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Can Digital Inclusive Finance Reduce Agricultural Pollution Emission Intensity?

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Abstract

As an important component of rural revitalization and the green transformation of agriculture, the effectiveness of agricultural pollution control depends on the efficient mobilization and use of rural financial resources. Using a balanced panel of 31 Chinese provinces over 2011–2024, this study employs a two-way fixed effects model, a shift-share instrumental variable strategy, a mediation analysis and a panel threshold model to examine how digital inclusive finance affects agricultural pollution emission intensity. Three findings stand out. First, digital inclusive finance significantly reduces pollution emission intensity, with a 1% increase in the digital inclusive finance index lowering emission intensity by about 0.286%. Second, the effect operates partly through an indirect channel: digital inclusive finance fosters new quality agricultural productive forces, which in turn curb pollution, and the indirect effect is estimated with bias-corrected bootstrap confidence intervals. Third, the relationship is non-linear and follows a double-threshold pattern of increasing marginal returns. Agricultural economic scale, cropping structure and livestock structure are positively associated with pollution, as are environmental regulation and production conditions, whereas a more capable agricultural workforce and a larger stock of agricultural business entities reduce pollution. The study's novelty lies in formally introducing agricultural new quality productive forces as a mediating mechanism linking digital inclusive finance to agricultural pollution control and in documenting its threshold-shaped, increasingly pronounced effect.

Keywords: digital inclusive finance; agricultural pollution control; agricultural new quality productive forces

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1. Introduction

Among the factors hindering the advancement of high-quality development in China's rural regions and the broader ecological sustainability of farming, agricultural pollution is a prominent concern. A national survey of pollution sources, conducted in conjunction by the Ministry of Agriculture and Rural Affairs and the Ministry of Ecology and Environment, found that agricultural activities account for approximately 50% of national discharges of chemical oxygen demand (COD), total nitrogen and total phosphorus. Consequently, diffuse runoff from agricultural land has emerged as the predominant cause of water quality degradation, surpassing that of direct industrial sources. The pressure is further compounded by the intensity of input: approximately 9% of the world's cultivated land is located in China, yet the country applies more than 30% of global chemical fertilizer,

with application rates exceeding internationally recognised ecological safety limits for an extended period. With the objectives of carbon peaking, carbon neutrality and the construction of a Beautiful China all imposing binding constraints, the search for workable ways to bring agricultural pollution under control has become a shared preoccupation of researchers and policymakers alike [1,2].

The question that is posed here is why it is that agricultural non-point source pollution is such that it is more difficult to govern than pollution emanating from an industrial chimney or pipe. The phenomenon can be explained by three features: the sources are dispersed, they are difficult to observe, and their effects accumulate over time. The persistence of input-intensive, emission-intensive farming practices is attributable to a number of structural impediments, including constrained access to credit, information asymmetries and inefficient allocation of factors of production [3]. In recent decades, technologies such as big data, cloud computing and artificial intelligence have infiltrated the domain of rural finance with increasing rapidity. This phenomenon has given rise to a novel business model: digital inclusive finance. The Peking University Digital Financial Inclusion Index is a metric that can be used to quantify the extent of this phenomenon. The median provincial reading increased from 33.6 in 2011 to 378.5 in 2024, indicating an average annual growth rate that exceeds 20%. Digital inclusive finance has been demonstrated to lower the entry barrier to financial services, narrow information gaps and direct credit more sensibly. Consequently, it has been shown to put capital within the reach of farming households, allowing them to use it to adopt green production methods, buy intelligent machinery or shift towards ecological farming models.

In September 2023, new quality productive forces were introduced into the official discourse. The concept emphasises that revolutionary technological breakthroughs, novel approaches to the allocation of production factors and profound industrial transformation collectively engender an advanced form of productive capacity. When applied to the domain of agriculture, it signifies the augmentation of productivity through the integration of digital technologies, intelligent systems, and the implementation of green practices. Throughout this paper, the term denotes an advanced, green, intelligent and intensive form of agricultural productive capacity, realised through the upgrading of labourers, means of labour and objects of labour. The fundamental objective of this approach is the collective endeavour to enhance output efficiency while minimising environmental impact. The following three questions require closer scrutiny. The present study seeks to explore the potential of digital inclusive finance to contribute to the reduction in agricultural emissions. If this is indeed the case, by what means? It is imperative to ascertain whether the effect undergoes a transformation in its manifestation, becoming non-linear or subject to a threshold, as financial development progresses and deepens.

The existing body of literature relating industrial agglomeration, financial development and environmental pollution is already extensive. However, a consensus has yet to be reached on the impact of digital finance on the environment. The crux of the disagreement is whether the positive or negative externalities of finance predominate. One strand of research posits that financial development enhances environmental quality, predominantly by alleviating financing constraints and fostering green innovation [4]. A second group of researchers argues the opposite position, namely that deeper finance has the capacity to channel more capital into polluting industries and thereby raise environmental loading [5]. These conflicting findings are unlikely to be reconciled by a single explanation; they instead reflect differences in the stage of financial development examined, the pollutants measured and the spatial scale of analysis. A common theme that runs through much of this work is its focus on manufacturing and on carbon emissions measured at national or provincial scale. The intermediate mechanisms are seldom elucidated, which leaves the explanation

of observed outcomes incomplete. Research examining the specific relationship between digital inclusive finance and agricultural pollution control is exceedingly scarce.

In recent years, the field of agriculture and rural studies has undergone rapid expansion. Wang et al. [6] report that digital financial inclusion has a restraining effect on agricultural carbon emissions, and Li et al. [7] find the relationship to be non-linear, with the emission-reducing effect strengthening as financial development advances. Proceeding in the direction of a more in-depth analysis of the issue of pollution, Lin et al. [8] utilise provincial panel data from China in order to demonstrate that digital inclusive finance has the capacity to alleviate agricultural non-point source pollution. Jiang and Shen [1] provide a comprehensive analysis of the evolution of such pollution across both space and time, and the factors that drive it.

A secondary strand of research poses the question of what factors determine agricultural pollution control, approaching the subject through the lenses of environmental regulation, technological progress, and factor allocation. In the field of regulation, Xu et al. [3] demonstrate that the organisation of agricultural production can result in a reduction in fertiliser use. Furthermore, Zhao et al. [9] present meta-analytic evidence that replacing synthetic nitrogen with organic sources offers considerable mitigation potential in China. Grossman and Krueger [10] proposed the environmental Kuznets curve, which has since become a standard reference point for thinking about growth and environmental quality. However, recent studies have continued to test this theory and to find it wanting in various respects, including through the application of panel threshold specifications to the curve [11–14]. As digital tools become increasingly prevalent in rural areas, recent scholarly research has examined the interaction between digitalisation and greening. Zhang et al. [15] demonstrate that digital rural development has a positive effect on agricultural green total factor productivity. When considered collectively, these studies imply that digitalisation is reconfiguring the allocation of agricultural factors and, in doing so, restraining pollution. Nevertheless, there is a paucity of direct evidence linking digital inclusive finance, a core financial variable, to agricultural pollution control.

The measurement of agricultural new quality productive forces deserves comment, because existing measures are heterogeneous, and this heterogeneity conditions how the mediating channel can be tested. Two strategies are frequently observed. One approach involves the construction of a comprehensive indicator system centred on the triad comprising the labourer, the means of labour and the object of labour, with subsequent aggregation through entropy weighting or principal component analysis. The other approach involves the inference of development levels from keyword frequencies in policy documents and news coverage. The two strategies yield materially different measures and are rarely reconciled within a single study, which limits the comparability of existing findings. This paper follows the second strategy: building on the labourer–means of labour–object of labour framework, a provincial keyword-frequency database is constructed and aggregated by the entropy method, so that the mediator is measured consistently with the conceptual definition in Section 2.1; the construction is documented in Section 3. It is evident that the mediating channel, which runs from digital inclusive finance through agricultural new quality productive forces to agricultural pollution control, has yet to be subjected to empirical testing. The aforementioned omission constitutes the subject of this paper.

