

# The impact of the integration of science, technology, and finance on innovation in listed agricultural enterprises through the lens of digital transformation

FANYE KONG<sup>1,2</sup>, HUINI ZHONG<sup>2</sup>, NANA CHAI<sup>3</sup>, BAOFENG SHI<sup>1\*</sup>

<sup>1</sup>College of Economics and Management, Research Center on Credit and Big Data Analytics, Northwest A&F University, Xi'an, P.R. China

<sup>2</sup>School of Economics and Management, Shanxi University, Taiyuan, P.R. China

<sup>3</sup>School of Economics and Management, Tongji University, Shanghai, P.R. China

\*Corresponding author: [shibaofeng@nwsuaf.edu.cn](mailto:shibaofeng@nwsuaf.edu.cn)

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**Abstract:** Digitisation enables the integration of science, technology and finance, and this trend toward integration can in turn enhance the innovation efficiency of listed agricultural enterprises. By leveraging the quasi-natural experiment of China's 2011 pilot program for technology finance – also known as science, technology, and finance, this paper uses the difference-in-differences (DID) model to demonstrate that the science and technology finance policy positively impacts the innovation levels of agriculture-related listed enterprises. That said, the policy's effect varies across different regions and enterprise sizes. Furthermore, moderating-effect analysis reveals that the digitalisation level of agriculture-related listed enterprises is a critical factor, while the evolutionary game model elucidates this factor's underlying mechanism. Based on these findings, policy recommendations are proposed to further develop science and technology finance platforms for agriculture-related listed enterprises.

**Keywords:** agricultural innovation; agriculture-related listed enterprises; DID model; digitalization; financing for science and technology innovation

In the agricultural sector, innovation relies heavily on technological advancements and the infusion of innovative capital. For example, the DrumNet model in Kenya (Okello et al. 2010) and the ITC e-Choupal model in India, described on the World Bank's Case Studies website (<https://www.wbcsd.org/resources/its-farmer-empowerment-program-india/>), have offered effective technological and financial support to agricultural enterprises through the establishment of electronic trading platforms and business network support centres. In such cases, the integration

of science, technology, and finance (STF) has gone through three stages or levels: an initial stage, a middle level, and a high level. The initial path mainly involves the mutual screening and benefit sharing of entrepreneurs (Laeven et al. 2015), which has contingency and directness. The middle level is reached when technology capital flows into the financial market to promote enterprise innovation activities (Hsu et al. 2014). In this process, the financial system gradually becomes an innovation centre to overcome financing difficulties in the technology commercialisation stage.

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The high level is marked by the complete integration of STF, which is present in the high-performance innovation digital network where knowledge variables and financial resources are interdependent (Purchase et al. 2014). In some developing countries, like China, the government has implemented specific policies aimed at accelerating the transition from the middle level to the high level, to facilitate innovation including agriculture.

Previous studies on the empowerment of agricultural enterprises through technology finance primarily concentrated on digital technology empowerment within the industrial economic paradigm of the initial two stages (Andriushchenko et al. 2019; Possner et al. 2022). While some research addressed specific issues, such as the urban-rural digital divide and the maintenance and upgrading of digital platforms (Mapanje et al. 2023), these earlier studies generally overlooked how the institutional reconstruction driven by the digital economy fosters innovation. Recently, an increasing number of studies have emphasised the importance of digital institutional empowerment (Sayfedinov and Sayfedinova 2021; Johnson 2024), conceptualising digitalisation as a process that reshapes operational frameworks (Fielke et al. 2020). This paper adopts these perspectives and pioneers an exploration from the standpoint of technology finance institutional design tailored to the digital economy.

Within this STF framework, agricultural-related listed enterprises (ARLEs), as large, publicly traded firms controlling critical midstream and downstream value-chain segments, are pivotal targets for institutional innovation policies (Ambler et al. 2023; Johnson 2024). ARLEs, being organisations adapted from ancient agricultural civilisation and yet functioning in the modern securities market, play a core role in driving agricultural science and technology innovation in China. This article focuses on the quasi-natural experiment of implementing the 'Science, Technology and Finance Combination Pilot Policy' launched by China in 2011. It empirically tests whether the STF policy has played a significant role in the innovation level of ARLEs, focusing in particular on issues of digital transformation. The studies mentioned previously suggest that a firm's capital strength, development stage, size, and regional location are all likely to affect the STF policy's effects (Ardito et al. 2021; Li et al. 2022; Feng et al. 2023; Kang et al. 2023). Nevertheless, there is a shortage of targeted research with Chinese ARLEs as the main subjects. Our research aims at studying the STF policy's effects on ARLEs through the lens of digital transformation.

We take Chinese ARLEs as an example while acknowledging their similarities and differences compared to ARLEs in other emerging economies.

### Research objectives

This paper has two research objectives:

*i)* Analyse the impact of the establishment of the STF policy on the overall innovation level of ARLEs in China, within China's STF demonstration zones.

*ii)* Describe the causal mechanisms through which STF elevates the innovation level of ARLEs by focusing on the pivotal factor of enhanced digitalisation.

The key contributions of this study are as follows: *(i)* The analysis delves into the policy ramifications of STF integration levels on agribusiness innovation endeavours, thereby expanding the horizons of meso-level research and augmenting the existing corpus of knowledge on technology finance in the digital economy. *(ii)* We posit that the augmentation of digitalisation levels is a pivotal moderating factor in nurturing innovation among ARLEs. In doing so, we fill a gap in the current literature and use methodological rigour to ensure a more nuanced understanding of the phenomenon. Our study also supplements existing research on the digital economy. *(iii)* We introduce an evolutionary game model anchored in the digital context to dissect the functional dynamics of STF demonstration zones, offering valuable insights for designing technology-based financial systems compatible with the digital economy. By scrutinising the operational mechanics of STF platforms, this analysis enhances the scientific basis for STF policies aimed at boosting agricultural innovation, providing a roadmap for future interventions and policy-design strategies.

### Literature review and hypothesis development

**Literature review.** Many scholars argue that STF policies enhance agricultural enterprises' innovation capacity by improving financial resource accumulation, allocation, and utilisation. Researchers have identified a number of reasons for this improvement. First, at the macro level, the policy spurs the involvement of multiple stakeholders, achieving extensive resource synergy and strengthening the financial connection of various entities (Cristobal-Fransi et al. 2020). By enhancing the infrastructure for STF services (Ashmore et al. 2017), firms stabilise and increase financing channels, which positively impacts agricultural production, technical efficiency (Afrin et al. 2017), and innovation investment. When information is aggregated from heterogeneous channels to interlink multiple entities, the fusion

of the demand and supply termini can be effectively instigated. Second, at the meso level, the STF platform bolsters the interaction frequency among stakeholders, leading to an integrated symbiosis within the financial ecosystem and propelling the process of value co-creation. The extensive adoption of digital technologies via the STF platform can likewise promote the advancement of the innovation factor market, reducing factor-price distortion and factor mismatch (Hong et al. 2024) when it comes to innovation. Third, at the micro level, the STF platform promotes the sharing of innovation factors such as data, technology, talent, and manufacturing. In this way, the platform can reduce transaction costs (He et al. 2024), information costs, and agency costs (Guo et al. 2022) in the financing process for agribusiness firms. Meanwhile, a risk compensation mechanism (Gai and Feng 2019) further lowers credit risks, easing constraints and fostering agribusiness innovation networks.

However, the integration of STF also creates a 'reverse siphon effect'. In other words, when STF policies are promoted in this context, the successful transformation of agriculture-related enterprises requires continuous absorptive capacity building. STF platforms fundamentally transform the organisational modes and business models of enterprises through digital technology, requiring agriculture-related firms to engage in collaborative innovation and obtain guarantee capabilities (Lee 2018). In turn, this process exacerbates information overload, causing information-processing bottlenecks. Only by enhancing the ability to identify and search for information, obtain guarantees, and manage risks (Possner et al. 2022) can the STF policy truly broaden the channels for agricultural innovation funding and effectively promote financing efficiency (Zakaria et al. 2019; Niemand et al. 2021). Thus, in order to achieve these capabilities, ARLEs need to invest a large amount of capital. This substantial imbalance may either reduce the R&D funds of agribusiness firms (Shi 2023) or create a tacit agreement to maintain the status quo and refrain from actively engaging in innovative activities due to collective self-interest.

These considerations lead to our first research question: Do the policies established in China's STF demonstration zone enhance the innovation level of ARLEs?

Since the 21st century, the relationship between institutions and technology has been reconceptualised as a dynamic, co-evolutionary process (Ruttan 1989; Dorward 2005), characterised by dialectical interaction. Specifically, institutions function both as constraining frameworks and enabling mechanisms for

technological progress. Simultaneously, technological innovation drives institutional change by reshaping price signals and reducing transaction costs. According to economic growth theory, institutional arrangements such as STF policies are the root causes of enterprises' growth, while the efficacy of their implementation hinges on technological transformation.

