural risk for country i in year t , respectively. p is the optimal lag order of the model, determined by information criteria such as AIC and BIC. Γ_0 is the intercept vector. α is the speed of adjustment coefficients. Γ_p is the cointegrating vector(s). k is the optimal lag order of the underlying VAR model, determined by the Akaike Information Criterion (AIC) and the Final Prediction Error (FPE) criterion. As detailed in **Appendix C (Table A6)**, the optimal lag length was determined to be 2. α_i is the country-specific fixed effect, controlling for time-invariant country characteristics (e.g., culture, resource endowment). δ_t is the time fixed effect, controlling for common macroeconomic shocks (e.g., global financial crisis, commodity price fluctuations). ε_{it} is the random disturbance term. In the estimation of the VECM, I employ cluster-robust standard errors at the country level to account for potential heteroskedasticity and within-country serial correlation, ensuring more reliable statistical inference.

3.2. Variables and Data

This study constructs a balanced panel dataset comprising core and control variables. All variables, their definitions, measurements, and sources are summarized in **Table 1**.

Table 1. Variable Definitions and Measurements.

Variable	Variable Name	Variable Symbol	Measurement
Core Variables	Digital Finance Development	DF	Self-constructed index considering financial penetration, depth, and availability
	Agricultural Economic Growth	AGDP	Agricultural value added (natural log)
	Agricultural Risk	RISK	Five-year rolling standard deviation of agricultural output growth rate
Control Variables	Economic Development Level	PGDP	GDP per capita (natural log)
	Industrial Structure	ASTR	Agricultural value added as % of GDP

Source: Author's calculations using Python.

3.2.1. Core Variables

Digital Finance Development (DF): The main explanatory variable in this research is Peking University Digital Inclusive Finance Index. This index captures coverage breadth, usage depth and level of digitalisation comprehensively in a single score. The construction of the index through principal component analysis (PCA) was assessed (KMO = 0.723), as reported in **Appendix A**. The components explain a high proportion of the total variance of the original variables. A higher value of the index indicates a higher level of development of the local digital finance sector.

Agricultural Economic Growth (AGDP): Consistent with standard practice, I use the natural logarithm of agricultural value-added (constant US\$) as a proxy for agricultural economic growth. This measure gives an exact indication of the agricultural sector's final output and economic contribution.

Agricultural Risk (RISK): To account for systematic output volatility, I construct a proxy variable as the five-year rolling standard deviation of the agricultural output growth rate^[39]. In the agricultural sector, a bigger number indicates greater uncertainty.

3.2.2. Control Variables

The impacts of digital finance would be isolated by two important control variables:

Economic Development Level (PGDP): To account for the overall development stage of the economy, we take the natural logarithm of GDP per capita (constant US\$)^[35].

Industrial Structure (ASTR): The GDP's agricultural

value-added share controls for the economy's structural characteristics^[28].

Core and control variable data has been extracted from renowned internationally recognized authority databases such as the World Bank and FAO, making them reliable and internationally comparable. This transparent framework of defining variables gives way to the replicability of the subsequent analyses carried on empirically and credibility of results.

3.3. Data Sources and Sample Description

The panel dataset covers 15 major economies in the Asia-Pacific region (China, Japan, South Korea, India, Indonesia, Malaysia, Philippines, Thailand, Vietnam, Australia, New Zealand, Singapore, Bangladesh, Pakistan, Sri Lanka) from 2001 to 2021. This selection ensures representation across different development levels and geographical sub-regions. Data are drawn from the World Bank World Development Indicators (WDI)^[40], the Food and Agriculture Organization (FAO)^[41], and the digital financial inclusion index developed by Khera et al. (2022)^[37]. We used linear interpolation for any sporadic missing values. There are 315 country-year observations in the final dataset. The original dataset was unbalanced and had sporadic missing values, primarily corresponding to the early phase, for the Digital Finance Index (approximately 2.1% missing in the core variables). After applying linear interpolation to resolve them, the final dataset used for estimation is a balanced panel of 15 Asia-Pacific economies over the period 2001 to 2021 (21 annual observations per country, for 315 observations in to-