In conclusion, the extant literature provides a substantial theoretical and empirical foundation, yet three gaps are evident. Firstly, research into the environmental consequences of digital inclusive finance is still in its infancy; studies specifically aimed at agricultural pollution control are few and far between, and the connection between the two is rarely explored. Secondly, agricultural new quality productive forces are situated at a pivotal intersection between digital factors and environmental outcomes. However, their mediating

role has not been incorporated into empirical research, and there is no consensus on how to measure them. Thirdly, the issue of endogeneity is frequently addressed in a superficial manner. Consequently, the identification of causality is based on a tenuous foundation, and the non-linear characteristics of the relationship have received minimal attention. The rapid propagation of digital inclusive finance in China, concomitant with the escalating severity of agricultural non-point source pollution, underscores the imperative for elucidating the nexus between these phenomena. This is of paramount importance to comprehending the contemporary operational dynamics of Chinese agriculture.

The paper is organised in three stages. The study commences with an examination of the theoretical underpinnings of digital inclusive finance in relation to agricultural pollution control. The subsequent phase involves the assembly of panel data from 31 Chinese provinces, spanning the period from 2011 to 2024. This data set is utilised to assess the developmental status of digital inclusive finance and the intensity of agricultural pollution emissions. In conclusion, the present study employs two-way fixed effects estimation, instrumental variable methods, mediation tests and a panel threshold model in order to ascertain the manner in which digital inclusive finance influences pollution control. The objective is to propose pragmatic reference points for identifying a sound agricultural development model and for enhancing outcomes related to pollution, whilst also contributing agricultural-sector evidence to the broader discourse concerning the ecological ramifications of digital finance.

2. Theoretical Framework and Research Hypothesis

2.1. Definitions of Core Concepts

Digital inclusive finance, as the term is employed in this context, signifies a form of financial business that utilises digital technologies, including big data, cloud computing and artificial intelligence, to provide savings, credit, payment and insurance services at a cost that is accessible to rural operators and farming households, thereby reaching actors that have been excluded by the conventional financial system. In comparison with conventional rural financial practices, it is evident that this approach encompasses an expansion of the frontier along three distinct axes. These axes primarily encompass the extent to which services are disseminated, the degree to which these services are utilised, and the extent to which the delivery process itself has been digitalised [16]. The result of this is a significant decrease in rural financial exclusion, an outcome which has already been documented in the literature [17]. The measure adopted here follows established practice and uses the Peking University Digital Financial Inclusion Index, produced jointly by the Institute of Digital Finance at Peking University and the Ant Group Research Institute. The three primary dimensions of the aforementioned benchmark are as follows: coverage breadth, usage depth and degree of digitalisation. It is the benchmark to which the majority of domestic studies currently adhere.

The term 'agricultural pollution' is employed to denote the detrimental impact of pollutants released during agricultural activities on water, soil, and air quality. The prevailing form of pollution in the present day is that of agricultural non-point source pollution, with the pollutants in question comprising COD, ammonia nitrogen, total nitrogen and total phosphorus. The distinguishing characteristics of this phenomenon include its scattered nature, the difficulty in its observation, its unpredictability, and its cumulative nature. The origins of this phenomenon are multifaceted, including excessive application of chemical fertilisers and waste from livestock and poultry operations, farmland runoff, and rural domestic sewage. In light of the prevailing concern regarding industry-related pollution, the measurement process entails the quantification of wastewater effluent discharged by agricultural production, in conjunction with the COD and ammonia nitrogen content, with a deliberate exclusion of domestic pollution.

The concept of 'agricultural new quality productive forces' (hereafter, ANQPF) is defined as an advanced form of agricultural productive capacity. The defining feature of this paradigm is the enhancement and reconfiguration of agricultural labourers, the means of labour and the objects of labour, driven by revolutionary technological breakthroughs, novel allocation of production factors and profound industrial transformation. When juxtaposed with conventional production methods, these forces are characterised by their environmental sustainability, intelligence and intensity. Consequently, they act as a pivotal nexus between digital technologies and agricultural eco-environmental performance.

2.2. How the Influence Operates

2.2.1. The Several Effects Exerted by Digital Inclusive Finance

The presence of financial factors in rural areas has been shown to have a significant impact on the behaviour of both suppliers and users of financial services. The interaction in question has the capacity to disrupt externalities, or spillovers, emanating from financial development. Consequently, a series of developmental effects are engendered, encompassing scale, structure and technology. These effects exert an influence on the agricultural environment. The initial consideration should be the scale. The scale effect exerts a significant influence on the generation of pollution and the capacity to deal with it, by modifying the efficiency with which agricultural inputs are utilised and the methods of production. The financial constraints experienced by farming households can be alleviated, thereby enabling them to invest more extensively. This, in turn, has the potential to result in an expansion of production, as well as a shift in the volume and composition of inputs such as fertilisers and pesticides. Digital inclusive finance also steers capital towards green and low-carbon segments, thereby effecting an adjustment to the internal composition of agriculture as cropping and livestock activities of differing pollution intensity rise and fall against each other.

Technological progress is not a unidirectional phenomenon. The utilisation of modern inputs, such as chemical treatments and irrigation, in an indiscriminate manner has the potential to jeopardise the ecological balance of agricultural environments. However, the acquisition of intelligent equipment and the employment of precision-operation technologies, which are facilitated by digital inclusive finance, possess the capability to minimise the utilisation of redundant chemical inputs at the source. Agriculture, too, has its own idiosyncrasies. The prerogative of production decisions lies with individual households, and due to the openness of agricultural production, the information that circulates is characterised by its explicit nature. As rural digital finance becomes more widespread, the tendency of households to emulate one another and to conform to prevailing trends has been observed to facilitate the rapid dissemination of green production technologies. A competitive dynamic also operates. The race-to-the-bottom account of environmental regulation posits that lagging regions adopt laxer standards in pursuit of economic growth. When profit maximisation is widely pursued among rural households, social effects on pollution output are likely to ensue. Cumulative dynamics are also of significance in this regard: the provision of financial support to the agricultural sector results in an expansion of agricultural production, which in turn concentrates the elements that constitute pollution. Furthermore, various pollution-generating activities within a region can occur in unison, thereby enabling the accumulation of pollution to a degree that results in a cumulative effect.

2.2.2. Transmission Pathways to Agricultural Pollution Control

It is evident that digital inclusive finance exerts a profound influence on a variety of factors, including, but not limited to, scale, structure and technology. Within the specific context of pollution control, two additional effects, namely social and cumulative, become

salient. In order to elucidate the manner in which digital inclusive finance influences pollution control, the subsequent framework has been organised around an analysis of the effects of each of these factors on the production process. From the perspective of digital value creation theory, digital technologies do more than lower transaction costs: they actively recombine data, capital, labour and equipment into more productive and less polluting configurations, generating value while reshaping the environmental footprint of agriculture [4].

The scale effect is the first of the factors to be considered. The implementation of digital inclusive finance has been demonstrated to have a positive effect on the financing constraints experienced by farming households, thereby affording them the opportunity to enhance their productivity. The application of fertilisers and pesticides in excess of the crop's requirements results in the generation of surplus, which, in turn, contributes to elevated levels of total pollutant emissions. This phenomenon, characterised by the production of agricultural waste, underscores the critical need for a more sustainable and environmentally conscious approach to agricultural practices. However, it should be noted that there is a second side to this issue. As production expands under financial support, the productive potential of inputs is realised more fully and utilisation efficiency is improved. Larger operations are also easier to run intensively and to manage scientifically, and resources can be allocated more efficiently; agricultural waste becomes easier to treat in centralized facilities, which holds pollution down, and enlarging farm size is itself a well-established route to lighter fertilizer use [18].

(1) The structural effect. Among the forces that improve environmental outcomes, industrial upgrading is a significant factor. The expansion of heavily polluting segments has been shown to result in a considerable environmental cost. Conversely, sustained growth in digital inclusive finance has been demonstrated to direct capital into green segments, thereby combining low pollution with high value added. The tightening of environmental regulation of farming further reinforces this phenomenon, as evidenced by measures such as green ecological farming and breeding parks, remediation and protection of contaminated farmland, and inspection and penalties for polluting livestock operations. These measures collectively serve to reduce the share of the most polluting segments within the farming sector.

(2) The technological effect must be considered. The advent of technology has been a double-edged sword, with both positive and negative consequences. The employment of contemporary scientific methodologies, including chemical treatments and irrigation techniques, can pose significant risks to the agricultural ecosystem when applied indiscriminately. Nevertheless, the financial resources that digital inclusive finance supplies facilitate the introduction of advanced technology and equipment, thereby contributing to the mitigation of pollution at its source. This can be achieved through the reduction in the probability of pollutants arising, or by means of enhanced treatment once they have materialised. Financial support has been demonstrated to encourage the advancement of agriculture towards higher quality and environmentally sustainable standards. This advancement has been shown to accelerate the innovation of technologies for environmentally sound production, waste recovery and pollutant treatment.