Agriculture exemplifies this institution-technology co-evolution: STF policies (as institutional arrangements) enable digital adoption, while ARLEs' digital transformation conversely drives institutional innovation (e.g. data-governance reforms). The digital transformation of ARLEs has unfolded as a gradual process, starting with technology adoption, then advancing to resource optimisation, and ultimately reaching system coordination. This process has been driven by the continuous development of digital infrastructure.

In the initial stage of the technological foundation, cloud computing and big data have strengthened the fintech infrastructure (Ashmore et al. 2017) and achieved basic efficiency improvements. This is consistent with the concept of 'programmability' being an early feature of fintech, as proposed by Fichman et al. (2014).

Next, in the intermediate stage of resource integration, digital platforms (Nambisan et al. 2017) have facilitated cross-actor innovation flows and enhanced the accessibility of financial products (Fang and Zhang 2021).

Finally, in the mature stage of ecosystem coordination, advanced digital features such as 'data homogenisation' have driven system innovation, and fintech policies have utilised platform-based governance to optimise resource allocation while also exposing social-technical challenges such as data fragmentation and skill gaps (Klerkx and Rose 2020).

Numerous studies have verified that digital transformation is the core impetus for driving technological innovation (Schulz and Börner 2023). Digitalisation is the introduction of digital technological innovation into the organisational, industrial, and social systems of existing listed agricultural enterprises, in a way that alters the operation mode of these systems (Fielke et al. 2020). Accordingly, the digitalisation of ARLEs can not only promote the positive effects of the STF platform but also alleviate its negative impacts (Hariry and Reza 2023). Through information-sharing and knowledge-integration effects, digitalisation in ARLEs primarily promotes the elevation of enterprise innovation level in three stages. First, during the input stage, digitalisation helps to identify service requirements and explore latent demands, corresponding to the driving factors of value co-creation (Pirola et al. 2020). Then, during

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the process stage, digitalisation helps firms develop service plans through the flow of resources and increases technological interactions among entities, furthering value co-creation (Chaudhary and Suri 2022). Lastly, during the output stage, digitalisation can help firms deliver new products and services to meet the value requirements of each entity.

However, the precise role of digitalisation remains an enigma, particularly in relation to revenue and costs. This issue leads to our second research question: Does the increase in the digitalisation level of ARLEs provide the preconditions to establish innovation networks by integrating STF policies? In other words, does this increase function as a moderating variable?

**Hypothesis development.** In the long run, digital transformation and patent innovation in ARLEs are mutually reinforcing. In the terms provided by institutional entrepreneurship theory (Battilana et al. 2009), ARLEs' digitalisation reconfigures institutional frameworks to exploit STF policies. Complementarily, systems of innovation theory (Edquist 1997) positions digital platforms as engines for value co-creation, by translating STF support into multi-stage innovation (Pirola et al. 2020). In the stage-based model of Markard et al. (2016), 'technological legitimacy' denotes the alignment between technological paradigms and institutional environments, with its absence indicating institutional misalignment. Science-and-technology-based financial policies (as institutional factors) significantly enhance the innovation capabilities of ARLEs (as technological actors) by ensuring cognitive, normative, and regulatory legitimacy. Meanwhile, digitalisation further resolves resource conflicts via dynamic capabilities (Tece 2007).

We thus propose the following two hypotheses:

$H_1$ : STF demonstration zones increase patent innovation in ARLEs, with heterogeneous effects across different firm sizes and regions.

$H_2$ : Digitalisation capabilities strengthen (moderate) the effectiveness of STF policy in increasing ARLEs' level of innovation.

## MATERIAL AND METHODS

**Data source.** This study is based on the 2012 industry classification standards of the China Securities Regulatory Commission. We selected ARLEs in the Shanghai and Shenzhen stock markets in China as samples, studying 369 enterprises from 2007 to 2022. Patent data, given its standardisation, accessibility, and close association with innovation and objective comparability, emerged as a crucial indicator for gauging firms'

level of innovation (Lanjouw and Schankerman 2004). Therefore, we derived the relevant financial indicators from the patent data of ARLEs included in the China Agricultural Research Database maintained by Zhejiang University's Carter Enterprise Research Institute. Data were also obtained through queries in the CSMAR database. For our analysis, we deleted enterprises under special treatment (ST) or particular transfer (PT) as well as ARLEs that belong to the financial industry.

The China Agricultural Research Database is founded on the entire business registration data of China and strictly complies with the standards provided in the Chinese National Bureau of Statistics' 'Statistical Classification of Agriculture and Related Industries' from 2020. The database encompasses agricultural-related enterprises falling into 10 major categories, 61 mid-level categories, and 215 minor categories. All agricultural-related enterprises in 243 'complete industries' are incorporated. In addition, relevant enterprises in 159 enterprises related to not fully agricultural-related industries are precisely screened through industry codes plus business scope keywords, which well represents the population of agricultural enterprises in China. In short, the database not only guarantees coverage breadth but also ensures data accuracy.

The control variables were available in CSMAR database. To accurately reflect the innovative capacity of ARLEs, we exclusively extracted the number of applications for invention patents and utility model patents, aggregated them, and employed their logarithm to analyse the explanatory variables presented in this paper. If there were missing values, the data for the year in question were automatically deleted. The data span is 15 years, covering 25 provinces, with a total of 1 698 data points drawn from the provincial panel data.

The research utilised Python crawler techniques on the annual reports of ARLEs from 2007 to 2022. We measured the presence and the degree of digital transformation within the ARLEs through textual analysis. The digitalisation transformation level of ARLEs was assessed by the objective and comparable number of ARLEs using digital technologies (including blockchain technology, cloud computing technology, AI technology, and big data technology) from 2007 to 2022 in the CSMAR database. In keeping with the method proposed by Wu et al. (2021), Python requests and Selenium tools were used to capture the annual report text of Juchao Net, and a digital transformation index was constructed using pre-defined digital technology keyword libraries (such as 'artificial intelligence', 'blockchain' etc.). The statistical analysis of the

digitisation level of Chinese ARLEs from 2007 to 2022 is presented in Table 1.

#### Baseline modelling and moderation-effect model.

This study categorised provinces based on the presence of a STF pilot area where ARLEs are located, taking into account that Hong Kong, Macao, and Taiwan lack corresponding data. The analysis included provinces from the pilot zones as the control group, and the remaining provinces constituted the experimental group. A total of 65 535 provincial-level observations were collected. Using the MTDID (multiple time periods difference-in-differences) method, we identified the causal disposal effect of the STF policy on innovation activities of regional ARLEs. This approach can better solve the endogenous issue. Equation (1) is the established benchmark model.

$$lpatent_{i,t} = \alpha_0 + \beta_1 treat_{i,t} \times post_{i,t} + \beta_2 control_{i,t} + \lambda_i + \mu_i + \varepsilon_{i,t} \quad (1)$$

where:  $\alpha_0$  – baseline constant intercept;  $\beta_1$  – treatment effect DID estimator;  $\beta_2$  – control variables coefficient;  $\lambda_i$  – year fixed effects;  $\mu_i$  – province fixed effects;  $\varepsilon_{i,t}$  – the residual term

The innovation level of ARLEs is influenced not only by STF policies, but also by the firms' own situation. In the spirit of comprehensive consideration, we combed through the relevant literature (Ardito et al. 2021; Li et al. 2022; Feng et al. 2023; Kang et al. 2023) and

screened out six indicators as control variables: gearing ratio, return on total assets (*ROA*), enterprise size, operating cost ratio, shareholding ratio of the top ten shareholders and *tobinq*. Controlling *ROA* and leverage ratio can avoid omitted variable bias and ensure the reliability of estimation results. As noted by Mugeru and Nyambane (2015) and Chladkova and Formankova (2016), *ROA* reflects the overall profitability of the enterprise's assets and is a key constraint for agricultural enterprise innovation. High-*ROA* enterprises are more likely to invest in innovation, while high leverage in low-*ROA* enterprises may reflect financial difficulties. The leverage ratio reflects the capital structure and directly affects financing capacity and innovation behaviour. The definitions of the main control variables are shown in Table 2.

The moderating effect examined how a third variable changes the relationship between two primary variables. The moderating effect is quantified using the following statistical model:

$$lpatent_{i,t} = \beta_0 + \beta_1 did_{i,t} + \beta_2 (did_{i,t} - dig_{i,t}) + \beta_3 dig_{i,t} + \varepsilon_{i,t} \quad (2)$$

where:  $lpatent_{i,t}$  – the dependent variable;  $did_{i,t}$  – the independent variable;  $dig_{i,t}$  – the moderator variable;  $did_{i,t} - dig_{i,t}$  – the interaction term reflecting moderation;  $\beta_0, \beta_1, \beta_2$  and  $\beta_3$  – regression coefficients;  $\varepsilon_{i,t}$  – the residual term.