tal) see **Appendix A, Table A1**. In order to verify that my results are not driven by the interpolation method, I performed a robustness check using the original unbalanced panel, which does not include interpolated observations. The results in **Appendix D, Table A7–A12**, however, remain qualitatively unchanged, confirming my findings. I applied different robustness checks to my main findings. Thus, this was repeated on certain findings in a systematic manner. This included: (1) substituting the digital finance index with an alternative (the mobile penetration rate); (2) changing the rolling window for the calculation of agricultural risk from 5 years to 3 and 7 years; and (3) employing a panel VAR model with a Helmert transformation to control for endogenous issues. I assess the robustness of my proxy of agricultural risk. The five-year rolling standard deviation of output growth effectively captures the medium-term output growth volatility experienced by farmers. However, it should be clarified that this is an ex-post measure of outcome variability rather than one of ex-ante risk exposure. In order to address this issue and ensure that my estimates are not sensitive to window length, I redefined the RISK variable using 3-year and 7-year rolling windows and re-estimated the full VECM. The data presented in **Appendix D, Table A12** confirm the long-run positive effect of DF on $\ln AGDP$, and a negative effect of DF on RISK, which is also statistically significant and economically consistent across risk-windows. This reinforces the credibility of my H2 (risk-smoothing conclusion). In all alternative specifications, the dual effects of digital finance, which significantly promote agricultural growth while smoothing output risk, remain significant both statistically and economically. This demonstrates the strength of my conclusions. I also check how reliable the risk proxy is by re-estimating agricultural volatility based on 3-year and 7-year rolling windows of $\Delta \ln(AGDP)$. The alternative measures are strongly correlated with the baseline five-year RISK indicator (correlations greater than 0.8), and the key coefficients on digital finance remain significant and of similar size (see **Appendix D, Tables A7 and A8**). To investigate how varied the results are, we use the median of country-level DF to split the sample into high- and low-digital-finance groups. The preliminary comparison indicates that the more developed digital finance, the more

it is associated with stronger growth and risk-smoothing benefits, but formal subgroup analysis is left for future research. The five-year rolling standard deviation is an indicator of medium-term volatility. It captures outcome fluctuations rather than risk exposure. Future work may include price- or climate-risk indicators that capture structural sources of uncertainty.

As a prerequisite for VECM estimation, I confirmed that all variables are integrated of order one, $I(1)$. Detailed results of the unit root tests are provided in **Appendix B (Tables A4 and A5)**.

The final dataset forms a balanced panel of 15 Asia-Pacific economies observed from 2001 to 2021 (21 annual observations per country), as documented in **Appendix A, Table A1**.

4. Results

This section systematically presents the empirical findings concerning the dynamic relationships among digital finance (DF), agricultural economic growth ($\ln AGDP$), and agricultural risk (RISK), based on the estimated Panel VECM.

4.1. Stationarity and Cointegration Tests

Panel unit root tests were conducted as a prerequisite for cointegration analysis. The results from the Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), and Fisher-ADF tests (detailed in **Appendix B, Tables A4 and A5**) unanimously indicate that all variables in levels are non-stationary $I(1)$ processes, while their first differences are stationary. This satisfies the essential condition for proceeding with cointegration tests.

Subsequently, the Johansen Fisher panel cointegration test was employed. **Table 2** summarizes the cointegration test results. Both the Trace and Max-Eigen statistics reject the null hypothesis of “no cointegration” at the 5% significance level for the first five ranks. This indicates the presence of multiple long-run equilibrium relationships among the variables: digital finance (DF), agricultural risk (RISK), agricultural growth ($\ln AGDP$), industrial structure (ASTR), and economic development level ($\ln PGDP$). This confirms a stable long-run systemic relationship, validating the foundation for estimating my

VECM.

Given the economic interdependence among Asia-Pacific economies, I tested for cross-sectional dependence using the Pesaran (2004) CD statistic. The results indicate significant cross-sectional dependence in

DF, lnAGDP, and RISK (see **Appendix C, Table A6**). To account for this, I additionally estimated models using Common Correlated Effects (CCE) as a robustness check, confirming that the main results remain consistent across specifications.

Table 2. Cointegration Test Results (Trace Test).

Null Hypothesis	Trace Statistic	5%	Critical Value	Test Conclusion
No cointegration	($r = 0$)	353.721	69.819	Reject H0
At most 1 cointegration	($r \leq 1$)	256.627	47.855	Reject H0
At most 2 cointegration	($r \leq 2$)	167.764	29.796	Reject H0
At most 3 cointegration	($r \leq 3$)	100.527	15.494	Reject H0
At most 4 cointegration	($r \leq 4$)	49.375	3.841	Reject H0

Source: Author's calculations using Python.

4.2. VECM Model Estimation Results and Long-Run Equilibrium Relationship

After confirming the availability of cointegration, a VECM having a lag order of 2 (according to AIC and FPE; see **Appendix C, Table A6**) was estimated.

