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Is County-Level Urban–Rural Integration Associated with Farmers' Green Production Capabilities? Evidence from 506 Vegetable Growers in Shandong and Zhejiang, China

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Abstract

This study examined the association between county-level urban–rural integration and farmers' green production capabilities, conceptualizing the county context as a local opportunity structure. It also examined whether this association differed by farm scale. Data were collected from 506 farmers in Shandong and Zhejiang between late 2024 and early 2025; 282 were primarily engaged in vegetable production, while 224 cultivated vegetables alongside other crops. A county-level urban–rural integration index (CURI) was developed covering four dimensions: economic, social, spatial, and ecological and agricultural production integration. The hypotheses were evaluated using ordered logit and city random-intercept models. The baseline CURI was positively associated with self-rated green production capabilities. A one-sample-standard-deviation increase in CURI corresponded to a 6.50 percentage point higher average predicted probability of attaining high green production capability, and the association was stronger among small-scale farmers. The analysis also showed a stable negative association between CURI and pesticide expenditure, while green production capability was positively associated with direct sales to urban end markets. Fertilizer expenditure and order- or contract-based sales showed no stable relationship. Overall, county-level urban–rural integration was a contextual correlate of green production capacity. The findings may inform the design and evaluation of future efforts to improve access to green-production services and market linkages, particularly for small-scale farmers.

Keywords: urban–rural integration; green production capability; local opportunity structure; small-scale operation; ordinal response model

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1. Introduction

Agricultural green transformation requires environmental objectives to be translated into production choices that farmers can understand, finance, and sustain. Research on sustainability transitions emphasizes that environmental improvement is a process of intuitional, organizational and behavioral change rather than a synonym for technological upgrading or the adoption of a single innovation [1,2]. At the farm level, green production capability therefore includes the ability to identify production risks, evaluate technical information, select appropriate inputs, and incorporate those choices into routine management [3,4]. These capabilities may support, but do not automatically guarantee, observable

changes in input use or technology adoption. The distinction is important because farmers may possess a technology without having the information, liquidity, risk-bearing capacity, or market conditions needed to use it consistently [5,6]. In vegetable production, where pest pressure is frequent and quality requirements are increasingly specific, the conversion of capability into practice is particularly dependent on the surrounding production and market environment [7]. Evidence on digital extension, organizational support, and information channels likewise indicates that sustainability transitions depend on complementary services and incentives, not on a single technology [8,9]. Studies of sustainable agricultural practices further emphasize the roles of socialized services, institutional incentives, and coordinated production arrangements [7,10,11].

Micro-level studies show that farmers' production choices are shaped by the interaction of individual endowments and external conditions. Information constraints, perceived risk, credit access, farm size, input prices, and expected returns influence whether an innovation is tested and retained [1,3,12,13]. Training and information intervention can improve knowledge, but their effects depend on practical content, repeated exposure, recipient selection, and the structure of social network [14,15]. Cooperative services and digital extension can reduce the cost of obtaining technical advice and production inputs [16–18]. E-commerce participation can also change access to markets and information, although the resulting incentives depend on the specific market arrangement [19,20]. This literature has generated important evidence on particular determinants of green practices, yet it generally treats local development conditions as background variables rather than as a multidimensional opportunity structure. It also cautions against interpreting low adoption as evidence of deficient environmental attitudes alone.

China's county-level urban–rural integration offers a comprehensive lens for analyzing these external conditions. This integration does not merely reflect urbanization, nor can it be reduced to government coordination or the mechanical convergence of urban and rural indicators. Instead, it signifies the continuous adjustment of two-way factor flows, equitable allocation of public resources, the provision of basic public services, improvements in living conditions, and productive interactions between urban and rural areas [17]. China's transition from "rural China" to "urban–rural China" is further reflected in farmer differentiation, the two-way allocation of capital and population, the multifunctionality of agriculture, and the restructuring of links between urban consumer demand and rural industries [3,21]. Accordingly, urban–rural integration is now assessed not only through economic gaps but also through broader factors concerning society, space, public services, and ecology, and composite indices are widely used to identify regional differences [22,23].

County-level urban–rural integration in China provides a relevant setting for examining this broader opportunity structure. It refers to the coordinated movement of labor, capital, technology, and information, together with more equal access to public services and improved living and spatial conditions [17,21,22]. It also includes stronger economic connections between urban demand and rural production [23]. This policy and development process has wider analytical relevance because it illustrates how place-based institutions and infrastructure can shape sustainability transitions among dispersed producers in a middle-income economy [24,25]. The county is a particularly useful unit of analysis: it is large enough to organize public services, markets, and agricultural infrastructure, but close enough to connect these conditions to villages and farm households [24]. Urban–rural integration is consequently assessed through economic, social, spatial, ecological, and agricultural dimensions rather than through urbanization alone [9,26].

Two gaps follow from these strands of research. First, studies measuring urban–rural integration at national, provincial, or prefecture scales have rarely linked composite regional conditions to farmer-level capabilities and production responses [23]. A regional

index can describe the opportunity environment, but it does not by itself establish whether farmers can access or use the resources represented by that index [26]. Second, micro-level studies usually examine training, markets, cooperatives, credit, or individual characteristics separately and therefore provide limited evidence on how these factors operate within a common county-level environment [16]. The missing link is an empirically testable account of whether county-level urban–rural integration functions as a local opportunity structure for green production, and whether its value differs across farm scales.

Against this background, the study addresses two research questions: (RQ1) Is county-level urban–rural integration associated with farmers' green production capability after accounting for individual, farm, and provincial differences? (RQ2) Does the strength of this association differ between small-scale and larger-scale operations? We examine these questions with an analytical distinction between self-rated capability, input-based correspondence, and market or service linkages. The empirical design identifies conditional associations rather than a definitive causal effect; this distinction guides the interpretation of the estimates and the scope of the conclusions.

This study makes three contributions. First, it connects a multidimensional county-level measure of urban–rural integration with a farmer-level measure of green production capability while keeping capability, input proxies, and market outcomes conceptually distinct. Second, it tests whether the local opportunity structure has a different marginal association for small-scale operations, rather than assuming that the average association is homogeneous. Third, it examines production and service linkages that help interpret the main association without claiming that they constitute a complete model of the green transition. The remainder of the article is organized as follows: Section 2 develops the theoretical framework, the literature-based research gap, and hypotheses; Section 3 describes the data, measurement, and econometric strategy; Section 4 presents the results; Section 5 discusses their implications and limitations; and Section 6 concludes the paper.