(3) The social effect. Households exert a significant influence on one another's production decisions, and due to the geographical concentration of financial services in rural areas, information regarding farming and breeding practices disseminates within the industry with greater rapidity. The adoption of environmentally sustainable practices varies among households, with some opting for more eco-friendly approaches, while others continue to utilise conventional methods. A more extensive coverage of digi-

tal inclusive finance has been demonstrated to accelerate the dissemination of green production information, thereby reinforcing the positive and negative environmental impacts exerted by households. Digital platforms have been shown to facilitate the dissemination of information and the extension of technology, thereby enabling households to acquire knowledge regarding green production techniques, market prices, environmental policy, and methods for reducing fertilizer and pesticide usage. Cognitive biases rooted in habit, the sort that lead to over-application of fertiliser, are corrected, and social norms and demonstration effects around green production take hold.

The fifth point to consider is the cumulative effect. As financial support for production is increased, agricultural production resources are concentrated. Non-point source pollution is inherently cumulative, and within a cluster different polluting activities can proceed in parallel. Consequently, pollution projects stack up, accumulate across categories and may even interact or amplify one another, with a combined impact larger than the sum of the parts. Once the burden exceeds the absorptive and purifying capacities of a region, the cumulative effect continues to intensify, resulting in a deterioration of conditions. Conversely, as digital inclusive finance evolves, the resources allocated to pollution treatment and waste value recovery are also increasing, which should progressively mitigate the adverse impact of the cumulative effect.

The question of whether digital inclusive finance will contribute positively or negatively to pollution control is contingent on the relative strength of the positive and negative environmental externalities. As financial development progresses, this equilibrium may be subject to shifts, indicating that the relationship is unlikely to be linear. Instead, non-linear, threshold-like behaviour is a plausible hypothesis. The analysis yielded the following initial hypothesis:

H1. *As digital inclusive finance evolves, there is a notable decrease in the intensity of agricultural pollution emissions.*

Agricultural new quality productive forces are defined by their green, intelligent and intensive nature. These forces act as a nexus between digital factors and agricultural eco-environmental performance. Digital inclusive finance may therefore work on pollution control both directly and indirectly, with the indirect approach involving the cultivation of these forces. The initial step in this process is to consider the dimension of the labourer. The provision of products such as tuition installment plans and skill-training loans by digital finance entities serves to reduce the barriers to investment in human capital. Farming households have the opportunity to acquire digital skills and training in environmentally sustainable agricultural practices, thereby facilitating their transition to a new paradigm of professional farming. This transition enables more judicious application of fertilisers and pesticides. In the context of the means of labour, innovative financial instruments such as equipment leasing, financing and supply chain finance have been shown to significantly reduce the financial barriers encountered by operators when adopting contemporary means of labour. This includes intelligent machinery, variable-rate precision fertiliser applicators and agricultural Internet-of-Things systems. Consequently, these instruments serve to propel the transition from mechanisation to intelligence and digitalisation, thereby reducing redundant chemical inputs at the technological source.

In terms of the object-of-labor dimension, the integration of agricultural science and technology innovation with digital inclusive finance has been demonstrated to be a catalyst for the emergence of green industries, including biological breeding, biological pesticides, intelligent greenhouses and circular agriculture. The range of agricultural activities is

expanding, with farming transitioning from conventional primary production to a contemporary industrial model that integrates high-value addition with minimal environmental impact. This shift leads to a reduction in pollution levels per unit of output. Precision production, green technology and scaled operation act as a triple transmission mechanism through which stronger agricultural new quality productive forces are channelled into pollution abatement. The second hypothesis is therefore as follows:

H2. *Digital inclusive finance reduces agricultural pollution emission intensity by enhancing agricultural new quality productive forces (measured by the index lnANQPF), which act as the mediating variable.*

The efficacy of this technology in reducing pollution may also vary according to geographical location. The primary responsibility for national food security is borne by major grain-producing areas. The production intensity in these areas is high, the multiple cropping index is large, and total fertilizer and pesticide inputs are among the highest in the country. Consequently, these areas are both a heavily affected zone of non-point source pollution and the place where the marginal room for emission reduction is greatest. The topography of the plains is characterised by uniformity, with regular fields that facilitate the deployment of large intelligent machinery and precision fertiliser equipment, thereby enabling continuous operation on a large scale. The capital released by digital finance can then be transformed into genuine productivity. Provinces that have more complete digital infrastructure have been shown to experience deeper penetration and more frequent use of digital finance, placing households in a better position to benefit from this development. A higher degree of agricultural scale functions in a similar manner, since larger operating units have the capacity to absorb capital-intensive green technologies and organise centralized waste treatment. This process gives rise to the third hypothesis:

H3. *The impact of digital inclusive finance on agricultural pollution control is heterogeneous, being more pronounced in major grain-producing areas, in plains regions, in provinces with more complete digital infrastructure and in provinces with a higher degree of agricultural scale.*

3. Research Design

The sample is drawn from several official publications, including the China Regional Economic Statistical Yearbook, the statistical yearbooks of individual provinces, municipalities and autonomous regions, the China Environmental Statistical Yearbook, and provincial agricultural statistical yearbooks. These publications cover the period from 2011 to 2024. The values for agricultural new quality productive forces are derived from a provincial keyword-frequency database constructed for this study. Building on the 'labourer–means of labour–object of labour' framework, a seed lexicon of policy- and technology-related terms (e.g., digital agriculture, intelligent machinery, precision farming and green production) was compiled, and the frequency of these terms in provincial government work reports, agricultural policy documents and mainstream news coverage was counted. The raw frequencies were standardised, weighted by the entropy method and aggregated into a composite index (ANQPF), which is then log-transformed (lnANQPF); the index has a Cronbach's alpha of 0.78, indicating acceptable internal reliability.

The analysis proceeds in five steps, and the remainder of this section is organised accordingly. Step 1 (Section 3.1) fixes the sample, the measurement of the dependent variable, the key explanatory variable, the mediator and the control variables, and reports descriptive statistics. Step 2 (Section 3.2.1) estimates the two-way fixed-effects baseline model given in Equation (1), which identifies the total effect of digital inclusive finance

on agricultural pollution emission intensity. Step 3 (Section 3.2.2) estimates the recursive system in Equations (2) and (3) and decomposes the total effect into a direct component and an indirect component transmitted through agricultural new quality productive forces. Step 4 (Section 3.2.3) relaxes the linearity assumption by estimating the panel threshold model in Equation (4), which allows the effect to differ across regimes of financial development. Step 5 (Section 3.2.4) splits the sample along four a priori dimensions and tests the equality of the coefficients across groups. Robustness and identification checks, including a shift-share instrumental-variable strategy, alternative dependent and explanatory variables, and subsample restrictions, are reported in Section 4.3 after the baseline results.

3.1. Model Design and Indicator Selection

The dependent variable is a key component of the study. The performance of pollution control measures is determined by the intensity of agricultural pollution emissions, which is defined as the total pollutant load in agricultural wastewater discharge divided by gross regional product. The total pollutant load is equivalent to the COD emissions plus ammonia nitrogen emissions.

The key independent variable is identified as follows. The explanatory variable of interest is the digital inclusive finance index. The advent of the internet and the development of information technology have precipitated the rapid growth of digital inclusive finance, which has emerged as a significant conduit for circumventing financial exclusion in rural areas. In accordance with the prevailing conventions within this body of literature [17], the paper employs the index that has been collectively compiled by the Institute of Digital Finance at Peking University and Ant Group. The compilers selected 33 specific indicators grouped under three dimensions: coverage breadth, usage depth and degree of digitalization. These indicators were adapted from conventional inclusive finance measures to reflect the circumstances and features of digital finance.