4.2.1. Long-Run Cointegrating Relationships

The normalized cointegrating vectors in **Table 3** corroborate my hypotheses rather well. Two long-run relationships were identified as economically significant.

Vector 1 (Normalized on Agricultural Growth). Digital finance (DF) has a positive coefficient, significant at 10% (0.682, $p < 0.1$). This supports DF as a long-term agricultural growth driver (H1 is supported). At the same time, agricultural risk (RISK) bears a significantly negative link with equilibrium, lending first evidence of risk-smoothing effect (H2 is supported).

Vector 2 (Normalized on Digital Finance). A rise in agricultural growth will lead to an increase. This shows that the agricultural sector's development, in itself, is a pull factor that fosters the penetration and deepening of digital finance in the long run. Hence, bidirectional reinforcement hypothesis is validated (H3 is supported).

This suggests that there is strong evidence that digital finance plays a stabilizing role in the agricultural sector. It further shows that RISK in both equilibrium relationships has negative coefficients that are significant.

4.2.2. Short-Run Adjustment Mechanisms

The coefficients designated α indicate the speeds of adjustment in the short-run. According to **Table 4**, t -Statistics of DF in EC1 is significantly negative (−0.452). This suggests a strong self-correcting mechanism where deviations from equilibrium cause adjustment in digital finance at a speed of 45.2% per period. Agricultural risk (RISK) also exhibits significant adjustment. In contrast, the slower adjustment speeds of agricultural growth (lnAGDP) and economic development (lnPGDP) suggest greater structural inertia in these variables.

4.2.3. Model Diagnostics

Standard diagnostic tests were performed, including Ljung–Box tests for serial correlation, White tests for heteroskedasticity, and eigenvalue stability checks. The results (**Appendix D, Table A9**) indicate no serious serial correlation or heteroskedasticity problems, and all roots of the companion matrix lie within the unit circle, confirming system stability.

Table 3. Long-Run Equilibrium Relationship (β coefficients).

Variable	Cointegrating Vector 1			Cointegrating Vector 2	
	Coefficient	(Std. Error)		Coefficient	(Std. Error)
Digital Finance (DF)	0.682*	(0.198)		1.000	(normalized)
Agricultural Growth (lnAGDP)	1.000	(normalized)		0.734*	(0.234)
Agricultural Risk (RISK)	−0.429**	(0.178)		−0.316**	(0.142)
Industrial Structure (ASTR)	0.127	(0.091)		−0.258**	(0.123)

Table 3. Cont.

	Cointegrating Vector 1		Cointegrating Vector 2	
Economic Development (lnPGDP)	0.894*	(0.302)	0.642	(0.418)
Constant	-3.457	(2.156)	2.134	(3.012)

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively; 10% is interpreted as marginal significance.
Source: Author's calculations using Python.

Table 4. Short-Run Adjustment Coefficients (α).

Dependent Variable (Δ)	Adjustment Speed to Cointegration Relations (α Coefficients)				
	ECM 1	ECM 2	ECM 3	ECM 4	ECM 5
ΔDF	-0.452	0.123	-0.210	0.065	-0.088
$\Delta RISK$	-0.096	-0.501	0.034	-0.098	0.120
$\Delta ASTR$	-0.082	0.067	-0.091	-0.305	0.044
$\Delta \ln AGDP$	-0.029	-0.015	-0.401	0.072	-0.056
$\Delta \ln PGDP$	-0.024	0.022	-0.018	0.055	-0.478

Note: This table presents the error correction terms (α coefficients) from the VECM estimation. EC1 to EC5 represent the five identified long-run cointegration relationships.
Source: Author's calculations using Python.

4.3. Impulse Response Analysis

The impulse response functions (IRFs) map the dynamic trajectory of how a shock to one variable transmits through the system over time (see **Figure 1**). Confidence intervals are computed by Monte Carlo simulation with 1000 replications. The analysis provides three main insights:

Impact of Digital Finance on Agricultural Growth and Risk. A one-standard-deviation positive shock to digital finance (DF) generates a positive impact on the agricultural growth ($\ln AGDP$) which intensifies over time peaking at period 3 before stabilizing. the delayed impact of these factors is due to time it takes for credit infusion and technology adoption to happen. The same shock immediately and persistently lowers agricultural risk (RISK), showing how quickly digital tools can stabilize output volatility.