2. Theoretical Framework

2.1. Green Transition, Technology Adoption, and Green Production Capability

At the farm level, green transition may be reflected in changes in production practices and their environmental implications, but it should not be equated with the adoption of a discrete technology [2,27]. Technology adoption denotes the observable use of a particular technique, input, or service. In this study, green production capability refers to a farmer's capacity to identify production risks, understand technical requirements, assess feasible alternatives, and implement appropriate practices under local constraints.

Knowledge and stated capability do not automatically translate into repeated use, because information, risk, credit, scale, and market conditions shape farm decisions [1,2,28]. Digital extension and information channels can improve the information environment around adoption [4,5,28]. In this study, the self-rated indicator captures a pest-management-related dimension of green production capability; it does not measure adoption of a specified technology, physical input use, or environmental performance.

2.2. Sustainability Transitions and Agricultural Innovation Systems

A sustainability transition is a system-level process in which technologies co-evolve with institutions, markets, infrastructure, and social practices [29–31]. This framing distinguishes system transformation from isolated technological adoption.

In agriculture, environmentally improved production commonly involves combinations of practices and the redesign of production systems rather than the uptake of a single technology [32]. Agricultural innovation systems further emphasize the coordination of knowledge, services, policies, and market arrangements around public goals [33]. Accord-

ingly, this study does not treat CURI, technology adoption, or self-rated capability as a direct measure of a completed sustainability transition; it examines a farm-level condition that may be relevant to such change.

2.3. County-Level Urban–Rural Integration as a Local Opportunity Structure

Urban–rural integration is operationalized in the Chinese literature through multidimensional economic, public-service, spatial, and production-related conditions rather than through urbanization alone [9,22,23]. This perspective makes it possible to examine the county as a local context in which urban and rural resources, services, and markets are connected.

Viewed as a local opportunity structure, these conditions may be associated with farmers' access to information, services, finance, infrastructure, and market coordination. Digital extension and network-based information targeting may improve farmers' access to production information [4,34]. Training can improve fertilizer-use knowledge [14]. Market access, cooperative services, and value-chain arrangements may shape incentives, quality requirements, and the feasibility of applying knowledge in practice [8,24,35,36].

The index is a composite representation of shared county conditions; it neither directly measures these channels nor identifies them as mediators. Its relationship with capability is therefore interpreted as a conditional cross-sectional association rather than evidence of a causal mechanism.

2.4. Farm-Scale Heterogeneity as Differences in Constraint Structures

Farm scale can be understood as a difference in constraint structures rather than as a simple proxy for performance. Smaller operations may face relatively tighter liquidity, information-search, fixed-cost, and market-entry constraints [1,37]. Access to socialized services and cooperative provision is also relevant to sustainable-practice and green-control adoption among smallholders [10,35].

These observations do not imply that small-scale operations necessarily benefit more from every county condition. Individual heterogeneity in green-technology adoption may also depend on behavioral factors, including time preferences [38]. Together, these considerations provide a reason to test whether the association between CURI and self-rated capability differs by scale within this sample.

2.5. Research Gap and Association-Based Hypotheses

Few studies have jointly connected a multidimensional county-level context with a farmer-level capability relevant to environmentally improved production. Micro-level studies typically examine adoption constraints and organizational support as separate factors [2,3]. Digital extension and training are likewise commonly examined as discrete interventions [4,14]. Urban–rural integration studies, by contrast, mainly measure regional conditions at aggregate scales [9,22,34]. This study links CURI to self-rated green production capability and treats input expenditure, market linkages, organizational support, and training as related but distinct empirical conditions.

RQ1 concerns the average conditional association between the local opportunity structure and farmer capability. The expectation is that counties with more favorable combinations of services, infrastructure, and market conditions may also be characterized by lower practical constraints on green production. This does not imply that the index measures every component of a green transition or that the relationship is causal. Accordingly, H1 is stated as follows:

H1. *County-level urban–rural integration is positively associated with farmers' green production capabilities, conditional on individual characteristics, farm characteristics, and provincial differences.*

RQ2 concerns distributional heterogeneity by farm scale. The relevant comparison is between small-scale and larger-scale operations within the analytical sample; it does not support an unrestricted claim about other populations. Accordingly, H2 is stated as follows:

H2. *The positive association between county-level urban–rural integration and green production capability is stronger for small-scale operations than for larger-scale operations within the sample.*

Urban end-market sales, order- and contract-based sales, organizational support, and training are analyzed as complementary empirical conditions rather than as observed mediators or additional causal pathways. Market and contractual arrangements may embody different forms of consumer demand, quality requirements, risk sharing, and enforcement [8,25,39]. Organizational support and training may provide information, inputs, technical guidance, supervision, or coordination [3,14,35]. The extended analyses therefore assess correspondence and conditional heterogeneity, not a complete causal mechanism through which the county index operates.

3. Materials and Methods

3.1. Data Source, Survey Areas, and Analytical Sample

Shandong and Zhejiang were purposively selected because of their policy relevance to China's urban–rural integration and their importance in vegetable production. Zhejiang's Green Rural Revival Program and Shandong's cluster-based rural revitalization practices represent influential approaches to improving rural infrastructure, public services, and industrial development. Both provinces are also major vegetable-producing regions, with Shouguang in Shandong serving as a prominent production and distribution center.

The survey was conducted between December 2024 and February 2025 across 41 county-level areas in 13 prefecture-level cities, with priority given to localities characterized by concentrated or specialized vegetable production. Respondents were crop operators, including individual farmers and family farms, who had continuously cultivated at least one vegetable crop during the preceding three years. Students from Shandong Women's University and Zhejiang A&F University recruited respondents through household visits, after which the questionnaires were completed online. A total of 506 valid responses were collected (278 from Shandong and 228 from Zhejiang). The final sample comprised 282 farmers primarily engaged in vegetable production and 224 diversified farmers who cultivated vegetables alongside other crops, including tea. The research area is shown in Figure 1.

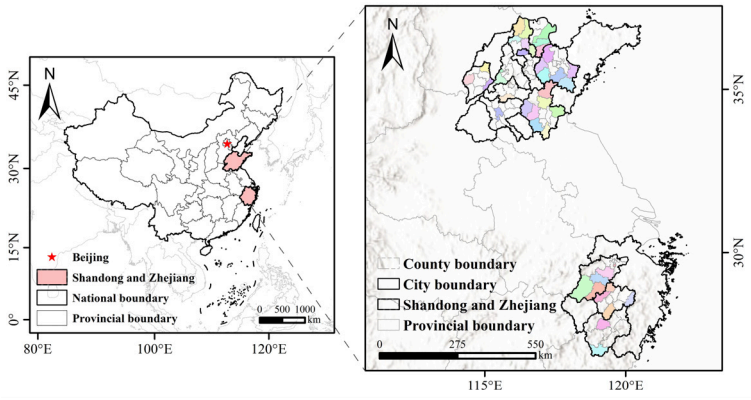


Figure 1. Study area.