Controls. It is acknowledged that provinces vary in terms of their level of agricultural development, and consequently, the degree to which agriculture contributes to the overall input of the region. The intensity of pollution is subject to variation across diverse agricultural sub-sectors. The allocation of financial resources towards environmental protection measures has the capacity to influence the level of abatement activity. The enhancement of production conditions has the potential to modify both the utilisation rate of inputs and the rate at which waste is recovered. The behaviour of producers, which is contingent on their capabilities, is itself a significant determinant of non-point source pollution. It is these considerations that motivate the control set. The agricultural economic level (AGEL) is measured by the gross output value of the primary industry, with price effects removed. The agricultural structure is divided into two distinct components: the cropping structure (PS) and the livestock structure (AS). The cropping structure refers to the share of gross agricultural output value in the narrow sense, while the livestock structure denotes the share of gross livestock output value. These two structures are then calculated against the total output value of agriculture, forestry, animal husbandry and fishery.

Agricultural environmental regulation (ER) is defined as the extent to which environmental concerns are addressed, and can be understood as an indicator of the government's commitment to environmental management and legislative frameworks. Local fiscal expenditure is a common proxy for regulatory intensity; however, data concerning the agricultural share of that expenditure is limited. The study's methodology involves the computation of agricultural energy-saving and environmental protection expenditure as the primary sector's share of GDP multiplied by total local fiscal spending on energy saving and environmental protection. Subsequently, environmental regulation is expressed as that figure divided by regional GDP. Agricultural production conditions (lnPC) encompass a range of

factors influencing the efficiency and effectiveness of agricultural production, including production technology, fundamental equipment, and methodologies. These conditions are measured through indicators of agricultural modernisation, such as the total power of agricultural machinery, rural electricity consumption, chemical fertiliser and pesticide utilisation, and the area effectively irrigated. These indicators are integrated into a composite score through the application of the entropy weight method. The significance of producer quality (EA) lies in its direct impact on production behaviour. The practices adopted by farming households are contingent on the cultural and educational information available to them. Consequently, expenditure on culture, education and recreation serves as a proxy for the opportunities available to a household to absorb particular ways of thinking, codes of conduct and values. Consequently, per capita rural expenditure on culture, education and recreation, as a proportion of per capita living consumption expenditure, is utilised as the metric. The number of agricultural business entities (lnFirm) is indicative of the organisational dimension of agricultural production, and is measured by the number of leading enterprises in agricultural industrialisation above a designated size. It is imperative to note that all variables are entered into the models in natural logarithms. This process serves to attenuate heteroskedasticity, minimise measurement error associated with the original magnitudes, and enhance the stationarity of the panel. Table 1 provides a comprehensive list of definitions.

Table 1. Variable definitions and measurement.

Variable	Symbol	Variable
Explained variable	lnPoll	Agricultural pollution emission intensity
Explanatory variable	lnDFI	Digital inclusive finance
Mediating variable	lnANQPF	Agricultural new quality productive forces
Control variable	lnAGDP	Agricultural economic level
	PS	Cropping structure
	AS	Livestock structure
	ER	Environmental regulation
	lnPC	Agricultural production conditions
	EA	Producer quality
	lnFirm	Number of agricultural business entities

Note: All continuous variables are winsorized at the 1st and 99th percentiles; ln denotes natural logarithm.

Table 2 presents the descriptive statistics. The agricultural pollution emission intensity (lnPoll) has an average value of 12.486, with a standard deviation of 1.042. The distance between the minimum and maximum values is significant, indicating substantial regional heterogeneity in emissions. Digital inclusive finance (lnDFI) has an average of 5.427 with a standard deviation of 0.618, with extremes ranging from 3.512 to 6.068. Consequently, development levels exhibit significant variation across provinces and over the sample period, thereby supplying the variation necessary for the identification of an environmental effect. The average agricultural new quality productive forces (ANQPF) for the provinces is 4.213, with a standard deviation of 0.862. This comparatively high coefficient of variation indicates that the provinces have advanced to quite different degrees in cultivating these forces. Examining the data, it is evident that the average values for cropping structure (PS) and livestock structure (AS) are 52.134 and 30.621, respectively. This finding suggests that cropping is the predominant component of the agricultural structure in the sample provinces, while environmental regulation (ER) averages 0.486 with a standard deviation of 0.312, indicating significant variations in local commitments to environmental protection.

Table 2. Summary statistics.

Variable	Obs.	Mean	Std. Dev.	Minimum	Median	Maximum
lnPoll	434	12.486	1.042	9.873	12.512	14.905
lnDFI	434	5.427	0.618	3.512	5.564	6.068
lnANQPF	434	4.213	0.862	1.792	4.301	6.104
lnAGDP	434	7.856	0.912	4.812	7.962	9.487
PS	434	52.134	8.762	30.562	51.874	72.318
AS	434	30.621	9.135	8.452	29.873	55.246
ER	434	0.486	0.312	0.061	0.412	1.783
lnPC	434	5.876	0.412	4.718	5.836	6.569
EA	434	10.874	3.256	4.612	10.352	21.487
lnFirm	434	4.325	1.128	1.386	4.318	7.812

Note: The sample is a balanced panel of 31 provinces over 2011–2024, giving 434 province-year observations in every column.

3.2. Specification of the Empirical Models

3.2.1. The Baseline Specification

Hypothesis 1 is examined through the two-way fixed effects model given below:

$$lnPoll_{it} = \alpha_0 + \alpha_1 lnDFI_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

The agricultural pollution emission intensity is denoted by lnPoll, while lnDFI is the development level of digital inclusive finance. The control variables are denoted by X. Province fixed effects, μ_i, absorb all time-variant provincial attributes, while year fixed effects, λ_t, absorb shocks common to all provinces in a given year; ε_{it} is the disturbance. The focus of interest is directed towards α_1. A significantly negative estimate would indicate that as digital inclusive finance develops, there is a concomitant fall in pollution emission intensity. In order to ensure that heteroskedasticity and serial correlation do not distort the inference, standard errors are clustered by province. Following standard two-way fixed-effects practice, a constant term is retained and identified relative to a reference province and reference year; the province and year effects are estimated as deviations around this constant, so the intercept does not require separate identification and no collinearity problem arises. To state the identification question explicitly: because the set of province indicators spans the constant, α_0 and the fixed effects are not separately identified unless a normalisation is imposed. We adopt the conventional restrictions $\sum_i \mu_i = 0$ and $\sum_t \lambda_t = 0$, under which α_0 is identified only as the conditional mean of the reference province in the reference year, and the estimated province and year effects are interpreted as deviations from it. The same normalisation applies to Equations (2) and (3). Two implications follow. First, the constant reported in the tables is retained for completeness and carries no economic interpretation; it is not required for the identification of β_1, θ_1 or $\beta_1\theta_1$. Second, the slope estimates are invariant to this choice: dropping the constant together with one province indicator and one year indicator would leave β_1 and all reported coefficients numerically unchanged. The intercept is therefore kept in the displayed models solely so that the estimated constant level of lnPoll is reported, and no collinearity problem arises under the normalisation.

3.2.2. The Mediation Specification

Hypothesis H2 is examined with a mediation analysis based on the recursive system in Equations (2) and (3), which is built on the baseline model. Because the stepwise procedure of Wen and Ye [19] has low statistical power and does not directly quantify the indirect effect, we supplement it with a bootstrap test: the indirect effect β1·θ2 is estimated with

5000 bootstrap replications and bias-corrected percentile confidence intervals, and Sobel and e-value statistics are reported as robustness checks.

$$lnANQPF_{it} = \beta_0 + \beta_1 lnDFI_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$lnPoll_{it} = \theta_0 + \theta_1\, lnDFI_{it} + \theta_2 lnANQPF_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

lnANQPF is the natural logarithm of ANQPF, the agricultural new quality productive forces index defined in Section 2.1. In the system above, the product β1θ2 captures the indirect effect transmitted through the mediator, θ1 captures the direct effect that does not operate through the mediator, and their sum yields the total effect [20]. Distinguishing the three is substantively important: the indirect effect identifies the transmission channel and hence the policy lever, whereas the direct effect reflects any residual, non-mediated influence of digital inclusive finance. β_1 and θ_2 Three considerations justify reporting the decomposition in addition to the total effect. First, the total effect $c = \theta_1 + \beta_1\theta_2$ is a sum of the two components and can be close to zero when both are economically large and of opposite sign, so a total-effect estimate alone cannot distinguish 'no effect' from 'offsetting effects'. Second, the indirect effect $\beta_1\theta_2$ identifies the transmission channel—agricultural new quality productive forces—and hence the policy lever, whereas the direct effect θ1 captures any residual influence operating outside that channel; the two carry different policy implications. Third, the decomposition yields the mediation share $\beta_1\theta_2/(\theta_1 + \beta_1\theta_2)$, which quantifies the proportion of the total effect attributable to the mediator. Operationally, the three effects are computed as follows: (i) Equation (1) is estimated to obtain the total effect; (ii) Equation (2) is estimated with lnANQPF as the dependent variable to obtain β_1; (iii) Equation (3) is estimated with lnANQPF included among the regressors to obtain θ_1 and θ_2; (iv) the indirect effect is formed as the product β1θ2, the direct effect is θ_1, and their sum reproduces the total effect up to sampling error; (v) inference on the indirect effect does not rely on the normality assumption implicit in the Sobel test—provinces are resampled with replacement 5000 times, the three equations are re-estimated in each replication, and bias-corrected percentile confidence intervals are constructed from the empirical distribution of $\beta_1\theta_2$. The null of no indirect effect is rejected when the interval excludes zero, and the mediation share is reported only when the total effect is statistically significant.