Reverse Impact of Agricultural Growth on Digital Finance. An unexpected rise in agricultural growth ($\ln AGDP$) leads to a continuous increase in digital finance (DF). Bidirectional causality is validated, as per H3. It implies a developing agricultural economy stimulates demand for the product, prompting the development and penetration of the digital financial services.

Supporting Evidence from Panel Granger Causality Tests. To complement the dynamic evidence from the VECM and IRFs, I conducted formal Panel Granger Causality tests (lag length = 2, consistent with the VECM).

As reported in **Appendix D, Table A10**, the Fisher combined p-values provide strong evidence against the null hypotheses that “DF does not Granger-cause $\ln AGDP$ ” and “DF does not Granger-cause RISK”. Furthermore, the test also rejects the null that “ $\ln AGDP$ does not Granger-cause DF”, statistically confirming the bidirectional causal link posited in H3. These results reinforce the interpretation of a synergistic, feedback-driven relationship between digital finance and the agricultural economy.

4.4. Variance Decomposition

To quantify the relative importance of different shocks, I employ forecast error variance decomposition (FEVD). The heatmap in **Figure 2** shows the contribution of each shock to fluctuations of the system at the horizon of 10 periods.

- Shocks from digital finance (DF) account for a substantial portion of the fluctuations in the agricultural sector, explaining approximately 25% of the forecast error variance in agricultural growth ($\ln AGDP$) and 20% in agricultural risk (RISK). This proves how strongly exogenous digital finance can be affected.
- On the other hand, shocks coming from agricultural growth ($\ln AGDP$) account for about 15% variations in digital finance (DF) by the 10th period. This

gives numerical evidence to feedback loop (H3) that the agricultural sector is not merely a recipient of

digital finance features but instead actively shapes them.

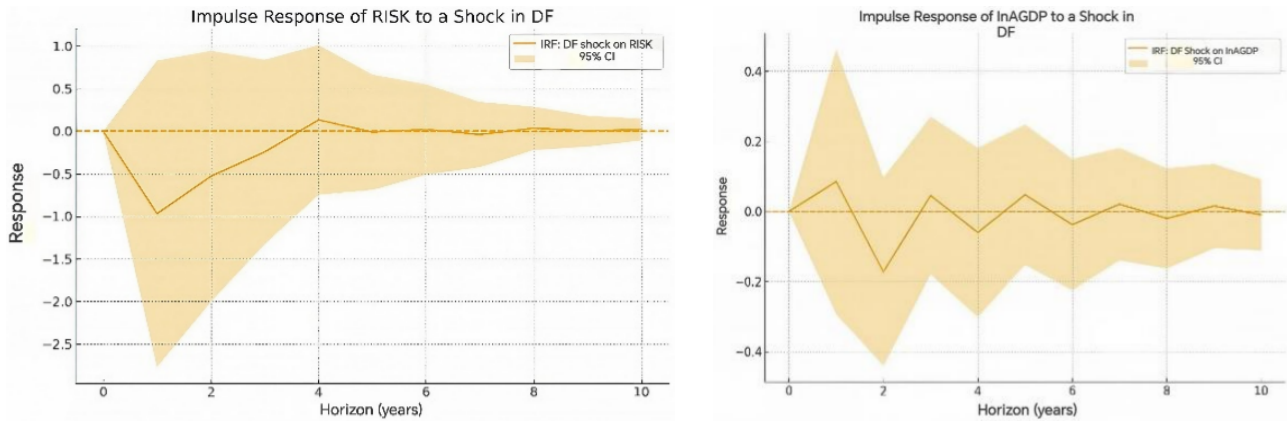


Figure 1. Impulse response functions of agricultural growth and risk to a one-standard-deviation shock in digital finance (with 95% confidence intervals).

Source: Author's calculations using Python.