Table 1. Statistical analysis of digitalisation level of agricultural-related listed enterprises in China from 2007 to 2022

| Year | Observation | Average     | SD        | Minimum | Maximum |
|------|-------------|-------------|-----------|---------|---------|
| 2007 | 137         | 0.372 262 8 | 1.475 323 | 0       | 12      |
| 2008 | 141         | 0.503 546 1 | 2.183 130 | 0       | 18      |
| 2009 | 152         | 0.500 000 0 | 2.222 700 | 0       | 20      |
| 2010 | 181         | 0.580 110 5 | 2.573 463 | 0       | 26      |
| 2011 | 197         | 0.847 715 7 | 2.776 938 | 0       | 20      |
| 2012 | 210         | 1.057 143   | 3.329 809 | 0       | 31      |
| 2013 | 214         | 1.738 318   | 4.960 570 | 0       | 40      |
| 2014 | 223         | 3.412 556   | 8.714 709 | 0       | 68      |
| 2015 | 240         | 5.216 667   | 10.813 89 | 0       | 95      |
| 2016 | 258         | 5.891 473   | 13.106 41 | 0       | 137     |
| 2017 | 284         | 6.577 465   | 13.959 22 | 0       | 116     |
| 2018 | 289         | 6.885 813   | 13.910 08 | 0       | 119     |
| 2019 | 300         | 7.620 000   | 16.436 02 | 0       | 174     |
| 2020 | 334         | 7.589 820   | 14.908 01 | 0       | 142     |
| 2021 | 353         | 6.617 564   | 12.644 1  | 0       | 142     |
| 2022 | 369         | 9.139 344   | 21.046 58 | 0       | 227     |

Source: Developed by authors based on web crawler technology (Wu et al. 2021; Zhai et al. 2022)

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Table 2. Definitions and descriptive statistics of major variables

| Variable      | Measurement   | Mean  | SD      | Min.    | Max.  |
|---------------|---|-------|---------|---------|-------|
| <i>patent</i> | practical new and invention patent number of 369 ARLE         | 10.92 | 21.88   | 1       | 256   |
| <i>lev</i>    | total assets/total liability                                  | 0.376 | 0.184   | 0.011 0 | 1.073 |
| <i>ROA</i>    | net profit/total assets                                       | 0.055 | 0.078 0 | -1.387  | 0.469 |
| <i>size1</i>  | ln (total market value of individual stocks)                  | 15.87 | 1.194   | 13.30   | 21.67 |
| <i>cost</i>   | operating cost ratio /business incomes                        | 0.651 | 0.214   | 0.071 0 | 1.376 |
| <i>top10</i>  | shareholding ratio of the top ten shareholders of 369 ARLE    | 60.05 | 15.23   | 20.30   | 95.84 |
| <i>tobinq</i> | enterprise market price (stock price)/enterprise's reset cost | 2.255 | 1.696   | 0.830   | 22.32 |

*cost* – operating cost; *lev* – leverage; *ROA*– return on total assets; *size1* – enterprise size; *tobinq* – Tobin's Q; *top10* – top ten shareholders' shareholding ratio; ARLE – agriculture related enterprises

Source: Calculated by authors

This formula assesses whether the impact of  $did_{i,t}$  on  $lpatent_{i,t}$  changes with  $dig_{i,t}$ .

**An evolutionary game model.** In analysing how digitalisation affect ARLEs' level of innovation, the evolutionary game model can facilitate a deeper examination of the empirical model based on our case studies. On the STF platform, the probability of continuous cooperation between listed agricultural enterprise A and financial intermediary B under debt and credit pressure is  $x$  and  $y$ , respectively. Assuming both parties insist on continuous cooperation, the common income is  $R$ , and the proportion of the ARLE is  $\theta$ , then the proportion of proceeds received by financial intermediaries is  $1-\theta$ . Due to the financing paradox, if one party breaches the contract midway, the potential return of the morally hazardous party is articulated as  $V_a$  and  $V_b$  respectively. The fixed costs associated with the operation of the STF platform are borne by A and B, specifically  $F_a$  and  $F_b$ . The variable costs of continuous cooperation by A and B are  $i$  and  $c$  respectively, and  $R > i + c, \theta R > i, (1-\theta)R > c$ . The government gives precise subsidies (Tang et al. 2024) to the two parties for adhering to cooperation and innovation through the STF platform,

with the subsidy amount of  $G_a$  and  $G_b$ , respectively. To account for a midway default, the platform uses the bad debt reserve withdrawn by midway default cooperation as a special fund for risk compensation, giving this to the party that insists on cooperation, with the amount recorded as  $M$ . So, the operation mechanism of the digital platform of STF can be expressed as shown in Table 3.

According to the theory of the evolutionary game, if the expected return of an ARLE choosing the strategy of 'continuous cooperation' is denoted as  $U_{ac}$ , then

$$U_{ac} = y(\theta R + G_a - F_a - i) + (1 - y)(-F_a - i + M) \quad (3)$$

If the expected return of a listed agribusiness firm choosing the 'mid-default' strategy is denoted as  $U_{au}$ , then

$$U_{au} = y(V_a - F_a - M) + (1 - y)(-F_a) \quad (4)$$

The average expected returns of the ARLE are:

$$\bar{U}_a = xU_{ac} + (1 - x)U_{au} \quad (5)$$

Table 3. Cooperative game model between agricultural-related listed enterprises (ARLEs) and financial institutions in the technology finance demonstration zone

|   |  | B   |  |
|---|--|---|--|
|   |  | Continuous cooperation ( $y$ )                            | Mid way breach of contract ( $1 - y$ ) |
| A | Continuous cooperation ( $x$ )         | $(\theta R + G_a - F_a - i, (1-\theta)R + G_b - F_b - c)$ | $(-F_a - i + M, V_b - F_b - M)$        |
|   | Mid way breach of contract ( $1 - x$ ) | $(V_a - F_a - M, -c - F_b + M)$                           | $(-F_a, -F_b)$                         |

Source: Authors' own elaboration

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The replication dynamic equation for the ARLE is:

$$\begin{aligned} S(x) &= x(U_{ac} - \overline{U}_a) = x[U_{ac} - xU_{ac} - (1-x)U_{au}] = \\ &= x(1-x)[y(\theta R + G_a - V_a) + M - i] \end{aligned} \quad (6)$$

Similarly, if the expected return to a financial institution choosing the 'continuous cooperation' strategy is characterised as  $U_{bc}$ , then

$$\begin{aligned} U_{bc} &= x[(1-\theta)R + G_a - F_a - c + \\ &+ (1-x)(-F_b - c + M)] \end{aligned} \quad (7)$$

If the expected return to a financial institution choosing a 'mid-default' strategy is characterised as  $U_{bu}$ , then

$$U_{bu} = x[V_b - F_b - M] + (1-x)(-F_b) \quad (8)$$

The average expected return for a financial institution is:  $\overline{U}_b = yU_{bc} + (1-y)U_{bu}$ . Thus, the equation for the replication dynamics of financial institutions is

$$\begin{aligned} S(y) &= y(U_{bc} - \overline{U}_b) = y[U_{bc} - yU_{bc} - (1-y)U_{bu}] = \\ &= y(1-y)[x(1-\theta)R + G_a - V_a] + M - c \end{aligned} \quad (9)$$

The evolutionary stability strategy (ESS) must meet the following two conditions at the same time: replicating the dynamic equations  $s(x) = 0, s(y) = 0$ ,

and having the first-order derivative  $s'(x) < 0, s'(y) < 0$ .

In addition, for this evolutionary game model, there are five local equilibria. According to Lyapunov stability theory (Table 4), an equilibrium point is ESS if and only if all the eigenvalues of the Jacobian matrix are negative. By contrast, if at least one eigenvalue is always positive, the equilibrium point is unstable.

Recent advancements in agricultural finance research have increasingly focused on integrating digitalisation and innovation through sophisticated methodologies, such as randomised controlled trials (RCTs) (Omotilewa et al. 2019; Nakano and Magezi 2020), simultaneous equation systems (SES) (Ouatara et al. 2020), and fully observed recursive mixed-process models (CMP) (Porgo et al. 2018). Our study makes a novel contribution by employing a quasi-natural experiment (DID) integrated with evolutionary game theory to examine the intersection of STF policies, digital transformation, and agricultural innovation. This approach addresses causal identification and dynamic stakeholder interactions more comprehensively than prior single-method designs. Unlike Abate et al. (2016), who utilised propensity score matching (PSM) to evaluate institutional credit designs, or Andriushchenko et al. (2019), whose case studies explored digital banking in Ukraine, our dual-method framework captures both immediate policy effects and long-term behavioural adaptations among farmers, financial institutions, and policymakers while controlling for endogeneity via the DID design.