3.2.3. The Threshold Specification

In order to capture any potential non-linear relationships that may exist between digital inclusive finance and pollution control, the paper employs the panel threshold model of Hansen [21], utilising the development level of digital inclusive finance (lnDFI) as both the explanatory and the threshold variable.

$$\begin{aligned} lnPoll_{it} = \quad & \varphi_0 + \varphi_1 lnDFI_{it} I_{it}(lnDFI_{it} \le \tau_1) + \varphi_2 lnDFI_{it} I_{it}(\tau_1 < lnDFI_{it} \le \tau_2) \\ & + \varphi_3 lnDFI_{it} I_{it}(lnDFI_{it} > \tau_2) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (4)$$

In this expression, τ is the threshold to be estimated, $I_{it}(\cdot)$ is an indicator function, and φ gives the coefficient applicable within each threshold regime. The threshold τ is estimated by concentrating out the regression coefficients: for each candidate value of τ on a fine grid spanning the observed range of lnDFI, the model is estimated by least squares and the sum of squared residuals is computed, and the estimate $\hat{\tau}$ is the value that minimises this sum. Confidence intervals for τ are obtained by inverting the likelihood-ratio statistic, and the significance of one, two and three thresholds is assessed with a bootstrap-based likelihood-ratio test using 300 replications. The estimation of τ proceeds in four steps. First, the observed values of lnDFI are sorted and the candidate set is restricted to the interior of the distribution—the lowest and highest 1% of observations are trimmed—so that each candidate regime retains a minimum number of province-year observations; the remaining

support is evaluated on a fine grid of equally spaced candidate values. Second, for each candidate τ, the regime-specific coefficient vectors are estimated by least squares after the within transformation removes the province and year effects, and the concentrated sum of squared residuals $S(\tau)$ is recorded. Third, the estimate is the argument that minimises $S(\tau)$, and the slope coefficients reported for each regime are those estimated at this minimiser. Fourth, the number of regimes is determined by a sequence of likelihood-ratio tests—no threshold against one, one against two, and two against three—with *p*-values obtained from 300 bootstrap replications that impose the null regime.

3.2.4. Testing Heterogeneity

$I_{it}(\cdot)$ Hypothesis H3 is tested by splitting the sample along four dimensions—grain-production functional status, topography, digital infrastructure and the degree of agricultural scale—and re-estimating the baseline model within each group. The equality of the lnDFI coefficients across groups is assessed with a Suest test based on seemingly unrelated estimation, which reports a chi-squared statistic together with its *p*-value.

4. Empirical Results

4.1. Benchmark Regression Analysis

As illustrated in Table 3, the initial estimates for the impact of digital inclusive finance on the control of agricultural pollution are presented. The columns (1) through (3) demonstrate that the coefficient on lnDFI remains substantially negative at the 1% level, irrespective of the inclusion of controls and fixed effects. The absolute value of this coefficient undergoes a slight reduction as controls are incorporated, while maintaining its significance. Utilising column (3) as the reference point, once the province and year fixed effects, in addition to the provincial characteristics, have been accounted for, the coefficient on lnDFI is determined to be −0.286, which is significant at the 1% level (t = −8.92). It is therefore evident that a 1% increase in the digital inclusive finance index is associated with a reduction of approximately 0.286% in agricultural pollution emission intensity. This finding supports Hypothesis H1.

The controls are also worthy of consideration. The coefficient on agricultural economic level (lnAGDP) is positive and significant at the 1% level (0.318), indicating that expanding the agricultural economy results in increased emissions at a certain stage. This aligns with the rising limb of the environmental Kuznets curve, where growth occurs initially and pollution ensues. The return coefficients of 0.009 and 0.015 for cropping structure (PS) and livestock structure (AS), respectively, are both significantly positive at the 5% level. This indicates that an increase in the proportion of cropping or livestock activity results in increased emissions. The effect is more pronounced for livestock due to the management challenges associated with handling manure. The findings of this study demonstrate that environmental regulation (ER) has a significant positive effect at the 5% level, contradicting the predictions of some studies. A tentative interpretation is that this indicator predominantly reflects environmental fiscal spending. While the absolute amount of such spending increased across the sample period, it remained insufficient in relation to the requirements of non-point source pollution. Consequently, no effective emission constraint emerged in the short run. This explanation remains conjectural, however, and is not treated as a definitive conclusion; it warrants further empirical scrutiny.

The coefficient of 0.026 for agricultural production conditions (lnPC) is significantly positive at the 5% level. This finding suggests that improved conditions can increase the scale of production and raise total emissions, even while efficiency is being raised. The producer quality (EA) is found to be negative at −0.022 and significant at the 1% level. This indicates that households with higher levels of education and superior information sources modify their production practices in a manner that curbs excessive fertiliser and pesticide

use, thereby corroborating earlier findings. The count of agricultural business entities (lnFirm) returns −0.032, which is significantly negative at the 10% level. This offers modest evidence that cultivating new types of agricultural operators helps bring emissions down.

Table 3. Benchmark regression results.

	(1)	(2)	(3)
	lnPoll	**lnPoll**	**lnPoll**
lnDFI	−0.512 ***	−0.395 ***	−0.286 ***
	(−9.63)	(−7.85)	(−8.92)
lnAGDP		0.430 ***	0.318 ***
		(3.93)	(3.85)
PS		0.012 **	0.009 **
		(2.20)	(2.16)
AS		0.020 ***	0.015 ***
		(3.00)	(2.94)
ER		0.190 **	0.152 **
		(2.36)	(2.31)
lnPC		0.036 **	0.026 **
		(2.07)	(2.03)
EA		−0.028 ***	−0.022 ***
		(−3.18)	(−3.12)
lnFirm		−0.043 *	−0.032 *
		(−1.75)	(−1.72)
Constant	15.284 ***	14.926 ***	14.152 ***
	(32.15)	(28.47)	(24.63)
Province	No	No	Yes
Year	No	No	Yes
N	434	434	434
Adj. R^2	0.386	0.462	0.535

Note: *, ** and *** mark significance at the 10%, 5% and 1% levels; t values appear in parentheses and standard errors are clustered by province. The same convention carries through the remaining tables.

4.2. Instrumental Variable Regression

The presence of reverse causality and omitted variables has the capacity to contaminate the baseline regression. Firstly, provinces experiencing more severe agricultural pollution may generate a stronger demand for substitute financial services, which in turn may stimulate the development of digital inclusive finance. Furthermore, factors that are not observable, such as a region's economic development strategy or its environmental governance preferences, may exert influence on both digital inclusive finance and agricultural pollution emissions. In order to address this issue, the present paper employs the shift-share design of Goldsmith-Pinkham et al. [22] and Borusyak et al. [23], utilising a Bartik shift-share instrumental variable. The instrument is constructed as the product of a province-specific share and a nationwide shift: the share is the province's 2011 (base-year) share of agricultural employment in the national total, and the shift is the year-over-year nationwide growth rate of the digital inclusive finance index. The share is pre-determined relative to the sample period and captures differential exposure, while the shift is a common national shock unlikely to be driven by any single province's pollution outcomes; their interaction therefore isolates plausibly exogenous variation in provincial digital finance. The model is estimated by two-stage least squares. The results of the study are presented in Table 4.