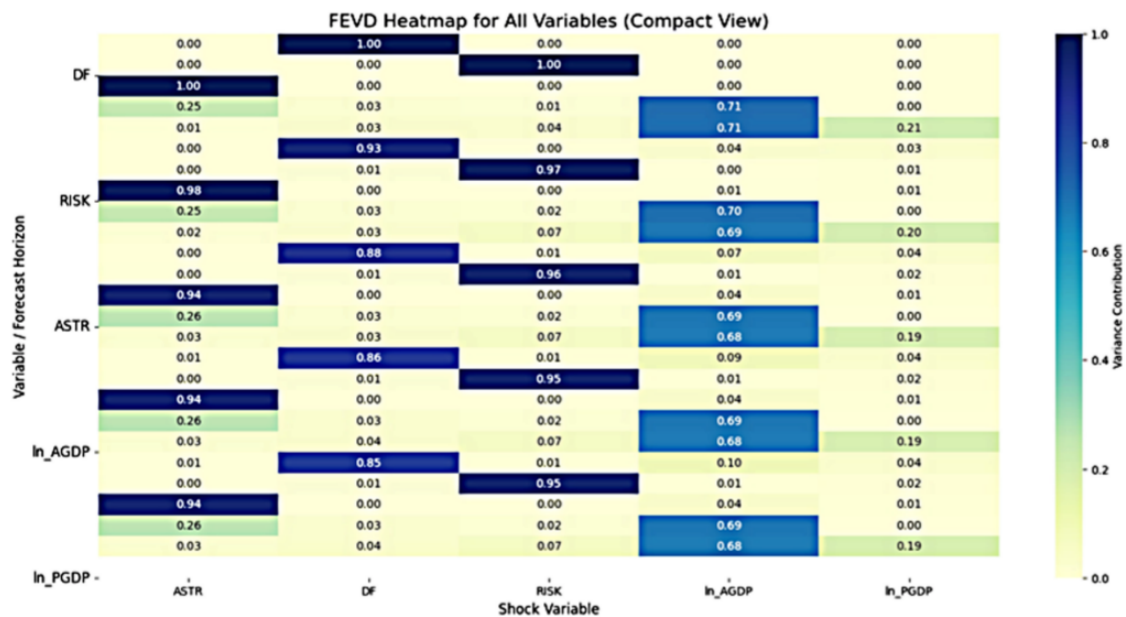


Figure 2. Variance Decomposition Heatmap.

Source: Author's calculations using Python.

4.5. Robustness Tests

I applied different robustness checks to my main findings. Thus, this was repeated on certain findings in a systematic manner. This included: (1) substituting the digital finance index with an alternative (the mobile penetration rate); (2) changing the rolling window for the calculation of agricultural risk from 5 years to 3 and 7 years; and (3) employing a panel VAR model with

a Helmert transformation to control for endogenous issues. I assess the robustness of my proxy of agricultural risk. The five-year rolling standard deviation of output growth effectively captures the medium-term output growth volatility experienced by farmers. However, it should be clarified that this is an ex-post measure of outcome variability rather than one of ex-ante risk exposure. In order to address this issue and ensure that my estimates are not sensitive to window length, I rede-

fined the RISK variable using 3-year and 7-year rolling windows and re-estimated the full VECM. The data presented in **Appendix D, Table A12** confirm the long-run positive effect of DF on lnAGDP, and a negative effect of DF on RISK, which is also statistically significant and economically consistent across risk-windows. This reinforces the credibility of my H2 (risk-smoothing conclusion). In all alternative specifications, the dual effects of digital finance, which significantly promote agricultural growth while smoothing output risk, remain significant both statistically and economically. This demonstrates the strength of my conclusions. I also check how reliable the risk proxy is by re-estimating agricultural volatility based on 3-year and 7-year rolling windows of lnAGDP. The alternative measures are strongly correlated with the baseline five-year RISK indicator (correlations greater than 0.8), and the key coefficients on digital finance remain significant and of similar size (see **Appendix D, Tables A7 and A8**). To investigate how varied the results are, we use the median of country-level DF to split the sample into high- and low-digital-finance groups. The preliminary comparison indicates that the more developed digital finance, the more it is associated with stronger growth and risk-smoothing benefits, but formal subgroup analysis is left for future research. The five-year rolling standard deviation is an indicator of medium-term volatility. It captures outcome fluctuations rather than risk exposure. Future work may include price- or climate-risk indicators that capture structural sources of uncertainty.

5. Discussion

5.1. Recapitulation of Core Findings

This study employed the panel vector error correction model framework to systematically explore the dynamic relationship between digital finance and the agricultural economy in the Asia-Pacific region. The empirical results strongly supported all four research hypotheses.