Table 4. The eigenvalues of the Jacobian matrix corresponding to the equilibrium points

| Balance point | Eigenvalue 1                    | Eigenvalue 2                       | Stability       | Stable conditions   |
|---------------|---------------------------------|------------------------------------|-----------------|---|
| $E_1(0,0)$    | $M - i$                         | $M - c$                            | progressive ESS | $M - i < 0$<br>$M - c < 0$  |
| $E_2(0,1)$    | $\theta R + G_a - V_a + M - i$  | $-M + c$                           | progressive ESS | $\theta R + G_a - V_a + M - i < 0$<br>$-M + c < 0$                            |
| $E_3(1,0)$    | $-M + i$                        | $(1-\theta)R + G_a - V_b + M - c$  | progressive ESS | $-M + i < 0$<br>$(1-\theta)R + G_a - V_b + M - c < 0$                         |
| $E_4(1,1)$    | $-\theta R - G_a + V_a - M + i$ | $-(1-\theta)R - G_a + V_b - M + c$ | progressive ESS | $-\theta R - G_a + V_a - M + i < 0$<br>$-(1-\theta)R - G_a + V_b - M + c < 0$ |

ESS – evolutionary stability strategy

Source: Calculated by authors

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**RESULTS AND DISCUSSION**

**Baseline regression results**

The empirical results showed that the coefficients are significantly positive at a 1% significance level. The STF demonstration zones owned by the provinces where ARLEs are located had a markedly positive stimulative impact on the number of patents applied for by the firms. The original model does not have serious sample selection errors, and the conclusions are reliable. According to models shown in Table 5, the patent growth rate of ARLEs in the region increased by about 0.4 percentage points after the establishment of the demonstration zone. Given the cumulative effect of policies, STF policies can undoubtedly significantly elevate the innovation level of ARLEs, which confirms the first half of  $H_1$ . They enhance innovation capabilities, at least in part, by ensuring cognitive, normative, and regulatory legitimacy of the required kind (Markard et al. 2016).

**Robustness tests**

**Parallel trend test.** The MTDID regression analysis was conducted assuming that the ARLEs in the experimental group had been impacted by the policy in the first and second periods before the policy implementation in 2011. This was reset and regressed two years before the STF policy was put into play. As shown in Figure 1 and Table 6, the regression coefficient was flat during the virtual policy occurrence time. After the real policy implementation time, the policy effect showed a positive upward trend.

Table 6 shows that, at a significance level of 1%, the growth rate for innovation levels of ARLEs in the region increased by about 0.43 percentage points in the first two years of the establishment of the demonstration zone; in the third year, the growth rate for innovation levels increased by about 0.6 percentage points. This significantly positive effect has existed for a long time, indicating that the impact of STF policy demonstration zones on innovation activities of ARLEs has

Table 5. Impact of technology finance on patent output of listed agricultural-related firms in science, technology and finance (STF) demonstration zones

|                       | (1)                 | (2)                 | (3)                 | (4)                  | (5)                  | (6)                  |
|-----------------------|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|
|                       | <i>lpatent</i>      | <i>lpatent</i>      | <i>lpatent</i>      | <i>lpatent</i>       | <i>lpatent</i>       | <i>lpatent</i>       |
| <i>did</i>            | 0.391***<br>(0.137) | 0.374***<br>(0.137) | 0.381***<br>(0.136) | 0.411***<br>(0.137)  | 0.409***<br>(0.140)  | 0.386***<br>(0.140)  |
| <i>lev</i>            | –                   | 0.236*<br>(0.129)   | 0.497***<br>(0.143) | 0.230*<br>(0.138)    | 0.005<br>(0.145)     | –0.055<br>(0.147)    |
| <i>ROA</i>            | –                   | –                   | 1.498***<br>(0.375) | –0.209<br>(0.365)    | 0.189<br>(0.325)     | 0.250<br>(0.322)     |
| <i>size1</i>          | –                   | –                   | –                   | 0.228***<br>(0.026)  | 0.246***<br>(0.026)  | 0.261***<br>(0.026)  |
| <i>cost</i>           | –                   | –                   | –                   | –                    | 0.616***<br>(0.139)  | 0.598***<br>(0.139)  |
| <i>top10</i>          | –                   | –                   | –                   | –                    | –                    | –0.005***<br>(0.002) |
| <i>_cons</i>          | 1.604***<br>(0.083) | 1.525***<br>(0.093) | 1.340***<br>(0.104) | –2.095***<br>(0.406) | –2.725***<br>(0.438) | –2.609***<br>(0.434) |
| <i>n</i>              | 1 697.000           | 1 697.000           | 1 697.000           | 1 697.000            | 1 697.000            | 1 697.000            |
| <i>R</i> <sup>2</sup> | 0.169               | 0.170               | 0.181               | 0.225                | 0.234                | 0.239                |
| province              |                     |                     |                     |                      |                      |                      |
| year                  |                     |                     |                     |                      |                      |                      |

\* and \*\*\*significance levels at 10% and 1%, respectively; standard errors in parentheses

*\_cons* – constant term; *did* – Difference-in-Differences estimator; *cost* – operating cost; *lev* – leverage; *lpatent* – Natural logarithm of patent count; *ROA* – return on total assets; *size1* – enterprise size; *tobinq* – Tobin's Q; *top10* – top ten shareholders' shareholding ratio

Source: Calculated by authors

<https://doi.org/10.17221/22/2025-AGRICECON>

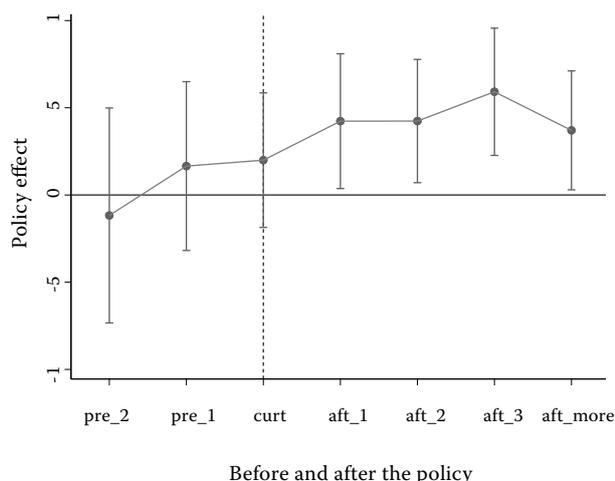


Figure 1. Dynamic impact of science, technology and finance (STF) on patent output of agriculture-related listed firms in the category of science and technology financial demonstration zones

The x-axis – event time relative to the policy implementation year ( $t = 0$ ); *pre\_2* and *pre\_1* – two years and one year before the policy, respectively; *curt* – the policy implementation year; *aft\_1*, *aft\_2*, *aft\_3* – one, two, and three years after the policy; *aft\_more* – four or more years after the policy

Source: Authors' composition

a cumulative effect. Besides, there was no marked disparity in the growth rates for innovation levels when the experimental group and the control group were compared. This met the parallel trend hypothesis.

**Placebo test.** Figure 2 showed no overlap between the benchmark model's estimated coefficients and the random estimation results. The estimated value of the coefficient kernel density of the random process was distributed around 0 and far less than the benchmark regression coefficient. This confirms that the STF platform's positive effect on ARLE innovation is stable and not attributable to random factors or unobservable variables, validating the benchmark regression results.

**PSM-DID.** Table 7 shows the test results for PSM DID. The PSM DID test adopted the 1 : 3 nearest neighbours matching and back sampling method. Based on the Logit model, the  $t$  value corresponding to the estimated value of the average treatment effect of the experimental group is 2.88, which was significant at the level of 5%. Consequently, the covariate test results supported the null hypothesis of no significant intergroup difference between the experimental and control groups. Following Logit model matching, the PSM matching effect was satisfactory, and the balance test was successfully passed.

Table 6. Dynamic impact of technology finance demonstration zones on patent output of agricultural-listed enterprises

|                      | (1)                 | (2)                  |
|----------------------|---------------------|----------------------|
|                      | <i>lpatent</i>      | <i>lpatent</i>       |
| <i>pre_2</i>         | -0.098<br>(0.350)   | -0.102<br>(0.379)    |
| <i>pre_1</i>         | 0.124<br>(0.293)    | 0.178<br>(0.297)     |
| <i>curt</i>          | 0.164<br>(0.224)    | 0.211<br>(0.234)     |
| <i>aft_1</i>         | 0.433*<br>(0.227)   | 0.431*<br>(0.234)    |
| <i>aft_2</i>         | 0.414**<br>(0.203)  | 0.427**<br>(0.214)   |
| <i>aft_3</i>         | 0.602***<br>(0.210) | 0.615***<br>(0.222)  |
| <i>aft_more</i>      | 0.394**<br>(0.197)  | 0.385*<br>(0.206)    |
| <i>lev</i>           | –                   | -0.089<br>(0.147)    |
| <i>ROA</i>           | –                   | 0.234<br>(0.318)     |
| <i>size1</i>         | –                   | 0.291***<br>(0.029)  |
| <i>cost</i>          | –                   | 0.548***<br>(0.140)  |
| <i>top10</i>         | –                   | -0.005***<br>(0.002) |
| <i>tobinq</i>        | –                   | -0.048***<br>(0.016) |
| <i>_cons</i>         | 1.586***<br>(0.116) | -2.974***<br>(0.473) |
| <i>n</i>             | 1 698.000           | 1 698.000            |
| <i>R<sup>2</sup></i> | 0.174               | 0.246                |
| province             |                     |                      |
| year                 |                     |                      |