Questionnaire administration and measurement. The questionnaire recorded respondent and farm characteristics, self-rated green production capability, pesticide and fertilizer expenditure categories, market-sales shares, training intensity, and enterprise or platform support. The capability item and supporting outcome measures follow the conceptual distinction between capability, technology adoption, input use, and environmental outcomes established in the theoretical framework [1,2]. The relevance of organizational and digital services to this distinction is documented in the literature [3,4,40]. The questionnaire was designed with prespecified item wording, response options, and coding rules. No pilot test was conducted before formal administration. It was administered online and began with an informed-consent statement. Respondents who selected "do not agree" were automatically exited from the survey, whereas only those who selected "agree" were permitted to proceed to the subsequent items. Ethical approval for the study protocol and questionnaire was granted by the Scientific Ethics Committee of Shandong Women's University (Approval No. 2026-LLSC-31).

Data processing and statistical analyses were performed using Python (version 3.5).

3.2. Construction of the County-Level Urban–Rural Integration Index

The county-level urban–rural integration index (CURI) was constructed to characterize the comprehensive opportunity structure of the survey areas. The index used 2024 data for 228 county-level units (139 county-level units in Shandong and 89 in Zhejiang). Data were collected from the 2025 Shandong Statistical Yearbook, 2025 Zhejiang Statistical Yearbook, county and city volumes of the China County Statistical Yearbook, county statistical materials, and the project's existing county-level database. Direct 2024 county-level measures were prioritized. For 84 county-level units in Zhejiang, the teacher indicator was estimated from county student enrollment and the province-wide student–teacher burden ratio. Data on hospital beds and value-added of the primary sector were supplemented with corresponding prefecture-level measures for 47 and 50 units, respectively, and one grain output indicator used the nearest available county-level observations from 2022.

The baseline CURI comprised 11 indicators across four dimensions: economic integration, social integration, spatial integration, and ecological and agricultural production integration. Economic integration encompassed GDP per capita, per capita disposable income among rural residents, the urban–rural income ratio, per capita deposit balance, and per capita loan balance. Social integration included the number of primary and secondary school teachers per 10,000 residents, hospital beds per 10,000 residents, and elder-care or civil-affairs service beds per 10,000 residents. Spatial integration was measured using the population density. Ecological and agricultural production integration covered the per capita value added of the primary sector and per capita grain output. The urban–rural income ratio was a negative indicator, whereas all other indicators were positive.

Indicator rationale. The baseline indicators operationalize four components of the county opportunity structure. Economic integration is represented by GDP per capita and rural disposable income, which capture the local resource and expected-return environment; the urban–rural income ratio captures distributional disparity; and deposits and loans per capita capture the availability of savings and credit channels. Social integration is represented by schoolteachers, hospital beds, and elder-care or civil-affairs beds per 10,000 residents, which capture the local capacity to provide education, health, and care services that support information access, labor availability, and basic security. Population density is used as a parsimonious spatial-integration proxy for settlement concentration, service accessibility, and contact with markets; it is not interpreted as a direct measure of environmental quality. Finally, per capita primary-sector value added and grain output capture the scale and linkage of local agricultural production. They describe the agricul-

tural production context and rural–urban production connection, not pesticide reduction, fertilizer efficiency, or environmental outcomes. The interpretation of these indicators is consistent with multidimensional measures of urban–rural integration that emphasize economic, public-service, and spatial conditions [9,34,41]. It is also consistent with evidence that sustainable practices are shaped by service access and production context [10,11], while institutional incentives can affect green technology adoption [42].

Further, CURI was constructed in the following manner. First, the indicators for the 228 county-level units were directionally aligned and normalized using min–max scaling. A positive indicator was calculated as follows.

$$z_{ij} = \frac{x_{ij} - min\left(x_j\right)}{max\left(x_j\right) - min\left(x_j\right)}$$

Meanwhile, a negative indicator was calculated as follows.

$$z_{ij} = \frac{max\left(x_j\right) - x_{ij}}{max\left(x_j\right) - min\left(x_j\right)}$$

where x_{ij} denoted the raw value of indicator j for county i, and z_{ij} denoted the normalized value on a scale of 0–1. The extrema were calculated from completed indicator data for the 228 evaluation units after the hierarchical supplementation procedure. No further imputation was performed at the normalization stage. The source year and spatial level of each supplemented observation were recorded.

The household survey covered 41 county-level areas. The baseline 11-indicator CURI therefore comprised 451 county-indicator observations for the survey areas. Of these, 439 observations (97.34%) were available as county-level data for 2024, and 12 observations (2.66%), distributed across six survey counties, were supplied using either the corresponding county-level value for 2023 or the corresponding prefecture-level statistic for 2024, following the sequence described above. The expanded 20-indicator CURI comprised 820 county-indicator observations for the same survey areas; 735 observations (89.63%) were available as county-level data for 2024, and 85 observations (10.37%), distributed across 21 survey counties, were supplied through the same procedure. No missing indicator value remained for the 41 survey areas after supplementation.

Second, within each dimension, the indicator weights were determined using the entropy method. Let $p_{ij} = z_{ij}/\Sigma_i z_{ij}$, with $p_{ij} ln\left(p_{ij}\right)$ defined as 0 when $p_{ij} = 0$. The entropy value, divergence coefficient, and within-dimension weight of each indicator were calculated as follows.

$$e_j = -\frac{1}{ln\ n}\Sigma_i\ p_{ij}\ ln(p_{ij}),\ d_j\ = 1\ -\ e_j,\quad w_j\ =\ \frac{d_j}{\Sigma_{j\in k}\ d_j}$$

Indicators with lower entropy and greater inter-county variation received larger within-dimension weights. The score of county i on dimension k was $D_{ik} = \Sigma_j \in {}_k w_j z_{ij}$.

Third, the four dimensions were aggregated using equal weights. To prevent the economic dimension from mechanically receiving a larger weight merely because it contains more indicators, we assigned each dimension a weight of 0.25.

$$CURI_i = \frac{1}{4}\Sigma_{k=1}^{4} D_{ik}$$

Therefore, the final effective weight of indicator j in the composite index was 0.25 w_j. Table 1 reports the estimated entropy weights and final effective weights. The final weights of the 11 indicators were summed to one. Population density was the only baseline indicator in the spatial integration dimension and therefore had a final effective weight of 0.25. The expanded 20-indicator CURI was constructed as an alternative measurement specification.