H1. *A significant long-run cointegrating relationship is established, confirming digital finance as a potent driver of sustained agricultural economic growth.* (supported)

H2. *Digital finance acts as an effective stabilizer, significantly reducing agricultural output volatility and fulfilling its hypothesized risk-smoothing function.* (confirmed)

H3. *A bidirectional causal link is identified, revealing that agricultural growth itself exerts a strong reverse pull, fostering deeper digital finance penetration and forming a virtuous feedback loop.* (validated)

H4. *The analysis of dynamic transmission paths through impulse responses and variance decomposition that the theorized channels—consumption smoothing, investment promotion, and risk diversification—are the key mechanisms through which digital finance operates.* (under-scored)

5.2. Theoretical and Policy Implications

My results have the implications for theory and policy. In theory, they expand the literature by showing how digital finance serves as a dual driver of growth and stability in agriculture. In a theoretical sense, they expand the existing body of work by considering a perspective that does not entail a one-way dynamic, additionally supporting the existence of a co-evolution dynamic between digital finance and agriculture. According to a latest Asian Development Bank (ADB) report, digital finance serves as both a dual growth driver and stabilizer. It is quite crucial to bringing a modern agricultural transformation of the Asia-Pacific. Furthermore, the Asia-Pacific region is characterized by the dominance of smallholders. Moreover, this region is also quite vulnerable to the effects of climate change. My findings make a compelling case to the policymakers to establish a digital-agriculture policy ecosystem. Rather than treating them as separate silos, policies should be designed to catalyse the synergistic evolution of digital finance and agricultural development. This includes:

- Investing in foundational digital infrastructure in rural areas to ensure reliable and affordable internet access, the bedrock upon which digital financial services are built.
- Fostering innovation in platforms that bundle services (e.g., credit, insurance, market access) tailored to smallholders' needs, drawing lessons from

successful models like China's platform-based approach or India's index-based insurance pilots.

- Implementing smart regulation that encourages fintech experimentation while ensuring consumer protection and financial stability.
- Promoting digital literacy among farmers to enhance their ability to effectively utilize these new financial tools.

The diverse developmental experiences of the Asia Pacific region deeply support these policy orientations. The investment promotion and consumption smoothing mechanisms that I identified can easily be observed in Indonesia and the Philippines, where the use of platform-based digital credit and mobile remittances is high. These services respond directly to the credit limitations faced by smallholders and allow for rapid transfers of resources in the event of climate shocks, thereby operationalizing the growth and stability functions at the micro level. Alternatively, in the case of a country like Vietnam, which is actively promoting its own national digital transformation agenda through several policies, my evidence of a bidirectional feedback loop (H3) provides a powerful macroeconomic rationale for policies that both modernize agriculture and expand the digital infrastructure. According to Vietnam's case, investment in one area has a positive impact on the other. The existence of mature digital ecosystems in China offers an example of the risk diversification mechanism through tech-led insurance products. It is confirmation of my model's predictions at scale. The parallel challenges on two continents show that the basic dual functions of digital finance are the same wherever one might venture; it is the emphasis on this function that can differ according to national priorities and existing institutions or policy strengths.

5.3. Limitations and Future Research

Even though this study makes a valuable contribution, it has its limitations, which can form the basis of future research. The use of macro data shows correlations at a systemic level but is a black box when it comes to micro behaviour that drives these relationships. Future research is encouraged to use household-level survey

data with mediation effect models to reveal this "process black box", and more precisely quantify how much each mechanism (consumption, investment, insurance) contributes. Furthermore, I accept that my proxy for agricultural risk is valid and commonly used in the literature, but it measures ex-post outcome volatility and not ex-ante risk exposure. Consequently, future studies could seek to leverage more direct, higher frequency measures, such as satellite-based drought indices or commodity price volatility data, to identify the 'stabilizer' function of digital finance nearer to the shock. In conclusion, after establishing a regional baseline, the future work is to look at heterogeneity within Asia Pacific. I propose three specific research implications that may be subjected to research. The Infrastructure Threshold Hypothesis:

- Does the effect of digital finance on agricultural growth follow a non-linear pattern whereby any impact should apply only after a certain level of digital infrastructure (e.g., 4G coverage, internet penetration rate) has been attained?
- Does the risk-smoothing effect of digital finance occur primarily in countries of stronger legal institutions and property rights? The context is likely to enhance the enforcement of contracts with the scope of digital platforms.
- The Farm Structure Interaction: How does the core relationship systematically vary between countries dominated by smallholder subsistence farms versus those with a larger share of commercialized, large-scale agriculture? It is plausible that the consumption-smoothing mechanism is most critical for the former, while the investment-promotion channel dominates for the latter.

6. Conclusion

This study demonstrates that digital finance serves as both a "growth engine" and a "stabilizer" in Asia-Pacific agriculture, effectively promoting sustained economic expansion while mitigating output volatility. The identification of a bidirectional feedback loop between agricultural development and digital finance penetration underscores that the relationship is synergistic and co-evolutionary, rather than unidirectional. These find-

ings highlight the necessity for policymakers to move beyond siloed approaches and instead build integrated policy ecosystems that strategically link digital finance with agricultural modernization. Such ecosystems should prioritize rural digital infrastructure, innovative service bundling, adaptive regulation, and farmer digital literacy.