\*,\*\* and \*\*\*significance level at 10%, 5% and 1%, respectively; standard errors in parentheses

*\_cons* – constant term; *aft* – after; *cost* – operating cost; *curt* – current; *lev* – leverage; *lpatent* – natural logarithm of patent count; *pre* – previous; *ROA* – return on total assets; *size1* – enterprise size; *tobinq* – Tobin's Q; *top10* – top ten shareholders' shareholding ratio

Source: Calculated by authors

<https://doi.org/10.17221/22/2025-AGRICECON>

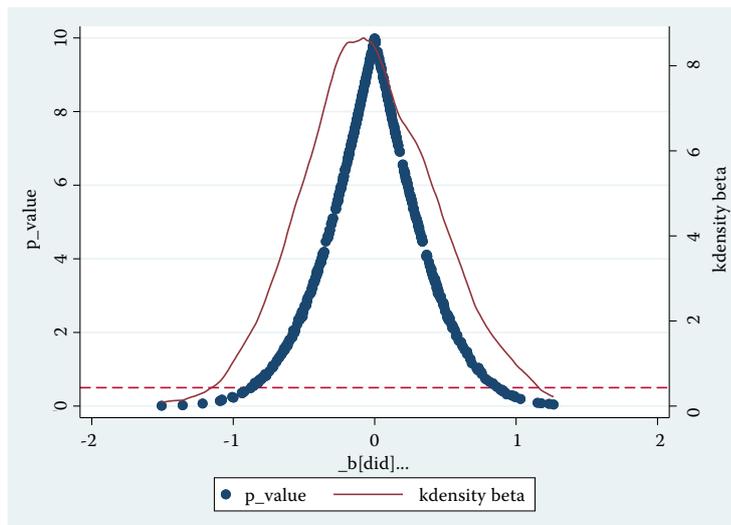


Figure 2. Dynamic impact of science, technology and finance (STF) on patent output of agriculture-related listed firms in science and technology financial demonstration zones

Source: Authors' composition

Table 7. Dynamic impact of PSM-DID and adjusted sample interval test results

|                      | (1)                  |
|----------------------|----------------------|
|                      | <i>lpatent</i>       |
| <i>did</i>           | 0.361**<br>(0.146)   |
| <i>lev</i>           | -0.250<br>(0.165)    |
| <i>ROA</i>           | 0.252<br>(0.486)     |
| <i>size1</i>         | 0.300***<br>(0.034)  |
| <i>cost</i>          | 0.717***<br>(0.157)  |
| <i>top10</i>         | -0.003*<br>(0.002)   |
| <i>tobinq</i>        | -0.054***<br>(0.016) |
| <i>_cons</i>         | -3.198***<br>(0.527) |
| <i>n</i>             | 1 325.000            |
| <i>R<sup>2</sup></i> | 0.259                |
| province             |                      |
| year                 |                      |

\*, \*\* and \*\*\*significance level at 10%, 5% and 1%, respectively; standard errors in parentheses

*\_cons* – constant term; *cost* – operating cost; *did* – Difference-in-Differences estimator; *lev* – leverage; *lpatent* – natural logarithm of patent count; *ROA* – return on total assets; *size1* – enterprise size; *tobinq* – Tobin's Q; *top10* – top ten shareholders' shareholding ratio

Source: Calculated by authors

### Heterogeneity test

**Scale heterogeneity.** We tested STF policy effects by dividing ARLEs into large and small groups, revealing heterogeneous innovation impacts across different firm sizes. We calculated the average market value of each enterprise in the sample time, and then took its median. If the average market value of each enterprise exceeded the median, it was recorded as a large enterprise. If it was lower than the median, it was recorded as a small enterprise. Table 8 shows the outcomes of this test. The effect of the STF policy on the increase in the number of patents applied for by small-scale ARLEs was not statistically significant.

**Regional heterogeneity.** To further elucidate the heterogeneity in the effects of STF policies on the innovation activities of ARLEs across eastern, central, and western regions of the country (Table 9, columns 1, 2 and 3), the test findings indicated that innovative patent applications among ARLEs were positively impacted by demonstration zones in both eastern and western regions. In contrast, STF's effect on patent growth for listed agricultural firms in the central region lacked statistical significance. There was therefore regional heterogeneity among the STF demonstration zones (Table 9).

STF is a universal policy tool; however, it is affected by the infrastructure, capital conditions, and labour factors in different regions, and the effects of these factors in different regions are different. Because ARLEs in the central region in China lack both the flexibility of full market leadership and the efficiency of full government leadership, the policy efficacy failed to meet expectations.

The foregoing heterogeneity analysis validates the second half of  $H_1$ .

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Table 8. Regional heterogeneity of large-scale and small-scale listed agricultural-related firms

|                       | (1)                  | (2)                 |
|-----------------------|----------------------|---------------------|
|                       | <i>lpatent</i>       | <i>lpatent</i>      |
| <i>did</i>            | 0.659***<br>(0.240)  | 0.048<br>(0.162)    |
| <i>lev</i>            | -0.050<br>(0.233)    | 0.174<br>(0.179)    |
| <i>ROA</i>            | -0.202<br>(0.631)    | 0.746**<br>(0.366)  |
| <i>size1</i>          | 0.256***<br>(0.042)  | 0.227***<br>(0.070) |
| <i>cost</i>           | 0.638***<br>(0.220)  | 0.341*<br>(0.200)   |
| <i>top10</i>          | -0.012***<br>(0.002) | -0.000<br>(0.002)   |
| <i>tobinq</i>         | -0.033*<br>(0.020)   | -0.069*<br>(0.041)  |
| <i>_cons</i>          | -2.136***<br>(0.700) | -2.003*<br>(1.078)  |
| <i>n</i>              | 920.000              | 771.000             |
| <i>R</i> <sup>2</sup> | 0.321                | 0.238               |
| province              |                      |                     |
| year                  |                      |                     |

\*, \*\* and \*\*\*significance level at 10%, 5% and 1% respectively; standard errors in parentheses

*\_cons* – constant term; *cost* – operating cost; *did* – Difference-in-Differences estimator; *lev* – leverage; *lpatent* – natural logarithm of patent count; *ROA* – return on total assets; *size1* – enterprise size; *tobinq* – Tobin's Q; *top10* – top ten shareholders' shareholding ratio

Source: Calculated by authors

### Mechanism-of-action tests

To understand how the impact of STF policies on the innovation capabilities of listed agricultural companies is influenced by the firms' digital maturity, we used the average number of these enterprises employing technologies such as block-chain, big data cloud computing, and artificial intelligence as a metric to assess their level of digital technology transformation. At the same time, the full sample was used, and the interactive item *did\_dig* was introduced.

The marginal impact of STF policies on enhancing the innovation levels of publicly traded ARLEs depended on the core explanatory variable *did*, as well as the moderating effect *dig* (Table 10, columns 1 and 2). This showed that the positive impact of STF policies on the innovation level of ARLEs was grounded

Table 9. Regional heterogeneity of listed agricultural-related firms in the east, central and west regions

|                       | (1)                  | (2)                  | (3)                  |
|-----------------------|----------------------|----------------------|----------------------|
|                       | <i>lpatent</i>       | <i>lpatent</i>       | <i>lpatent</i>       |
| <i>did</i>            | 0.419**<br>(0.184)   | -0.240<br>(0.265)    | 0.802***<br>(0.264)  |
| <i>lev</i>            | -0.190<br>(0.214)    | -0.387<br>(0.309)    | 0.319<br>(0.271)     |
| <i>ROA</i>            | 0.757<br>(0.567)     | -2.852***<br>(0.986) | 1.023<br>(0.635)     |
| <i>size1</i>          | 0.313***<br>(0.042)  | 0.417***<br>(0.073)  | 0.208***<br>(0.048)  |
| <i>cost</i>           | 1.055***<br>(0.209)  | -0.594**<br>(0.293)  | 0.863***<br>(0.249)  |
| <i>top10</i>          | -0.008***<br>(0.002) | -0.002<br>(0.004)    | -0.001<br>(0.003)    |
| <i>tobinq</i>         | -0.033<br>(0.020)    | -0.120***<br>(0.034) | -0.018<br>(0.034)    |
| <i>_cons</i>          | 3.547***<br>(0.699)  | -3.549***<br>(1.038) | -2.536***<br>(0.759) |
| <i>n</i>              | 845.000              | 508.000              | 345.000              |
| <i>R</i> <sup>2</sup> | 0.220                | 0.293                | 0.346                |
| province              |                      |                      |                      |
| year                  |                      |                      |                      |

\*\* and \*\*\*significance level at 5% and 1%, respectively; standard errors in parentheses

*\_cons* – constant term; *cost* – operating cost; *did* – Difference-in-Differences estimator; *lev* – leverage; *lpatent* – natural logarithm of patent count; *ROA* – return on total assets; *size1* – enterprise size; *tobinq* – Tobin's Q; *top10* – top ten shareholders' shareholding ratio

Source: Calculated by authors

in the extent of the firms' digital transformation, with the digital indicators having a significant moderating effect. By adopting digital technologies, ARLEs expanded their digital reach, accelerated information flow, reduced information asymmetry, improved financial literacy, and enhanced STF integration – with all these factors ultimately increasing STF policy effectiveness. In short, the improvement of the innovation level of ARLEs by STF policies was based on their digital level. The more proactive an ARLE's capabilities in digital transformation, the more efficiently it can enjoy STF policy benefits, which confirms  $H_2$  and also reflects the dialectical interaction of institutions and technologies (Markard et al. 2016).