Table 1. Baseline urban–rural integration index: indicator system and final weights.

Dimension	Indicator	Direction	Entropy Weight	Dim. Weight	Final Weight
Economic integration	GDP per capita	+	0.2956	0.25	0.0739
	Per capita disposable income of rural residents	+	0.1979	0.25	0.0495
	Urban–rural income ratio	−	0.0096	0.25	0.0024
	Per capita deposit balance	+	0.2514	0.25	0.0628
	Per capita loan balance	+	0.2455	0.25	0.0614
Social integration	Primary and secondary school teachers per 10,000 residents	+	0.183	0.25	0.0457
	Hospital beds per 10,000 residents	+	0.2856	0.25	0.0714
	Elder-care or civil-affairs service beds per 10,000 residents	+	0.5314	0.25	0.1329
Spatial integration	Population density	+	1	0.25	0.25
Ecological and agricultural production integration	Per capita value added of the primary sector	+	0.3506	0.25	0.0877
	Per capita grain output	+	0.6494	0.25	0.1623

Note: Within-dimension entropy weights sum to 1 within each dimension. The final effective weight equals the within-dimension entropy weight multiplied by 0.25, and the 11 final weights sum to 1. Values are calculated from 228 county-level evaluation units and reported to four decimal places.

CURI operationalizes the county-level local opportunity structure across economic, social, spatial, and ecological and agricultural production dimensions. It does not measure every institutional, cultural, or ecological aspect of urban–rural integration. The baseline specification contains 11 indicators, and the expanded 20-indicator specification was used to assess sensitivity to indicator coverage.

Finally, the CURI scores for the 41 county-level survey areas were matched to the questionnaires using province, prefecture-level city, and county-level location. All 506 questionnaires were matched to their corresponding county-level CURI scores, and no questionnaire was excluded because of missing CURI information. To facilitate coefficient comparisons, the raw CURI was standardized within the 506 questionnaires as follows.

$$CURI_i^{std} = \frac{CURI_i - mean(CURI_s)}{sd(CURI_s)}$$

where $CURI_s$ denoted the distribution of the local CURI values used by the 506 questionnaires. Therefore, in the regression analysis, the CURI coefficient represented the change in the latent ordinal response associated with a one-sample standard deviation increase in the local index. To assess the sensitivity of the indicator system, we used an expanded 20-indicator CURI as an alternate measure of county-level urban–rural integration.

3.3. Variable Selection

3.3.1. Dependent Variables

Research on green production generally distinguishes between knowledge, technology adoption, inputs, and environmental outcomes. These represent different stages of green technology application and cannot be substituted for each other [1,2]. Green production first requires producers to identify pests, understand technical standards, and translate relevant knowledge into field practices. Existing research has also shown that green cognition, technical information, and organizational services are important foundations for farmers' adoption of green production technologies [27,35]. Accordingly, we used the following question to determine green production capabilities: "Can you accurately identify common pests and carry out green production?"

To assess whether capability evaluations corresponded to production-input adjustments, we measured pesticide and fertilizer expenditure per mu. Pest management is directly related to choosing pesticides, application methods, and safety intervals, whereas fertilizer use depends heavily on soil conditions, nutrient requirements, and yield targets. Therefore, pesticide expenditure was used to examine the direct correspondence between capability and production. Meanwhile, fertilizer expenditure was used to determine whether adjacent agricultural inputs exhibited similar changes [14,16]. Pesticide and fertilizer expenditures per mu were both recorded in five categories, with higher values indicating higher expenditure categories.

3.3.2. Core Explanatory Variable

Urban–rural integration encompasses two-way factor flows, public service allocation, spatial linkages, and ecological and agricultural production conditions. A single measure, such as the urbanization rate, income gap, or infrastructure indicator, cannot fully capture this multidimensional concept [17,23]. These county-level conditions provide a descriptive context in which growers may face different opportunities to access technical information, public services, financial resources, market opportunities, and agricultural production support [22]; the present CURI does not measure these opportunities at the farm level or identify their mediating role. Accordingly, the core explanatory variable was the baseline CURI of the corresponding county-level unit. The baseline CURI was standardized within the 506 questionnaires with identified county-level locations. Additionally, we constructed a 20-indicator CURI to assess whether the measurement specifications of urban–rural integration affect the estimates.

3.3.3. Conditional Variables and Variables for Extended Analyses

Market access and value-chain governance can alter the expected returns on green technologies through consumer demand, price incentives, quality standards, risk sharing, and enforcement arrangements [8,25,39]. Therefore, we selected urban end-market sales to represent farmers' links to urban consumer markets and order- and contract-based sales to represent the degree of organization in transaction relationships. Urban end-market sales were measured as the share of total sales to urban supermarkets, wet markets, fresh food shops, and other urban retail channels. Order- and contract-based sales were measured as the share of total sales made through orders or contracts. Both variables had five ordered share categories, with higher values indicating a larger share of the corresponding sales channel. These indicators described sales destinations and sales-share structures; price premiums, green certification, quality supervision, contractual terms, and fulfillment quality constituted separate dimensions of transaction quality.

Prior literature relates digital extension and network-based information targeting to improved access to production information [4,43]. Training can improve fertilizer-use

knowledge [14]. Enterprises, platforms, and cooperative organizations are associated with green-technology adoption through input provision, technical guidance, production supervision, and sales coordination [3,13,35]. Farm scale is associated with differences in the ability to absorb the fixed costs of information search, experimentation, and market entry [1,37]. In the present analysis, training intensity, enterprise and platform support intensity, and small-scale operation are modeled as conditional covariates, not as identified causal mechanisms.

Training intensity was measured using a five-point scale for green agriculture-related training. The main model retained the full scale and standardized it; as a robustness measure, the original values of 4 and 5 were coded as a high-intensity-training dummy [15,44]. The intensity of enterprise and platform support was measured using a five-point scale covering investment, cooperation, and order support from urban enterprises or e-commerce platforms. The main model retained and standardized the full scale. As an alternate measure, the original values of 2–5 were coded as the presence of support. Small-scale operation was determined based on the farm-size category; it equaled one when the category equaled the sample median of 1, and 0 otherwise. The interaction model retained the continuous farm-size category, the main effect of small-scale operations, and its interaction with CURI.

Adoption studies associate age, gender, education level, and farm scale with differences in information processing capability, risk bearing ability, labor allocation, resource constraints, and technology-related decisions [15,45]. Regional characteristics may likewise be related to the conditions under which green technology adoption occurs [1,2]. Therefore, we included age category, gender, education category, farm-size category, training intensity, enterprise and platform support intensity, and a Zhejiang-sample dummy as control variables. Training intensity and enterprise and platform support intensity were also used in interaction terms to assess conditional relationships with CURI. Except for the provincial dummy, continuous or ordinal variables were standardized within the 506 observations, and binary variables entering the interaction terms were mean-centered. The definitions of variables are shown in Table 2.