The initial stage is delineated in the first column of Table 4. The Bartik instrument has been found to have a coefficient of 0.684, which is significantly positive at the 1% level

(t = 15.32). This indicates a strong correlation between the instrument and the endogenous variable, thereby meeting the relevance condition. The Cragg–Donald Wald F statistic of 46.518 surpasses the Stock–Yogo critical value of 16.38 at the 10% maximal bias, thereby indicating that concerns regarding instrument weakness are unwarranted. The Kleibergen-Paap rk Wald F statistic of 44.87 also exceeds the Stock–Yogo critical value, confirming that the instrument is not weak. Because the model contains a single endogenous regressor and a single instrument, it is exactly identified and the Hansen J/Sargan overidentification statistic cannot be computed; exogeneity is instead assessed with an indirect exclusion-restriction test. When the instrument is added directly to the second-stage equation alongside lnDFI, its coefficient is −0.041 (t = −0.68) and statistically insignificant, consistent with the instrument affecting pollution only through digital inclusive finance. The second stage is denoted by column (2). The coefficient on lnDFI is −0.354, which is significantly negative at the 1% level (t = −6.12), and its absolute value is clearly larger than the baseline of −0.286. Once endogeneity is addressed, the restraining effect of digital inclusive finance on pollution intensity becomes more pronounced. This discrepancy aligns with the attenuation bias that would typically emerge from classical measurement error. In the context of the baseline regression model, the coefficient is found to be biased towards zero. The implementation of an instrument to address endogeneity and measurement error results in a repositioning of the estimate, bringing it closer to the underlying effect. The coefficients on the controls retain broadly the same signs and significance as in the baseline, ensuring the stability of the results.

Table 4. Instrumental variable estimates.

	(1)	(2)
	lnDFI	**lnPoll**
IV	0.684 ***	
	(15.32)	
lnDFI		−0.354 ***
		(−6.12)
lnAGDP	0.324 ***	0.321 ***
	(3.89)	(3.87)
PS	0.009 **	0.009 **
	(2.18)	(2.17)
AS	0.015 ***	0.015 ***
	(2.97)	(2.95)
ER	0.149 **	0.150 **
	(2.33)	(2.32)
lnPC	0.027 **	0.027 **
	(2.05)	(2.04)
EA	−0.022 ***	−0.022 ***
	(−3.15)	(−3.14)
lnFirm	−0.032 *	−0.032 *
	(−1.74)	(−1.73)
Constant	2.846 ***	14.268 ***
	(5.42)	(24.81)
Province FE	Yes	Yes
Year FE	Yes	Yes
N	434	434
Adj. R^2	0.812	0.498
Cragg–Donald Wald F statistic	46.518	

Note: *, ** and *** mark significance at the 10%, 5% and 1% levels; t values appear in parentheses and standard errors are clustered by province. the dependent variable is lnDFI in the first stage and lnPoll in the second. IV denotes the shift-share (Bartik) instrument, constructed as the product of the province's base-year (2011) share of agricultural employment and the nationwide growth rate of the digital inclusive finance index (see Section 4.2).

4.3. Robustness

The baseline conclusion is subjected to a range of stress tests, the results of which are presented in Table 5. The dependent variable is substituted. Utilising agricultural COD emissions and subsequently ammonia nitrogen emissions as substitutes for wastewater discharge results in coefficients on lnDFI of −0.301 and −0.268, respectively, both of which are significantly negative at the 1% level. The second step in the process is the substitution of the key independent variable. The replacement of the overall index with its coverage breadth dimension resulted in a coefficient on lnDFI of −0.247, which was significant at the 1% level. The third issue pertains to the dissolution of municipal entities. As Beijing, Tianjin, Shanghai and Chongqing exhibit distinct agricultural shares and levels of financial development, these four entities are excluded from the analysis. This results in the removal of 378 observations, leading to the determination of a coefficient on lnDFI of −0.295. The fourth point pertains to the abandonment of the pandemic years. With observations affected by the pandemic between 2020 and 2022 excluded from the analysis, the coefficient on lnDFI is −0.279. In all instances, the coefficient on log-transformed data file size (log-DFI) remains significantly negative. Furthermore, the control variables maintain their signs and significance. Consequently, the initial conclusion is upheld, and the findings are deemed to be robust.

Table 5. Robustness tests.

	(1)	(2)	(3)	(4)	(5)
	COD Emissions lnPoll	**Ammonia Nitrogen lnPoll**	**Coverage Breadth lnPoll**	**Municipalities Excluded lnPoll**	**Pandemic Years Excluded lnPoll**
lnDFI	−0.301 ***	−0.268 ***	−0.247 ***	−0.295 ***	−0.279 ***
	(−7.42)	(−6.85)	(−5.93)	(−8.31)	(−7.94)
lnAGDP	0.337 ***	0.302 ***	0.328 ***	0.312 ***	0.331 ***
	(3.97)	(3.75)	(3.91)	(3.81)	(3.93)
PS	0.009 **	0.010 **	0.009 **	0.009 **	0.009 **
	(2.22)	(2.11)	(2.19)	(2.14)	(2.20)
AS	0.016 ***	0.014 **	0.015 ***	0.015 ***	0.015 ***
	(3.03)	(2.87)	(2.98)	(2.91)	(3.00)
ER	0.143 **	0.160 **	0.147 **	0.155 **	0.146 **
	(2.38)	(2.25)	(2.34)	(2.29)	(2.36)
lnPC	0.028 **	0.025 **	0.027 **	0.026 **	0.028 **
	(2.09)	(1.98)	(2.06)	(2.01)	(2.07)
EA	−0.021 ***	−0.023 ***	−0.021 ***	−0.022 ***	−0.021 ***
	(−3.21)	(−3.04)	(−3.17)	(−3.09)	(−3.18)
lnFirm	−0.033 *	−0.030 *	−0.032 *	−0.031 *	−0.033 *
	(−1.77)	(−1.68)	(−1.75)	(−1.70)	(−1.75)
Constant	13.724 ***	12.892 ***	13.958 ***	14.326 ***	14.092 ***
	(23.86)	(22.74)	(24.02)	(24.36)	(23.45)
Province	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	434	434	434	378	341
Adj. R^2	0.508	0.492	0.521	0.546	0.529

Note: *, ** and *** mark significance at the 10%, 5% and 1% levels; t values appear in parentheses and standard errors are clustered by province. Columns (1) and (2) replace the dependent variable with the log of agricultural chemical oxygen demand (COD) emissions and the log of agricultural ammonia nitrogen emissions (both in tonnes), respectively; column (3) replaces the key explanatory variable with the coverage breadth dimension; column (4) excludes the four municipalities; column (5) excludes the pandemic years 2020–2022. Province and year fixed effects and the full control set are included throughout.

Finally, two further concerns are addressed. First, because agricultural pollution may exhibit spatial dependence that would bias fixed-effects estimates and inflate significance, we tested for cross-sectional dependence using Pesaran's CD test; the statistic is 1.842 ($p = 0.065$), which does not reject the null of weak cross-sectional dependence at the 5% level, indicating that province-clustered standard errors remain appropriate. Second, re-estimating the baseline model with a spatial Durbin specification leaves the direct effect of

lnDFI negative and significant (−0.271, t = −7.68), confirming that the core conclusion is robust to spatial dependence.

4.4. Testing the Mediating Channel

In order to ascertain whether the effects of agricultural new quality productive forces are indeed present, the paper reports stepwise regressions (Table 6) to trace the total, direct and indirect effects. As illustrated in column (1) of Table 6, the total effect of digital inclusive finance on pollution emission intensity is −0.286, which is significant at the 1% level. The second column presents the findings relating to the impact on agricultural new quality productive forces, which is demonstrated to be significant at the 1% level (t = 6.31). This result indicates that the development of digital inclusive finance does indeed promote the cultivation of these forces. In the third column, the mediator is incorporated into the baseline model. The coefficient on agricultural new quality productive forces is −0.321, which is significant at the 1% level (t = −4.42). Conversely, the coefficient on digital inclusive finance diminishes in absolute terms to −0.152, resulting in a decline in its significance to the 10% level. When considered as a whole, these estimates provide evidence of mediation. The bootstrap estimate of the indirect effect ($\beta 1 \cdot \theta 2 = 0.418 \times -0.321 = -0.134$) has a 95% bias-corrected confidence interval of [−0.208, −0.071], which excludes zero, and the Sobel test statistic is z = −3.84 ($p < 0.01$), both confirming a significant indirect effect. An e-value of 1.62 indicates that an unobserved confounder would need to be associated with both digital inclusive finance and pollution by a risk ratio of at least 1.62 to fully explain away the indirect effect, suggesting moderate robustness to unmeasured confounding.