Furthermore, THIS study uses a multi period lagged variable regression model to strictly exclude reverse

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Table 10. Impact of technology finance on patent output of listed agricultural-related firms in STF demonstration zones

|                      | (1)                 | (2)                  | (3)                  | (4)                 |
|----------------------|---------------------|----------------------|----------------------|---------------------|
|                      | <i>lpatent</i>      | <i>lpatent</i>       | <i>lpatent</i>       | <i>dig</i>          |
| <i>did</i>           | 0.285**<br>(0.142)  | 0.312**<br>(0.146)   | –                    | –                   |
| <i>did_dig</i>       | 0.248***<br>(0.062) | 0.171***<br>(0.062)  | –                    | –                   |
| <i>dig</i>           | 0.009<br>(0.009)    | 0.010<br>(0.010)     | –                    | –                   |
| <i>L.did</i>         | –                   | –                    | 0.691***<br>(0.194)  | –                   |
| <i>L.did_dig</i>     | –                   | –                    | 0.210***<br>(0.077)  | –                   |
| <i>L.dig</i>         | –                   | –                    | 0.016<br>(0.011)     | 1.007***<br>(0.053) |
| <i>L.lpatent</i>     | –                   | –                    | –                    | 0.003<br>(0.040)    |
| <i>lev</i>           | –                   | –0.118<br>(0.146)    | –0.041<br>(0.182)    | –0.057<br>(0.206)   |
| <i>ROA</i>           | –                   | 0.396<br>(0.316)     | 0.136<br>(0.364)     | 0.004<br>(0.387)    |
| <i>size1</i>         | –                   | 0.276***<br>(0.030)  | 0.276***<br>(0.036)  | –0.025<br>(0.045)   |
| <i>cost</i>          | –                   | 0.568***<br>(0.139)  | 0.666***<br>(0.178)  | 0.224<br>(0.196)    |
| <i>top10</i>         | –                   | –0.005***<br>(0.002) | –0.006***<br>(0.002) | 0.006***<br>(0.002) |
| <i>tobinq</i>        | –                   | –0.048***<br>(0.015) | –0.036**<br>(0.017)  | –0.000<br>(0.024)   |
| <i>_cons</i>         | 1.583***<br>(0.085) | –2.710***<br>(0.466) | –2.876***<br>(0.583) | 0.081<br>(0.649)    |
| <i>n</i>             | 1 698.000           | 1 698.000            | 1 211.000            | 1 211.000           |
| <i>R<sup>2</sup></i> | 0.184               | 0.250                | 0.268                | 0.826               |
| province             |                     |                      |                      |                     |
| year                 |                     |                      |                      |                     |

\*\* and \*\*\*significance levels at 5% and 1%, respectively; standard errors in parentheses

*\_cons* – constant term; *cost* – operating cost; *did* – Difference-in-Differences estimator; *did\_dig* – policy and digitalisation interaction term; *L.* – lag one period behind; *lev* – leverage; *lpatent* – natural logarithm of patent count; *ROA* – return on total assets; *size1* – enterprise size; *tobinq* – Tobin's Q; *top10* – top ten shareholders' shareholding ratio

Source: Calculated by authors

causality. The empirical results show that the lagged *did* and lagged interaction term still have a significant positive impact on *lpatent*, while the lagged *lpatent* has no significant impact on the lagged *did* and lagged interaction term. This result (Table 10, columns 3 and 4) confirms the promoting effect on innovation of policy-driven (rather than enterprise-driven) digital transformation.

### Further analysis

The adoption of digital technologies enabled more transparent internal information within enterprises, enhancing the degree of understanding and supervision of internal decisions of ARLEs by external stakeholders, thereby reducing  $V_a$ . Figure 3 shows that the higher the  $V_a$  of the default return that an ARLE gives up midway, the more inclined the ARLE is to choose the strategy of giving up at the mid-point. At that point, cooperating financial institutions quickly and firmly adhered to the decision of cooperative strategy selection.

The adoption of digital technology mitigated the asymmetry of internal and external information. It enabled the STF platform to precisely identify targets, with more timely and distinct rewards and punishments, by providing more targeted bad debt provision  $M$  or government subsidy  $G_a$ . Figures 4 and 5 show that the larger the bad debt provision  $M$  accrued by the platform, the greater the government subsidy  $G_a$  to ARLEs, with more and more ARLEs tending to choose a strategy of adhering to the rules for cooperation. Regardless of the amount of bad debt reserves and government subsidies accumulated, cooperative financial institutions tend to maintain their commitment to cooperation.

The adoption of digital technologies boosts ARLEs' proficiency in gathering, storing, and analysing data in technology finance projects in a more efficient manner. It also enhances information quality, and reduces the variable costs  $i$  of technology finance projects. Figure 6 indicates that the smaller the variable costs  $i$  for ARLEs and cooperative financial institutions, the more ARLEs tend to adhere to cooperative strategies, and the more cooperative financial institutions tend to maintain their commitment to cooperation.

Meanwhile, the curve changes from an upward trend to a downward effect at a certain specific parameter value, which may indicate that a threshold effect exists in the system. This pattern is worthy of further study in the future, because it suggests the presence of an optimal point (Shi 2023).

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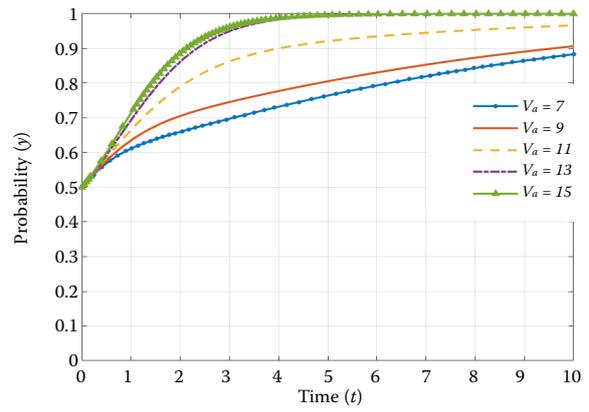
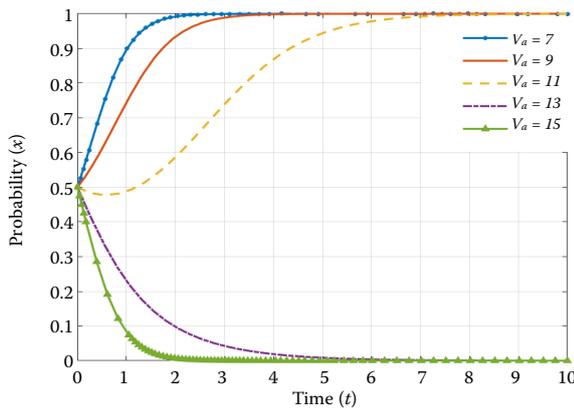


Figure 3. Simulation results of the benefits  $V_a$  of mid default strategies of agricultural listed companies and cooperative financial institutions

$V_a$  – the simulated expected net benefit for the ARLEs of choosing a midway default strategy at time  $t$

Source: Authors' composition

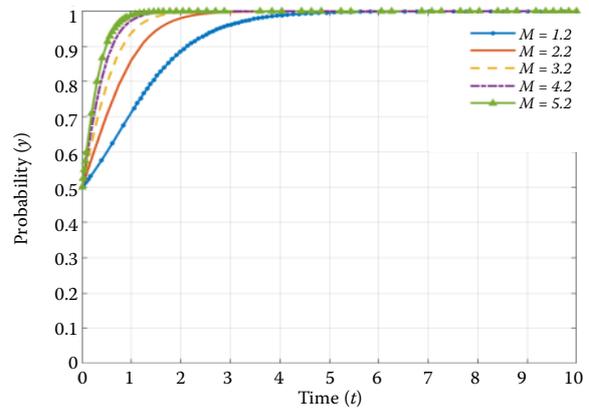
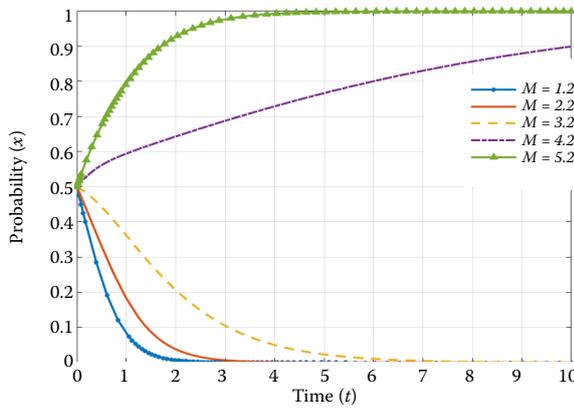