Table 2. Definitions of main variables.

Type	Variable	Measurement and Coding
Primary outcome	Self-rated green production capability	Five categories; higher values indicate stronger self-rated pest-identification and green production capability
Auxiliary outcome	Pesticide-input reduction proxy	6 minus the pesticide-expenditure category per mu; higher values indicate a lower expenditure category
	Fertilizer-input reduction proxy	6 minus the fertilizer-expenditure category per mu; higher values indicate a lower expenditure category
Core explanatory variable	Baseline CURI	11 indicators aggregated across four equally weighted dimensions; standardized within the farmer sample
Alternative explanatory variable	Expanded CURI	20 indicators aggregated across four equally weighted dimensions; standardized within the farmer sample

Table 2. *Cont.*

Type	Variable	Measurement and Coding
Market-linkage variable	Urban end-market sales	Five sales-share categories; higher values indicate a larger share of urban end-market sales
	Order- or contract-based sales	Five sales-share categories; higher values indicate a larger share of order- or contract-based sales
Conditional variable	Training intensity	Standardized in the main model; a binary indicator for categories 4–5 is used as an alternative measure
	Enterprise or platform support intensity	Five categories; standardized in the main model, with a binary indicator for categories 2–5 as an alternative measure
	Small-scale operation	Equals 1 when the farm-size category equals the sample median of 1, and 0 otherwise
Control variables	Farmer characteristics and region	Age, gender, education, continuous farm size, and a Zhejiang-sample dummy

3.4. Specification of the Econometric Model

Because self-rated green production capability was an ordinal variable with five categories, and the distances between categories cannot be assumed to be equal, we used the ordered logit model as the baseline specification [46,47]. Let the questionnaire observation i be located in survey area j, and let the latent continuous response be the following.

$$Y^*_{ij} = \beta CURI_j + \gamma' X_{ij} + \delta Zhejiang_i + \varepsilon_{ij}$$

where Y^*_{ij} denoted the unobserved propensity for green production capability; $CURI_j$ represented the standardized county-level urban–rural integration index; X_{ij} included age, gender, education, farm size, training intensity, and enterprise and platform support intensity; and $Zhejiang_i$ denoted a dummy for observations from Zhejiang. The observed category was determined by the thresholds, and a higher capability category was observed when the latent response crossed a higher threshold.

The ordered logit model was estimated by maximum likelihood, while an ordered probit was used to assess sensitivity to the link function specification. The coefficients indicated latent associations between explanatory variables and higher-capability categories. For interpretation, model-based predicted values were calculated at the observed CURI values and at CURI values one sample standard deviation higher, while other observed covariates were held unchanged. We report sample-average predicted differences for each category, the probability of high capability $P(Y \geq 4)$, and the expected category $E(Y)$. These model-based contrasts are descriptive and are not interpreted as causal effects.

3.5. Conditional Associations, Extended Analyses, and Robustness Design

To test H2, we estimated a conditional-association model for the farm scale. The interaction between standardized CURI and small-scale operation was included together with the main effects and the control variables.

$$Y^*_{ij} = \beta CURI_j + \eta Z_{ij} + \rho\left(CURI_j \times Z_{ij}\right) + \gamma' X_{ij} + \delta Zhejiang_i + \varepsilon_{ij}$$

In the H2 model, Z_{ij} denoted small-scale operation. The model simultaneously retained continuous farm size, the main term for small-scale operations, and the interaction term. The interaction coefficient ρ represented the difference in the CURI slope between observations classified as small-scale operations and other observations.

Urban-market and contract-sales relationships were examined in two extended analyses. The first analysis used the urban end-market sales category and the order- and contract-based sales category as separate ordinal dependent variables and estimated their relationships with CURI.

$$M^*_{ij} = \alpha CURI_j + \theta' X_{ij} + \delta Zhejiang_i + u_{ij}$$

The second analysis incorporated both sales variables into the green production capability equation, as shown below.

$$Y^*_{ij} = \beta' CURI_j + \lambda_1 UrbanSales_{ij} + \lambda_2 ContractSales_{ij} + \gamma' X_{ij} + \delta Zhejiang_i + \varepsilon_{ij}$$

This model compares the conditional CURI coefficient before and after urban end-market sales and order- and contract-based sales were included, and it estimates the conditional associations between sales linkages and green production capability. The comparison does not estimate an indirect effect or a mediation pathway.

The conditional-association models for enterprise and platform support intensity and training intensity estimated the corresponding interaction terms while retaining CURI, the conditional variables, and other controls. They were used to assess whether the association between targeted services and green production capability differed across the local opportunity structures.

To test the robustness of our findings, we (1) replaced the baseline CURI with the expanded 20-indicator CURI; (2) recoded training intensity and enterprise and platform support intensity as binary indicators; and (3) replaced the primary outcome with pesticide- and fertilizer-input reduction proxies.

3.6. Standard Errors and Hierarchical Structure

Questionnaire observations from the same survey area shared the same county-level CURI. Therefore, the standard ordered logit and probit models reported both conventional model-based standard errors and CR1 cluster-robust standard errors calculated for 41 survey-area units, allowing the stability of statistical inference to be assessed. Because the questionnaire observations were nested within 13 prefecture-level cities, a city random-intercept ordered logit model was estimated to assess the sensitivity of the baseline association to city-level clustering and unobserved city heterogeneity.

These clustered and hierarchical specifications are treated as sensitivity checks for dependence and city-level structure. Because the number of survey-area clusters is limited, the CR1 results are interpreted cautiously, and a random-intercept model with incomplete convergence is not treated as independent confirmation of the baseline association.

4. Results

4.1. Survey Areas and CURI Measurement

The two survey batches resulted in a total of 506 responses. Table 3 reports the survey areas, response counts, and ranges of raw CURI values in those areas. And it describes the 41 county-level survey areas represented in the questionnaire sample.

The mean CURI of the Shandong evaluation units was higher than that of the Zhejiang units, whereas the dimension scores exhibited different regional configurations.

Table 3. Survey areas, questionnaire counts, and baseline CURI ranges.