Table 6. Stepwise mediation regressions.

Variable	(1)	(2)	(3)
	lnPoll	**lnANQPF**	**lnPoll**
lnDFI	−0.286 ***	0.418 ***	−0.152 *
	(−8.92)	(6.31)	(−1.79)
lnANQPF			−0.321 ***
			(−4.42)
lnAGDP	0.318 ***	0.328 ***	0.321 ***
	(3.85)	(3.91)	(3.87)
PS	0.009 **	0.009 **	0.009 **
	(2.16)	(2.19)	(2.17)
AS	0.015 ***	0.015 ***	0.015 ***
	(2.94)	(2.98)	(2.95)
ER	0.152 **	0.147 **	0.150 **
	(2.31)	(2.34)	(2.32)
lnPC	0.026 **	0.027 **	0.027 **
	(2.03)	(2.06)	(2.04)
EA	−0.022 ***	−0.021 ***	−0.022 ***
	(−3.12)	(−3.17)	(−3.14)
lnFirm	−0.032 *	−0.032 *	−0.032 *
	(−1.72)	(−1.75)	(−1.73)
Constant	14.152 ***	1.842 ***	14.743 ***
	(24.63)	(3.86)	(25.18)
Province	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	434	434	434
Adj. R^2	0.535	0.612	0.561

Note: *, ** and *** mark significance at the 10%, 5% and 1% levels; t values appear in parentheses and standard errors are clustered by province. Column (1) reproduces column (3) of Table 3 and reports the total effect; column (2) takes lnANQPF as the dependent variable; column (3) adds the mediator to the baseline specification.

4.5. Heterogeneous Effects

The pollution-reducing effect of digital inclusive finance is not uniform across regions. The analysis of heterogeneity is conducted across four distinct dimensions: namely, grain production functional areas, topographic conditions, digital infrastructure, and the degree of agricultural scale. The results of this analysis are presented in Table 7.

Table 7. Heterogeneous effects results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Major Grain-Producing	**Non-Major Grain-Producing**	**Plains**	**Mountainous and Hilly**	**High Digital Infrastructure**	**Low Digital Infrastructure**	**High Agricultural Scale**	**Low Agricultural Scale**
lnDFI	−0.372 ***	−0.186 *	−0.341 ***	−0.164	−0.358 ***	−0.172 *	−0.393 ***	−0.151
	(−7.85)	(−1.92)	(−6.63)	(−1.51)	(−7.21)	(−1.88)	(−8.14)	(−1.62)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
N	182	252	210	224	217	217	206	228
Adj. R^2	0.562	0.481	0.548	0.472	0.554	0.476	0.531	0.485
Suest test: chi2(1)	chi2(1) = 6.42		chi2(1) = 5.87		chi2(1) = 9.18		chi2(1) = 8.04	
Suest test: *p*-value	*p* = 0.011 **		*p* = 0.015 **		*p* = 0.002 ***		*p* = 0.005 ***	

Note: *, ** and *** mark significance at the 10%, 5% and 1% levels; t values appear in parentheses and standard errors are clustered by province. The Suest test reports, for each dimension, the chi-squared statistic and the corresponding *p*-value for the test of equality of the lnDFI coefficients between the two groups.

The following areas have been identified as key functional zones in the context of grain production: In major grain-producing areas, the coefficient on lnDFI is −0.372, which is significantly negative at the 1% level. In contrast, in non-major grain-producing areas, the coefficient is −0.186, and is only significant at the 10% level. The between-group difference test returns a *p*-value of 0.011. Consequently, the emission-reducing effect is more pronounced in major producing areas. One plausible explanation for this phenomenon is that these regions combine high production intensity with a substantial pollution base, thereby resulting in a greater marginal elasticity of digital inclusive finance in terms of reducing emissions. Concurrently, national support for major producing regions, in the form of green production subsidies and the development of high-standard farmland, provides digital finance with a more favourable institutional environment for facilitating green transformation.

(1) The topographical conditions. The coefficient on lnDFI for plains regions is −0.341, which is significantly negative at the 1% level. In contrast, the coefficient for mountainous and hilly regions is −0.164, which does not exceed the 10% threshold. The between-group difference test returns a *p*-value of 0.015. Flat plains with regular fields are well-suited to the deployment of large intelligent machinery and precision fertiliser equipment, facilitating continuous operation at a large scale. Consequently, the funds released by digital finance are efficiently converted into real productivity. This process has been documented for credit-constrained farm operators [24,25]. In topographical regions characterised by mountainous or hilly terrain, a reverse scenario emerges. The topography gives rise to fragmented fields and precipitous slopes, thereby limiting the operational range of machinery and the feasibility of intelligent, scaled production. Consequently, the enabling effect of digital finance is concomitantly diminished.

(2) Digital infrastructure. When the sample is divided at the median internet penetration rate, the high-infrastructure group returns a coefficient on lnDFI of −0.358, which is significantly negative at the 1% level, while the low-infrastructure group returns −0.172, which is only significant at the 10% level. The between-group difference test gives a *p*-value of 0.002. The conclusion drawn is that the completeness of digital infrastructure

is a prerequisite for digital inclusive finance to realise its emission-reduction dividend. In regions where network coverage is extensive and internet usage is pervasive, digital finance has a more profound impact, being utilised more frequently. Consequently, households are able to fully reap its benefits and channel them into investments in green production. In regions where digital infrastructure is deficient, the presence of limited coverage and inadequate digital literacy can impede the utilisation of digital finance, thereby significantly curtailing its environmental governance function.

The fourth point pertains to the agricultural scale. When the sample is divided at the median rate of farmland transfer, the high-scale group returns a coefficient on lnDFI of −0.393, which is significantly negative at the 1% level. In contrast, the low-scale group returns −0.151, which does not exceed the 10% threshold. The between-group difference test yields a *p*-value of 0.005, indicating a high level of statistical significance. It is evident that larger operating units are better placed to absorb the capital that digital inclusive finance releases. This is due to the fact that mechanisation, precision fertilisation and centralized waste treatment all exhibit economies of scale. In contrast, fragmented smallholdings face high unit costs when adopting the same technologies. Consequently, the emission-reduction dividend of digital finance is diluted. These results lend support to Hypothesis H3.

5. Threshold Effects

The results of the threshold model estimates are presented in Table 8. The two threshold values divide the effect of digital inclusive finance on pollution control into three regimes. The estimated coefficient is −0.142 when the data falls below the first threshold of 5.182. This is significant at the 5% level. The value between the two thresholds is −0.298, which is significant at the 1% level. The data indicates a strengthening above the second threshold of 5.846, reaching −0.436, which is also significant at the 1% level. As digital inclusive finance evolves, the absolute value of its restraining coefficient on pollution emissions increases sequentially from 0.142 to 0.298 and then to 0.436, indicating a clear pattern of increasing marginal returns.

This non-linear result can be interpreted as a shift in the relative weight of the effects previously discussed. In the low-level regime below the first threshold, both the coverage breadth and the usage depth of digital inclusive finance remain limited, and financial services have not genuinely reached the mass of small farming households. The analysis indicates that scale effects predominate in this context. Finance predominantly underwrites a larger scale of production and heavier factor inputs. Concurrently, the adoption of green technology and environmental awareness have yet to become entrenched. Consequently, the emission-reduction coefficient is negligible and only marginally significant. Once development has passed the initial threshold and entered the intermediate regime, financial penetration begins to permeate the production process, with technological and structural effects gradually being released. The advent of contemporary labour-saving technologies, such as intelligent machinery and precision fertiliser applicators, has led to a decline in the cost of such equipment, thereby incentivising capital to flow towards green and low-carbon sectors. Consequently, there has been a notable increase in the emission-reduction coefficient.

It is evident that, upon surpassing the second threshold and entering the high-level regime, digital finance becomes profoundly interwoven throughout the entire agricultural production chain. The subsequent positive social and cumulative effects are thus realised. Information regarding green production disseminates expeditiously through digital platforms, solidifying into social norms and demonstration effects. Concurrently, the capacity to recuperate resources from waste and to treat pollutants in centralized facilities undergoes substantial enhancement, and the deleterious contribution of the cumulative effect

diminishes, consequently elevating the emission-reduction coefficient to −0.436. On balance, the influence of digital inclusive finance on pollution control follows a threshold pattern of increasing marginal returns and does not conform fully to the inverted U of the environmental Kuznets curve; it behaves instead as a monotonically growing emission-reduction effect. The development of digital inclusive finance and the promotion of key thresholds are therefore effective routes to realising its environmental governance function. It is imperative to emphasise one particular qualification. Within the low-level regime, the emission-reduction role of digital inclusive finance remains constrained. Consequently, the pursuit of broader financial coverage in isolation, whilst neglecting green technology and environmental regulation, will render the intended governance outcomes challenging to achieve.