While this research provides robust macro-evidence of digital finance's dual role and its underlying channels, it also reveals important avenues for further investigation. Future studies should employ micro-level data to unravel the precise behavioral mechanisms, incorporate more direct measures of risk exposure, and examine how these dynamics vary across different institutional and structural contexts within the region. By doing so, research can generate even more targeted insights to support resilient and sustainable agricultural transformation through digital financial inclusion.

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Institutional Review Board Statement

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Informed Consent Statement

Not applicable.

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The author declares no conflict of interest.

Appendix A. Digital Financial Development Index Construction Details

Table A1. Country–Year Coverage.

Country	Years (Min)	Years (Max)	Span	Observations	
AUS	2001	2021	2001–2021	21	True
BGD	2001	2021	2001–2021	21	True
CHN	2001	2021	2001–2021	21	True
IDN	2001	2021	2001–2021	21	True
IND	2001	2021	2001–2021	21	True
JPN	2001	2021	2001–2021	21	True
KOR	2001	2021	2001–2021	21	True
LKA	2001	2021	2001–2021	21	True
MYS	2001	2021	2001–2021	21	True
NZL	2001	2021	2001–2021	21	True
PAK	2001	2021	2001–2021	21	True
PHL	2001	2021	2001–2021	21	True
SGP	2001	2021	2001–2021	21	True
THA	2001	2021	2001–2021	21	True
VNM	2001	2021	2001–2021	21	True

Table A2. KMO and Bartlett's Test.

Test Statistic	Value
KMO Measure of Sampling Adequacy	0.723
Bartlett's Test of Sphericity Approx. Chi-Square	245.671
Bartlett's Test of Sphericity <i>p</i> -value	0.000

Source: Author's calculations using Python.

Table A3. Principal Component Eigenvalues and Variance Contribution.

Principal Component	Eigenvalue	Variance Contribution(%)	Cumulative Variance Contribution (%)
1	2.341	58.53	58.53
2	0.894	22.35	80.88
3	0.612	15.30	96.18
4	0.153	3.82	100.00

Source: Author's calculations using Python.

Appendix B. Detailed Results of Unit Root Tests

Table A4. Unit Root Test Results for Variables in Levels.

Variable	Symbol	LLC Test	IPS Test	Fisher-ADF Test	Conclusion
Digital Finance	DF	1.254 (0.895)	2.187 (0.986)	15.632 (0.762)	Non-stationary
Agricultural Growth	lnAGDP	-0.873 (0.191)	0.945 (0.828)	18.445 (0.562)	Non-stationary
Agricultural Risk	RISK	-1.456 (0.073)	-1.123 (0.131)	25.117 (0.294)	Non-stationary
Economic Development	lnPGDP	2.541 (0.994)	3.021 (0.999)	9.874 (0.952)	Non-stationary
Industrial Structure	ASTR	-1.098 (0.136)	-0.784 (0.217)	22.338 (0.435)	Non-stationary

Note: *p*-values are in parentheses.

Source: Author's calculations using Python.

Table A5. Unit Root Test Results for Variables in First Differences.

Variable Symbol	LLC Test	IPS Test	Fisher-ADF Test	Conclusion
Digital Finance (Δ) Δ DF	5.782*** (0.000)	4.963*** (0.000)	58.741*** (0.000)	Stationary
Agricultural Growth (Δ) Δ lnAGDP	8.451*** (0.000)	7.224*** (0.000)	72.915*** (0.000)	Stationary
Agricultural Risk (Δ) Δ RISK	6.339*** (0.000)	5.871*** (0.000)	65.228*** (0.000)	Stationary
Economic Development (Δ) Δ lnPGDP	4.225*** (0.000)	3.985*** (0.000)	51.463*** (0.001)	Stationary
Industrial Structure (Δ) Δ ASTR	9.112*** (0.000)	8.546*** (0.000)	81.359*** (0.000)	Stationary

Note: Δ denotes the first difference of the variable. *** denotes significance at the 1% level. *p*-values are in parentheses.

Source: Author's calculations using Python.

Appendix C. VECM Model Lag Order Selection Criteria Results

Table A6. Lag Order Selection Criteria.