Province	Prefecture-Level City	County-Level Survey Areas	Questionnaires	Range of Raw CURI in Survey Areas
Shandong	Dongying	Dongying District, Guangrao County, and Kenli District	58	0.2116–0.2438
	Weifang	Qingzhou, Shouguang, Anqiu, Linqu County, Zhucheng, and Gaomi	66	0.1214–0.1694
	Binzhou	Bincheng District, Zhanhua District, Yangxin County, Wudi County, and Boxing County	31	0.1818–0.2266
	Linyi	Yishui, Junan, Yinan, Tancheng, Lanling, Fei, and Pingyi counties	54	0.0989–0.1045
	Jinan	Changqing District and Huaiyin District	14	0.1806–0.1899
	Zibo	Linzi District	14	0.1902
	Jining	Rencheng District	16	0.1852
	Tai'an	Ningyang County	10	0.1542
	Liaocheng	Dong'e, Guan, and Gaotang counties	15	0.1202–0.1292
Zhejiang	Jinhua	Pan'an County, Lanxi, Wuyi County, and Pujiang County	84	0.1360–0.1442
	Lishui	Songyang County and Qingyuan County	62	0.1202–0.1211
	Hangzhou	Fuyang District, Binjiang District, Jiande, Tonglu County, and Chun'an County	70	0.1513–0.1846
	Shaoxing	Shengzhou	12	0.1489

Note: The CURI ranges are calculated from the county-level survey locations reported in the table.

4.2. Sample Characteristics and Descriptive Statistics

The analytical sample is the 506 valid responses defined in Section 3.1. Table 4 reports descriptive statistics for the variables in the models; the primary-vegetable and diversified-farming composition is reported in Section 3.1.

Regarding the core variables, the dependent variable, self-rated green production capability, has a mean of 3.308 and a standard deviation of 0.921 on a five-point scale. The numbers of observations in Categories 1 through 5 were 20, 54, 229, 157, and 46, respectively. A total of 203 respondents (40.3%) reported relatively high capability (Categories 4 and 5), indicating a basic foundation for green production among the respondents, although fewer than half reported high-level capability. The raw baseline CURI of the survey area had a mean of 0.162. After standardization, it had a mean of 0 and a standard deviation of approximately 1, which facilitates comparison of estimated coefficients and interaction terms in the subsequent regression models.

Table 4. Descriptive statistics for CURI and main variables (N = 506).

Variable	Mean	SD	Min	Max
Baseline CURI of survey area (raw)	0.162	0.034	0.099	0.244
Baseline CURI of survey area (standardized)	0	1.002	−1.868	2.454
Self-rated green production capability	3.308	0.921	1	5
Training intensity	2.036	1.186	1	5
Enterprise or platform support intensity	1.502	0.894	1	5
Urban end-market sales category	2.344	1.18	1	5
Order- or contract-based sales category	1.925	1.094	1	5
Pesticide-input reduction proxy	3.751	1.171	1	5
Fertilizer-input reduction proxy	3.411	1.211	1	5
Age category	2.779	0.963	1	5
Gender code	1.364	0.49	1	3
Education category	2.462	1.006	1	5
Farm-size category	1.822	1.118	1	5
Small-scale operation (0/1)	0.518	0.501	0	1

Regarding farmers' and operational characteristics, small-scale operations accounted for 51.8% of the sample, while the mean farm-size category was 1.822. This composition provided a micro-level basis for heterogeneity analysis. The mean age category was 2.779, and the mean education category was 2.462, reflecting that the agricultural operators were predominantly middle-aged or older and had low to moderate levels of education.

Regarding market linkages and service access, the mean urban end-market sales category was 2.344. This was slightly higher than the mean for order- and contract-based sales (1.925). Regarding targeted support, the mean training intensity was 2.036. In contrast, the intensity of enterprise and platform support was relatively limited, demonstrating a mean of only 1.502. The pesticide- and fertilizer-input reduction proxies exhibited a mean of 3.751 and 3.411, respectively.

4.3. Urban–Rural Integration and Self-Rated Green Production Capability

Table 5 reports the baseline estimates. The coefficient for standardized CURI was 0.3458 in the ordered logit model ($p = 0.0405$; CR1 $p = 0.0364$), 0.1680 in the ordered probit model and significant at the 10% level, and 0.3459 in the city random-intercept ordered logit model ($p = 0.0345$). The positive CURI coefficient was consistent with H1, across the three specifications, although statistical significance was somewhat sensitive to the link-function specification.

Training intensity had a positive estimate across the models, with an ordered logit coefficient of 0.7255 ($p < 0.001$). In contrast, the estimated main term for enterprise and platform support intensity was close to zero. Age was positively associated with capability, while the positive association for farm size was sensitive to clustered inference. The Zhejiang-sample dummy had a negative coefficient across the models.

Table 5. Urban–rural integration and self-rated green production capability: baseline ordinal response models.

Variable	Ordered Logit	Ordered Probit	City Random-Intercept Ordered Logit
CURI (standardized)	0.3458 ** (0.1688) [0.1653]	0.1680 * (0.0940) [0.1019]	0.3459 ** (0.1636)
Training intensity (standardized)	0.7255 *** (0.1515) [0.1595]	0.4101 *** (0.0851) [0.0850]	0.7255 *** (0.1419)
Enterprise or platform support intensity (standardized)	0.0341 (0.1450) [0.2247]	0.0195 (0.0784) [0.1057]	0.0341 (0.1457)
Age (standardized)	0.4446 *** (0.1716) [0.1627]	0.2892 *** (0.0995) [0.0896]	0.4446 *** (0.1715)
Gender (standardized)	0.0934 (0.1270) [0.1688]	0.0482 (0.0699) [0.0945]	0.0933 (0.1283)
Education (standardized)	−0.1716 (0.1711) [0.1599]	−0.0854 (0.0976) [0.0928]	−0.1716 (0.1718)
Farm size (standardized)	0.3352 ** (0.1433) [0.2262]	0.1901 ** (0.0785) [0.1155]	0.3352 ** (0.1400)
Zhejiang-sample dummy	−1.2573 *** (0.3656) [0.3304]	−0.7864 *** (0.2069) [0.2012]	−1.2572 *** (0.3255)
Sample size	506	506	506
Survey-area units/no. of city groups	41	41	13
SD of city random intercept	—	—	0.0001

Note: Parentheses contain conventional maximum-likelihood standard errors; brackets contain CR1 cluster-robust standard errors calculated for 41 survey-area units with a finite-sample correction. Significance stars are based on the standard errors in parentheses: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.4. Average Discrete Changes and Input Outcomes

As shown in Table 6, model-based predicted values were calculated at each observation's observed CURI and at a CURI Value one sample standard deviation higher, while all other covariates were held at their observed values. The sample-average predicted probability of high capability, $P(Y \geq 4)$, was 40.59% at observed CURI values and 47.10% at CURI + 1 SD, a predicted difference of 6.50 percentage points. The corresponding expected capability category was 3.315 and 3.453, respectively, a predicted difference of 0.138 points.