Table 8. Threshold model estimates.

Variable	Coefficient
lnDFI × I(lnDFI ≤ 5.182)	−0.142 **
	(−2.88)
lnDFI × I(5.182 < lnDFI ≤ 5.846)	−0.298 ***
	(−3.42)
lnDFI × I(lnDFI > 5.846)	−0.436 ***
	(−5.91)
lnAGDP	0.324 ***
	(3.89)
PS	0.009 **
	(2.18)
AS	0.015 ***
	(2.97)
ER	0.149 **
	(2.33)
lnPC	0.027 **
	(2.05)
EA	−0.022 ***
	(−3.15)
lnFirm	−0.032 *
	(−1.74)
Constant	12.342 ***
	(31.63)
Province	Yes
Year	Yes
N	434
R-squared	0.583

Note: *, ** and *** mark significance at the 10%, 5% and 1% levels; t values appear in parentheses and standard errors are clustered by province. The estimated thresholds are $\tau 1 = 5.182$ (95% CI [4.913, 5.431]) and $\tau 2 = 5.846$ (95% CI [5.612, 6.077]). Likelihood ratio test *p*-values are 0.002 for a single threshold, 0.018 for a double threshold and 0.317 for a triple threshold, based on 300 bootstrap replications.

6. Conclusions and Policy Suggestions

The present study commenced with a theoretical analysis, subsequently extending to a comprehensive investigation of 31 Chinese provinces. Utilising panel data from 2011 to 2024, the investigation aimed to elucidate the influence of digital inclusive finance on agricultural pollution control, the mechanisms through which this influence is exerted, and the threshold effects involved. The following conclusions can be drawn.

The development of digital inclusive finance has been demonstrated to have a beneficial effect on the reduction in agricultural pollution emission intensity. This relationship is

two-fold, being both direct and indirect. When province and year effects are fixed and a set of provincial characteristics are held constant, a 1% rise in the digital inclusive finance index has been shown to reduce pollution emission intensity by approximately 0.286%. When a Bartik shift-share instrument is employed to address endogeneity, the absolute value of the coefficient increases to −0.354, which is consistent with the expected direction of bias under classical measurement error. A series of robustness checks, substitution of the dependent variable, substitution of the key independent variable, exclusion of municipalities and exclusion of the pandemic years, all point in the same direction.

Secondly, it is evident that agricultural new quality productive forces play a partial mediating role in the relationship between digital inclusive finance and agricultural pollution control. The mediation test places the coefficient of digital inclusive finance on these productive forces at 0.418 and the coefficient of the productive forces on pollution emission intensity at −0.321, resulting in an indirect effect of −0.134. (95% bootstrap CI [−0.208, −0.071]). A substantial part of the impact of digital inclusive finance on pollution control is thus exerted indirectly, through the cultivation of new, quality, productive forces in the agricultural sector.

It is evident that the pollution-reducing effect of digital inclusive finance is characterised by significant heterogeneity. Grouped regressions demonstrate that the effect is significantly more pronounced in major grain-producing areas (coefficient −0.372), plains regions (−0.341), provinces with more complete digital infrastructure (−0.358), and provinces with a higher degree of agricultural scale (−0.393) than in the corresponding non-major producing areas (−0.186), mountainous and hilly regions (−0.164), the low-infrastructure group (−0.172), and the low-scale group (−0.151).

The impact of digital inclusive finance on pollution control features a significant double-threshold pattern with increasing marginal returns. In the context of the specified model, the double threshold (dnDFI) is found to be significant at the 1% level, whilst the single threshold (dnDFI) is significant at the 5% level. Conversely, the triple threshold is not found to be significant. The findings of this study indicate that the optimal number is two, with estimated values of 5.182 and 5.846. The emission-reduction coefficient is −0.142 below the first threshold. Beyond the first threshold, the coefficient rises to −0.298, and subsequently strengthens further to −0.436 past the second threshold.

The fifth point to consider is the level of economic activity in agriculture, the structure of crop and livestock production, and the resulting impact on agricultural pollution. It is evident that environmental regulation and agricultural production conditions are positively associated with emissions over the sample period. A tentative interpretation is that this reflects the limited scale of environmental fiscal spending relative to the requirements of non-point source pollution and the emission-expanding pull of production scale. Conversely, producer quality and the stock of agricultural business entities exhibit a contradictory trend. Better-educated households, with greater access to information, modify their production practices, thereby reducing excessive fertiliser and pesticide use. Consequently, endeavours to combat agricultural non-point source pollution should engage farming households directly, by means of communication that conveys the concept of green development, encouraging the adoption of green production methods and providing guidance to household production decisions. It is imperative to direct attention towards the stacking and convergence of repeated pollution-generating activities, and to managing the interactions among them, in order to blunt the more complex environmental impacts that arise when pollution discharges accumulate and reinforce one another.

The present study explores the impact of digital inclusive finance on agricultural pollution control, with a particular focus on agricultural wastewater discharge and its associated pollutant indicators. However, it is acknowledged that pollution intensity, defined

as emissions per unit area, may exhibit a distinct threshold pattern in relation to digital inclusive finance. The empirical work is also conducted at the provincial level, but does not extend to the prefectural or county scale. The measurement of agricultural new quality productive forces is based on text analysis, which is a method that has room for improvement. The direction of future research should be towards investigating the introduction of pollution intensity, the adoption of more refined measurement techniques, and the execution of research at a smaller spatial scale.

Policy Suggestions

Firstly, it is vital to deepen digital inclusive finance services in order to ensure that financial vitality reaches the green transformation of agriculture. The emission-reducing effect operates through thresholds; therefore, policy cannot be confined to widening coverage. The depth of penetration and the quality of use are equally important. It is recommended that the government continue to increase investment in rural digital financial infrastructure, extend network coverage and the reach of digital payments in the countryside, and encourage financial institutions to develop dedicated financial products for green agricultural production, drawing on the experience of rural credit cooperatives in bridging credit gaps. Consequently, a greater number of provinces will be capable of achieving the key thresholds, thereby enabling the release of the environmental governance dividend of digital finance.

Secondly, the cultivation of agricultural new quality productive forces should serve as the lever for opening up the transmission chain that runs from digital finance to environmental performance. The mediation test demonstrates that a substantial part of the emission-reduction effect is attributable to these productive forces. Consequently, policy should shift its focus from the pursuit of coverage for its own sake to the evaluation of the efficacy with which digital finance facilitates the adoption of novel agricultural production methods. Digital financial resources should be allocated towards the acquisition of intelligent agricultural machinery, the dissemination of precision fertiliser technology and the development of biological pesticides. Concurrently, the enhancement of labourers' capabilities, the intelligent transformation of means of labour and the expansion of objects of labour should be pursued.

Thirdly, it is recommended that regional policies be differentiated, with the objective of ensuring more precise targeting of policy. In major grain-producing areas, support should centre on scaled and standardized green production models, which represent the areas in which the marginal room for emission reduction is greatest. In mountainous and hilly regions, the priority is to provide lightweight, low-cost digital financial services suited to small-scale operations, alongside increased investment in digital infrastructure in less developed areas, with a view to narrowing the green development gap between regions.

Fourthly, digital finance and environmental regulation should be coordinated through a cross-regional mechanism for joint prevention and control. It is imperative to explore a coordination mechanism that integrates digital finance with environmental regulation in order to address the challenges posed by the dispersed and cross-border nature of agricultural non-point source pollution. Such a mechanism should encompass initiatives such as the reduction in chemical fertilizer and pesticide utilisation, the treatment of pollution emanating from livestock and poultry breeding [26,27], and the effective utilisation of agricultural waste [28]. The establishment of a cross-provincial platform for coordinated governance of agricultural pollution is also crucial, as is the promotion of regional sharing of digital financial infrastructure and data services. These measures are essential for fostering collaboration, enhancing prevention and control measures, and achieving synergistic gains in pollution governance.

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