Figure 4. Simulation results of provision for bad debt provision ( $M$ )

$M$  – the bad debt provision

Source: Authors' composition

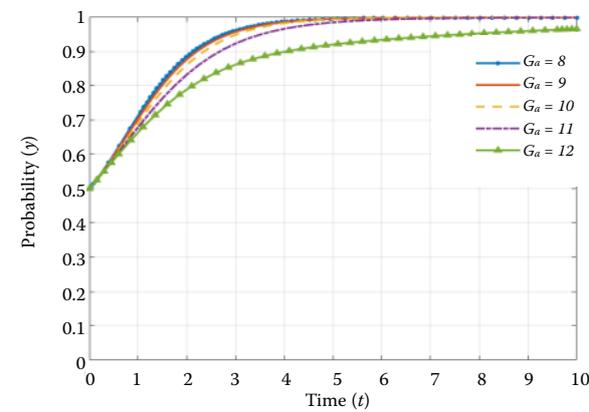
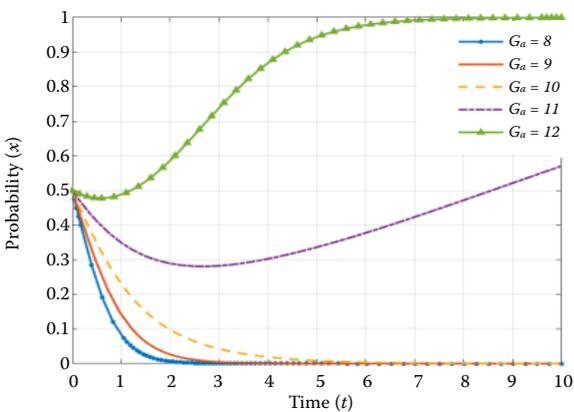


Figure 5. Simulation results of agricultural listed companies and cooperative financial institutions receiving government subsidies  $G_a$

$G_a$  – subsidy amount

Source: Authors' composition

<https://doi.org/10.17221/22/2025-AGRICECON>

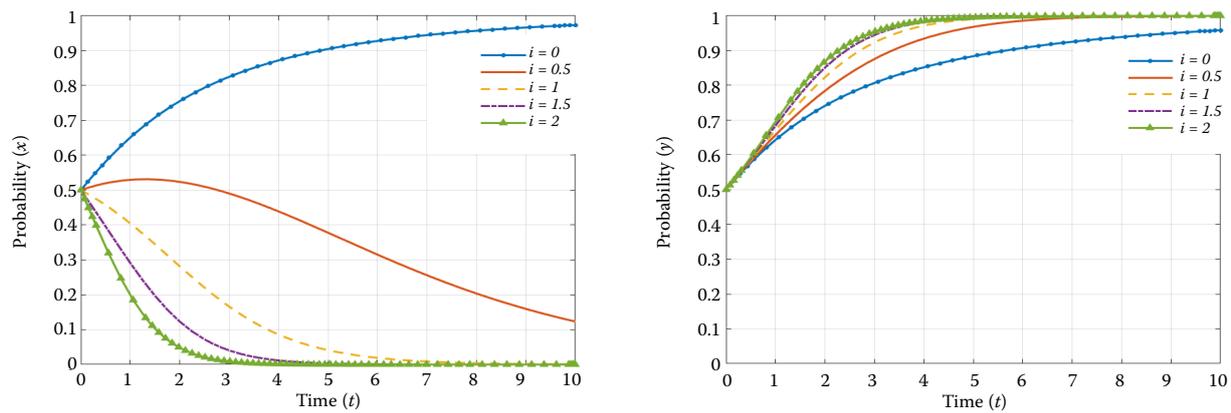


Figure 6. Simulation results of variable costs  $i$  for agricultural listed companies

$i$  – variable costs

Source: Authors' composition

## CONCLUSION

In the context of agricultural innovation in emerging economies, this study provides empirical support for Institutional Entrepreneurship Theory (Battilana et al. 2009) and the stage-based model proposed by Markard et al. (2016). Moreover, the moderating role of digital transformation underscores that digitalisation of ARLEs is a dynamic process of mutual adaptation between technological achievements and institutional expectations, offering robust evidence for the co-evolutionary development of technology and institutions (Teece 2007).

Several key findings should be emphasised. First, the integration of STF policies has greatly enhanced the innovation efforts of ARLEs. This finding remains consistent even after conducting various robustness checks. Second, the impact of STF policies in improving the innovation ability of ARLEs varies by geographical location and the size of enterprises. Third, the impact the policies is moderated by firms' level of digitalisation. Digitalisation plays more of a moderating role than an intermediary role; therefore, improving the digitisation level of ARLEs is a necessity.

Drawing on prior research (Abate et al. 2016; Nakano et al. 2020), we confirm that STF policy impacts vary significantly by region and firm size. Importantly, ARLE digitisation levels moderate policy effectiveness and help determine optimal points for STF policies' impact. This explains the most effective medium-sized credit outcomes in Bangladesh (Afrin et al. 2017) and partially effective policies in Tanzania (Nakano et al. 2020) and Côte d'Ivoire (Ouattara et al. 2020). In short, our findings support the design of differentiated agricultural

financial policies in developing countries. Policymakers should consider regional digital infrastructure when formulating STF policies and improve implementation precision via digital technology.

In light of aforementioned conclusions, this paper offers the following policy suggestions: *i*) To enhance stakeholder collaboration in the development of agricultural STF digital platforms, ARLEs should expedite data collection by leveraging open information resources while mitigating financing challenges arising from inefficient assessments, auditing cost spillovers, delayed disclosures, and sluggish returns (Chen et al. 2016). STF platforms are encouraged to establish an inclusive financial system comprising three essential components: a transaction platform, an innovation platform, and an integration platform. This system can serve as a benchmark for developing countries. Yet policy design must consider the diverse enterprise types and growth stages among ARLEs to prevent institutional overload. Specifically, enterprises with weaker digital foundations require moderate investment to avoid efficiency traps and strengthen their self-sustaining capabilities.

*ii*) To ensure the effective implementation of STF policies, policymakers should provide differentiated and targeted services aligned with ARLEs' spatial layouts and service objectives. Under identical policy conditions, support should be customised based on geographical location and enterprise size. Governments must enhance collateral management frameworks and offer significant financing incentives to direct resources toward large-scale agricultural enterprises. Simultaneously, they should lower access thresholds for smaller ARLEs by implementing staged funding allocations and essential assistance programs

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to promote comprehensive innovative growth. These measures should consider the specific conditions of developing countries. Although our framework is designed to be generalisable, institutional variations across emerging economies may influence the interpretation of parameters. Therefore, future studies should test this approach in diverse economic and regulatory contexts to confirm its broader applicability.

*iii*) Digital platforms and innovation constitute the core of agricultural STF policies, necessitating ARLEs to cultivate three critical digital capabilities: willingness to embrace digitalisation, capability to implement it effectively, and boldness to leverage its full potential. Developing a strategic digital vision is essential for enhancing process-innovation capabilities. These enterprises must acknowledge that digitalisation has fundamentally reshaped STF platforms, fostering new value creation for entrepreneurial innovation. When selecting digital technologies, firms should systematically assess network effects and dynamically adapt platform connections based on the evolving interdependencies among STF stakeholders. Complementary policy measures, such as 'specialised digital', can offer targeted financial support via dedicated funds to encourage spontaneous digital upgrading. Comparative case studies (e.g. Kenya's DrumNet and India's e-Choupal) demonstrate that sustainable development is constrained by the digital divide, underscoring the importance of shifting focus from infrastructure alone to strengthening enterprises' endogenous digital transformation capabilities. Although further empirical validation is required, these findings provide actionable insights for refining STF policy design in the context of digital transformation.