When the pesticide-input reduction proxy was used as the dependent variable, the CURI coefficients in the ordered logit and probit models were 1.2188 and 0.6105, respectively, and both were significant at the 1% level. When the fertilizer-input reduction proxy was used as the dependent variable, the corresponding coefficients were 0.1954 and 0.1285 and failed to reach statistical significance. The results concerning pesticide use were more closely aligned with the technical aspects of green production capability, whereas fertilizer adjustments reflected a different set of production conditions.

Table 6. Average discrete changes from a one-standard-deviation increase in CURI.

Outcome	Model-Based Predicted Value at Observed CURI	Model-Based Predicted Value at CURI + 1 SD	Predicted Difference
Y = 1	0.0384	0.0279	−0.0105
Y = 2	0.1078	0.0842	−0.0236
Y = 3	0.4479	0.417	−0.0309
Y = 4	0.3122	0.3491	0.0369
Y = 5	0.0937	0.1219	0.0281
P(Y ≥ 4)	0.4059	0.471	0.065
E(Y)	3.315	3.4528	0.1378

4.5. Extended Analysis: Urban Markets and Contract Sales

Table 7 reports the estimated associations between CURI, market-linkage measures, and green production capability. CURI had positive coefficients for urban end-market sales in the ordered logit and ordered probit models (0.2603 and 0.1264, respectively), although the conventional and clustered inferences differed. Urban end-market sales were positively associated with self-rated green production capability in both model classes. In contrast, the estimates for CURI and order- or contract-based sales did not reach statistical significance in either model, providing no stable evidence of an association in this sample.

Table 7. Associations among CURI, market linkages, and green production capability.

Association Examined	Ordered Logit Coefficient	*p* (Conv./CR1)	Ordered Probit Coefficient	*p* (Conv./CR1)
CURI and urban end-market sales	0.2603	0.096/<0.001	0.1264	0.165/0.002
CURI and order- or contract-based sales	0.183	0.270/0.118	0.0963	0.320/0.222
CURI and green production capability, with sales variables included	0.2896	0.088/0.094	0.1394	0.142/0.181
Urban end-market sales and green production capability	0.6934	<0.001/0.003	0.3447	<0.001/0.003
Order- or contract-based sales and green production capability	0.002	0.991/0.995	0.0327	0.749/0.844

Note: All models control for age, gender, education, farm size, training intensity, enterprise or platform support intensity, and provincial differences.

The second analysis included both sales variables in the capability equation. In the ordered logit model, the coefficient for urban end-market sales was 0.6934, with conventional $p < 0.001$ and CR1 $p = 0.0026$. In the ordered probit model, the coefficient was 0.3447 and both the conventional and CR1 inferences yielded $p < 0.01$. The coefficient for order- and

contract-based sales was insignificant in both models under both sets of standard errors. After the sales variables were included, the CURI coefficient remained positive; however, it reached 10% statistical significance only in the ordered logit model and did not reach significance in the ordered probit model.

4.6. Heterogeneity in Conditional Associations by Farm Scale and Other Relationships

The interaction coefficient between CURI and small-scale operation was 1.2475 in the ordered logit model and 0.7071 in the ordered probit model; both conventional and CR1 inferences yielded $p < 0.001$. In the city random-intercept model, the interaction coefficient was 1.2475 ($p < 0.001$), as reported in Table 8. After controlling for continuous farm size and the main effect of small-scale operations, the estimated CURI-capability association was stronger among small-scale farmers, consistent with H2. Table 8 reports these interaction estimates together with the city random-intercept results and convergence information.

Table 8. Interaction estimates for conditional associations.

Interaction Term	Ordered Logit	p (Conv./CR1)	Ordered Probit	p (Conv./CR1)	City Random-Intercept Model
CURI × small-scale operation	1.2475	<0.001/<0.001	0.7071	<0.001/<0.001	1.2475, $p < 0.001$, converged normally
CURI × enterprise or platform support intensity	−0.5164	<0.001/<0.001	−0.275	<0.001/<0.001	−0.5164, $p < 0.001$, did not fully converge
CURI × training intensity	−0.3294	0.009/0.003	−0.1654	0.020/0.003	−0.3294, $p = 0.006$, converged normally

The interaction coefficient between CURI and enterprise and platform support intensity was −0.5164 in the ordered logit model and −0.2750 in the ordered probit model, and both were significant at the 1% level. The direction remained negative when the variable was recoded as a binary indicator. This interaction is consistent with a weaker estimated CURI-capability association at higher organizational-support intensity, but it does not identify why the estimated slope differs. The city random-intercept model did not fully converge.

Training intensity had a positive estimated main association with green production capability. Its interaction with CURI was −0.3294 in the ordered logit model and −0.1654 in the ordered probit model, and both were statistically significant. This interaction coefficient was −0.3294 ($p = 0.0059$) in the city random-intercept model. The interaction also remained negative when the variable was recoded as a high-intensity dummy, indicating a conditional association between training intensity and the local opportunity structure.

4.7. Robustness Tests

The results for high-intensity-training, binary-organizational-support, and pesticide-input reduction retained their original directions, whereas the result for fertilizer-input reduction remained statistically insignificant. The full set of robustness and sensitivity estimates is reported in Table 9.

When the expanded 20-indicator CURI replaced the baseline index, the coefficients remained positive but became statistically insignificant in both the ordered logit and probit models, indicating that the overall relationship is sensitive to the indicator system.

Table 9. Main robustness and sensitivity tests.

Test	Ordered Logit	p (Conv./CR1)	Ordered Probit	p (Conv./CR1)	Assessment
County-level location identified	0.3485	0.040/0.032	0.1685	0.075/0.098	Close to the baseline result
Expanded 20-indicator CURI	0.0878	0.490/0.652	0.0483	0.500/0.660	Baseline association not retained
Pesticide-input reduction proxy	1.2188	<0.001/<0.001	0.6105	<0.001/<0.001	Stable positive association
Fertilizer-input reduction proxy	0.1954	0.226/0.291	0.1285	0.158/0.253	No stable relationship
CURI × binary organizational-support measure	−1.0693	<0.001/<0.001	−0.5595	<0.001/<0.001	Negative interaction retained
CURI × high-intensity training	−0.9028	0.010/0.025	−0.4744	0.021/0.032	Negative interaction retained

Overall, the baseline CURI was positively associated with green production capability, and this estimated association was stronger among small-scale farmers. Pesticide input reduction, urban end-market sales, organizational support, and training intensity displayed auxiliary or conditional patterns related to the main relationship, whereas fertilizer input and order- and contract-based sales showed no stable relationships. The expanded 20-indicator CURI did not reproduce the baseline main effect, indicating that the index specification is an important condition for interpreting the overall relationship.