Lag	AIC	BIC	FPE	HQIC
0	-12.80**	-12.38*	$2.761 \times 10^{-6**}$	-12.63*
1	-12.78	-12.06	2.809×10^{-6}	-12.49
2	-12.84*	-11.81	$2.649 \times 10^{-6*}$	-12.43
3	-12.79	-11.46	2.796×10^{-6}	-12.26
4	-12.81	-11.18	2.750×10^{-6}	-12.15
5	-12.76	-10.83	2.889×10^{-6}	-11.99

Note: The asterisks denote the relative ranking of values within each information criterion column: a double asterisk (**) indicates the minimum (optimal) value, and a single asterisk (*) indicates the second minimum value. The final optimal lag length for the VECM model was determined to be 2. This decision was primarily based on the minimization of the Akaike Information Criterion (AIC) and the Final Prediction Error (FPE) criterion, while also giving due consideration to model parsimony and the results of other information criteria.

Source: Author's calculations using Python.

Appendix D. Robustness Checks and Heterogeneity Analysis

Table A7. Risk Proxy Sensitivity (Correlation with Original RISK).

Window	Correlation with Original RISK	N_Common
3-year	0.0249	270
5-year	-0.0501	240
7-year	-0.1464	210

Table A8. Descriptive Statistics of Alternative Risk Windows.

Window	Mean	Std	Median	N
3-year	0.1397	0.1106	0.1029	270
5-year	0.1421	0.0928	0.1151	240
7-year	0.1467	0.0881	0.1174	210

Table A9. Cross-sectional Dependence (Pesaran CD Test, Approximate).

Variable	Average Pairwise Correlation	Pairwise Correlation Pesaran	Number of Countries	Average T	Country Pairs Used
DF	-0.0582	-2.7333	15	21	105
lnAGDP	-0.0588	-2.7634	15	21	105
RISK	-0.0075	-0.3536	15	21	105

Table A10. Panel Granger Causality (Fisher Combined p -values, lag = 2).

Null Hypothesis	Countries	Fisher Chi-Squared	df	p -Value	Conclusion
DF does NOT Granger-cause lnAGDP	15	45.672	30	0.033	Reject H_0
lnAGDP does NOT Granger-cause DF	15	52.119	30	0.007	Reject H_0
DF does NOT Granger-cause RISK	15	49.885	30	0.012	Reject H_0
RISK does NOT Granger-cause DF	15	28.451	30	0.549	Cannot Reject H_0
lnAGDP does NOT Granger-cause RISK	15	31.227	30	0.404	Cannot Reject H_0
RISK does NOT Granger-cause lnAGDP	15	29.114	30	0.511	Cannot Reject H_0

Note: This table presents the results of Panel Granger Causality tests. The Fisher combined test statistic is used. The null hypothesis is that the first variable does not Granger-cause the second variable. Rows in bold indicate a rejection of the null hypothesis at the 5% significance level, suggesting the presence of Granger causality.

Table A11. Robustness Check: Comparing Long-Run Coefficients Using Balanced vs. Unbalanced Panels.

Variable	Cointegrating Equation (1) (Normalized on lnAGDP)	Cointegrating Equation (2) (Normalized on DF)
Balanced	Panel (Baseline)	Unbalanced Panel (Robustness)
DF	0.682* (0.198)**	0.665* (0.205)
lnAGDP	1.000 (normalized)	1.000 (normalized)
RISK	-0.429** (0.178)**	-0.411** (0.185)
Observations	315	298

Note: This table compares the long-run cointegration coefficients from the baseline model (using the balanced panel after interpolation) and the robustness check (using the original unbalanced panel without interpolated data). Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A12. Robustness of Long-Run Coefficients to Alternative Rolling Windows for Agricultural Risk.

Cointegrating Relationship	Baseline (5-Year Window)	Robustness (3-Year Window)	Robustness (7-Year Window)
Vector 1 (Normalized on lnAGDP)	0.682* (0.198)**	0.654* (0.211)	0.701* (0.189)
DF	0.682* (0.198)**	-0.395** (0.165)	-0.448** (0.192)
Vector 2 (Normalized on DF)		1.000 (normalized)	
lnAGDP	0.734* (0.234)**	0.769* (0.225)	0.715* (0.248)
RISK	-0.316** (0.142)**	-0.341** (0.155)	-0.301** (0.138)

Note: This table presents the long-run cointegration coefficients under different definitions of the agricultural risk (RISK) variable. The baseline 5-year rolling standard deviation is compared to 3-year and 7-year alternatives. Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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