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## REFERENCES

- Abate G.T., Rashid S., Borzaga C., Getnet K. (2016): Rural finance and agricultural technology adoption in Ethiopia: does the institutional design of lending organizations matter? *World Development*, 84: 235–253.
- Afrin S., Haider M.Z., Islam M.S. (2017): Impact of financial inclusion on technical efficiency of paddy farmers in Bangladesh. *Agricultural Finance Review*, 77: 484–505.
- Ambler K., de Brauw A., Herskowitz S., Pulido C. (2023): Finance needs of the agricultural midstream. *Food Policy*, 121: 102530.
- Andriushchenko K., Ishchenko M., Sahaidak M., Tepliuk M., Domina O. (2019): Prerequisites for the creation of financial and credit infrastructure of support for agricultural enterprises in Ukraine. *Banks and Bank Systems*, 14: 63–75.
- Ardito L., Raby S., Albino V., Bertoldi B. (2021): The duality of digital and environmental orientations in the context of SMEs: Implications for innovation performance. *Journal of Business Research*, 123: 44–56.
- Ashmore F.H., Farrington J.H., Skerratt S. (2017): Community-led broadband in rural digital infrastructure development: Implications for resilience. *Journal of Rural Studies*, 54: 408–425.
- Battilana J., Leca B., Boxenbaum E. (2009): How actors change institutions: Towards a theory of institutional entrepreneurship. *The Academy of Management Annals*, 3: 65–107.
- Chaudhary S., Suri P.K. (2022): The impact of digitalisation on the agricultural wholesale prices to aid agrarian income. *Agric. Econ. – Czech*, 68: 361–370.
- Chen Q.Q., Zhang J.B., Huo Y. (2016): A study on research hot-spots and frontiers of agricultural science and technology innovation—visualization analysis based on the Citespace III. *Agric. Econ. – Czech*, 62: 429–445.
- Chladkova H., Formankova S. (2016): Strategy for SMEs in the area of primary agricultural production. *Agric. Econ. – Czech*, 62: 395–406.
- Cristobal-Fransi E., Montegut-Salla Y., Ferrer-Rosell B., Daries N. (2020): Rural cooperatives in the digital age: An analysis of the Internet presence and degree of maturity of agri-food cooperatives' e-commerce. *Journal of Rural Studies*, 74: 55–66.
- Dorward A., Kydd J., Morrison J., Poulton C. (2005): Institutions, markets and economic co-ordination: Linking development policy to theory and praxis. *Development and Change*, 36: 1–25.
- Edquist C. (1997): *Systems of Innovation: Technologies, Institutions and Organizations*. Abingdon, Routledge: 36–40.
- Fang D., Zhang X. (2021): The protective effect of digital financial inclusion on agricultural supply chain during the COVID-19 pandemic: Evidence from China. *Journal of Theoretical and Applied Electronic Commerce Research*, 16: 3202–3217.
- Feng C., Hu Q.Y., Kang Y.K., Li C.Y., Zhang Y. (2023): The effects of Tech – Fin on corporate innovation: Evidence from China. *Accounting and Finance*, 63: 3739–3762.
- Fichman R.G., Dos Santos B.L., Zheng Z. (2014): Digital innovation as a fundamental and powerful concept in the information systems curriculum. *MIS Quarterly*, 38(2): 329–354.
- Fielke S., Taylor B., Jakku E. (2020): Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. *Agricultural Systems*, 180: 102763.

<https://doi.org/10.17221/22/2025-AGRICECON>

- Gai J., Feng L.W. (2019): Research on the impact of Chinese science and technology finance on entrepreneurial efficiency. *Journal of Modern Economy*, 2: 7.
- Guo C., Wang X., Yuan G. (2022): Digital finance and the efficiency of household investment portfolios. *Emerging Markets Finance and Trade*, 58: 2895–2909.
- Hariry R.E., Reza V.B. (2023): Embracing digital technologies in the pharmaceutical industry. In: Azizi A. (ed): *Control Engineering in Mechatronics*. Singapore, Springer Singapore: 141–165.
- He Y., Deng J., Zhang X. (2024): How does the technological finance cooperation pilot policy affect prefecture-level cities' high quality economic development in China? *Finance Research Letters*, 67: 105892.
- Hong X., Chen Q., Wang N. (2024): The impact of digital inclusive finance on the agricultural factor mismatch of agriculture-related enterprises. *Finance Research Letters*, 59: 104774.
- Hsu P.H., Tian X., Xu Y. (2014): Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, 112: 116–135.
- Johnson D. (2024): Food security, the agriculture value chain, and digital transformation: The case of Jamaica's agricultural business information system (ABIS). *Technology in Society*, 77: 102523.
- Kang Y.L., Wang M., Chen K.J. (2023): Can science and technology finance promote high-quality development of enterprises? *Science Research Management*, 44: 83–96.
- Klerkx L., Rose D. (2020): Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? *Global Food Security*, 24: 100347.
- Laeven L., Levine R., Michalopoulos S. (2015): Financial innovation and endogenous growth. *Journal of Financial Intermediation*, 24: 1–24.
- Lanjouw J.O., Schankerman M. (2004): Patent quality and research productivity: Measuring innovation with multiple indicators. *The Economic Journal*, 114: 441–465.
- Lee S. (2018): Growth, profits and R&D investment. *Economic research – Ekonomiska istraživanja*, 31: 607–625.
- Li R., Rao J., Wan L. (2022): The digital economy, enterprise digital transformation, and enterprise innovation. *Managerial and Decision Economics*, 43: 2875–2886.
- Mapanje O., Karuaihe S., Machethe C., Amis M. (2023): Financing sustainable agriculture in sub-Saharan Africa: A review of the role of financial technologies. *Sustainability*, 15: 4587.
- Markard J., Wirth S., Truffer B. (2016): Institutional dynamics and technology legitimacy – A framework and a case study on biogas technology. *Research Policy*, 45: 330–344.
- Mugera A.W., Nyambane G.N. (2015): Impact of debt structure on production efficiency and financial performance of Broadacre farms in Western Australia. *The Australian Journal of Agricultural and Resource Economics*, 59: 208–224.
- Nakano Y., Magezi E.F. (2020): The impact of microcredit on agricultural technology adoption and productivity: Evidence from randomized control trial in Tanzania. *World Development*, 133: 104997.
- Nambisan S., Lyytinen K., Majchrzak A., Song M. (2017): Digital innovation management: reinventing innovation management research in a digital world. *MIS Quarterly*, 41(1): 223–238.
- Niemand T., Rigtering J.C., Kallmünzer A., Kraus S., Maal-aoui A. (2021): Digitalisation in the financial industry: A contingency approach of entrepreneurial orientation and strategic vision on digitalisation. *European Management Journal*, 39: 317–326.
- Okello B., Ndirangu J. J. A. (2010): Does the environment in which ICT-based market information services (MIS) projects operate affect their performance? Experiences from Kenya. Aaa Third Conference/aeasa Conference. African Association of Agricultural Economists (AAAE) & Agricultural Economics Association of South Africa (AEASA).
- Omotilewa O.J., Ricker – Gilbert J., Ainembabazi J.H. (2019): Subsidies for agricultural technology adoption: Evidence from a randomized experiment with improved grain storage bags in Uganda. *American Journal of Agricultural Economics*, 101: 753–772.
- Ouattara N.B., Xiong X., Traore L., Turvey C.G., Sun R., Ali A., Ballo Z. (2020): Does credit influence fertilizer intensification in rice farming? Empirical evidence from Côte D'Ivoire. *Agronomy*, 10: 1063.
- Pirola F., Boucher X., Wiesner S., Pezzotta G. (2020): Digital technologies in product-service systems: A literature review and a research agenda. *Computers in Industry*, 123: 103301.
- Porgo M., Kuwornu J.K., Zahonogo P., Jatoo J.B.D., Egyir I.S. (2018): Credit constraints and cropland allocation decisions in rural Burkina Faso. *Land Use Policy*, 70: 666–674.
- Possner A., Bruns S., Musshoff O. (2022): A Cambodian smallholder farmer's choice between microfinance institutes and informal commercial moneylenders: The role of risk attitude. *Agricultural Finance Review*, 82: 183–204.
- Purchase S., Olaru D., Denize S. (2014): Innovation network trajectories and changes in resource bundles. *Industrial Marketing Management*, 43: 448–459.
- Ruttan V.W. (1989): Institutional innovation and agricultural development. *World Development*, 17: 1375–1387.
- Sayfetdinov A.R., Sayfetdinova P.V. (2021): Basic economic principles of the digital transformation in Russian agriculture. *IOP Conference Series: Earth and Environmental Science*, 745: 012009.

<https://doi.org/10.17221/22/2025-AGRICECON>

- Schulz D., Börner J. (2023): Innovation context and technology traits explain heterogeneity across studies of agricultural technology adoption: A meta-analysis. *Journal of Agricultural Economics*, 74: 570–590.
- Shi X. (2023): How does sci-tech finance affect the structural upgrading of China's service industry? *Highlights in Business, Economics Management*, 9: 729–737.
- Tang Y., Liao H., Wu Y., Lei G. (2024): Unravelling the bi-directional impact of Chinese agricultural subsidy policy on agricultural efficiency and farmers' income through panel data analysis. *Agric. Econ. – Czech* 70: 165–177.
- Teece D.J. (2007): Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28: 1319–1350.
- WBCSD (n.d.): ITCS Farmer Empowerment Program (India). World Business Council for Sustainable Development. <https://www.wbcsd.org/resources/itcs-farmer-empowerment-program-india/>
- Wu F., Hu H., Lin H., Ren X. (2021): (Enterprise digital transformation and capital market performance: Empirical evidence from stock liquidity). *Management World*, 37: 130–144. (in Chinese)
- Zakaria M., Jun W., Khan M.F. (2019): Impact of financial development on agricultural productivity in South Asia. *Agric. Econ. – Czech*, 65: 232–239.
- Zhai H., Yang M., Chan K.C. (2022): Does digital transformation enhance a firm's performance? Evidence from China. *Technology in Society*, 68: 101841.

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