5. Discussion

5.1. Baseline Association Between the Local Opportunity Structure and Green Production Capability

As shown in Table 5, the baseline 11-indicator CURI was positively associated with self-rated green production capability after controlling for age, gender, education, farm size, training intensity, enterprise and platform support intensity, and provincial differences. The direction of this association remained consistent across the ordered logit, ordered probit, and city random-intercept models. Table 6 reports a model-based predicted difference of 6.50 percentage points in the probability of high capability when CURI is evaluated one sample standard deviation higher. Table 9 further reports a positive association between CURI and lower pesticide expenditure per mu; whereas the association between CURI and fertilizer expenditure did not reach statistical significance. Because the input measures are expenditure-based proxies rather than observed quantities or direct environment outcomes, these estimates describe corresponding between the measures and should not be interpreted as evidence that the CURI caused the input changes.

These findings are consistent with adoption research emphasizing the joint relevance of information availability, risk, credit constraints, and market conditions on green production [1,2]. Research on urban–rural integration likewise characterizes factor flows, public services, and living conditions as interrelated dimensions of regional development [17,22,23]. By linking these studies at the county-farmer level, the present analysis documents an empirical correspondence between a multidimensional local context and farmers' reported

green production capability [48]. The sensitivity result in Table 9 further indicates that this correspondence depends on the indicator specification [49].

5.2. The CURI-Capability Association Is Stronger Among Small-Scale Farmers

Table 8 shows a positive and statistically significant interaction between CURI and small-scale operation across the three models. Conditional on the specification, the estimated association between CURI and self-rated capability was steeper for small-scale than for larger-scale operations, consistent with H2.

This pattern describes scale-related heterogeneity within the analytical sample; it does not establish that changes in county conditions have a larger causal effect on small-scale farmers.

The small-scale category was defined using the sample median of the farm-size category and therefore supports only an internal comparison within the sample [28,36]. Quality standards, traceability requirements, and continuous-supply obligations may condition how operators of different scales can translate capability into market performance [8,26,50].

5.3. Associations with Pesticide Expenditure and Urban Market Linkages

Table 9 shows that CURI was robustly associated with the pesticide-input reduction proxy, whereas its association with the fertilizer-input reduction proxy did not reach statistical significance. Pest identification and green production capability are more directly related to pesticide choice and control methods, whereas fertilizer adjustments also depend on soil conditions, nutrient requirements, and yield objectives. This contrast indicates that the pesticide measure was more closely aligned with the observed CURI-capability correspondence in the present data.

As shown in Table 7, urban end-market sales were positively associated with self-rated green production capability, whereas the association between CURI and urban sales was sensitive to the inference specification. Order- and contract-based sales showed no stable relationship with capability or with CURI. Prior research relates market access, credit availability, and extension services to the conditions under which farmers consider technology options [8,12,19]. In the present data, urban market linkages and reported capability were jointly associated, but the sales measures do not identify the channels underlying that correspondence [51].

Research on contract governance emphasizes that prices, quality standards, risk sharing, and enforcement arrangements may matter more for smallholders' transaction returns than contractual form alone [24,25,39]. Accordingly, the absence of a stable association with the order- and contract-sales share means that contractual form alone does not account for observed capability differences in this sample. Unmeasured contractual attributes remain an important topic for future research.

5.4. Conditional Association of Training and Organizational Support with the Local Opportunity Structure

Table 8 shows that the estimated main association between enterprise and platform support intensity and green production capability was not statistically significant, while its interaction with CURI was negative. Training intensity was positively associated with green production capability, and its interaction with CURI was also negative. These patterns are consistent with conditional differences between targeted services and broader county conditions, but they do not establish that organizations or training cause a weaker CURI-capability association. The present data do not identify the source of the interaction pattern.

Research on cooperatives and value chains documents that organizations can provide services such as input supply, technical guidance, production inspection, quality assur-

ance, and sales coordination [3,13,35]. Training and information-diffusion studies likewise distinguish knowledge acquisition from longer-term behavioral change [14,43]. Future research should distinguish service content, providers, timing of entry, and duration when examining how targeted services are related to county-level conditions.

5.5. Implications for Future Policy Design and Evaluation

The study links a multidimensional measure of urban–rural integration with farmers' green production capability at the county-farmer level while distinguishing capability from technology adoption, input use, and environmental outcomes. It also treats farm scale as a source of conditional heterogeneity and places market linkages and targeted services alongside county-level conditions without presenting them as a completed causal pathway. More broadly, the framework raises a multilevel question for future research: how subnational public services, infrastructure, finance, and market connections are associated with the production capabilities of dispersed small-scale producers.

The evidence does not identify the effects of particular service packages or policy instruments. It identifies service-access and market-linkage questions that merit pilot testing and independent evaluation, especially for small-scale operations. Future implementation should document service exposure, participation, verified production practices, physical input quantities, output, returns, and farmer welfare rather than inferring policy effects from aggregate county conditions.

Zhejiang's Green Rural Revival Program and Shandong's cluster-based rural revitalization practices provide a policy context emphasizing rural infrastructure, public services, and agricultural-industrial coordination. Their broad, place-based orientation may be relevant for coordinating county development, but aggregate investment does not demonstrate equal access to green-production services for small-scale growers. Possible measures, such as pest monitoring and diagnosis, small-batch procurement or targeted input support, mobile technical guidance, quality testing and traceability services, and market matching, should therefore be treated as candidates for pilot testing rather than as effects established by the present analysis.

Any future policy evaluation would need to track pesticide active-ingredient use, verified green-practice adoption, service coverage, output, returns, and the distribution of benefits across farm sizes. Such evaluations should also assess fiscal and administrative costs, uneven service coverage, and the possibility that certification or traceability requirements exclude small-scale operators without adequate technical and financial support.

5.6. Limitations

Because the study employed purposive regional selection and field-based respondent recruitment rather than national probability sampling, the sample should not be interpreted as statistically representative of all Chinese farmers. The findings are primarily applicable to vegetable-producing areas with relatively active urban–rural integration.

The cross-sectional survey cannot establish temporal ordering among local conditions, market linkages, training, and capability. The single-item self-assessment and expenditure-category measures may also introduce measurement error. The sales variables did not record prices, certification, contractual terms, or fulfillment quality, and CURI was affected by indicator definitions and data sources. The analysis therefore does not identify causal effects or observed mediating mechanisms. Future research should combine knowledge tests, field-practice verification, actual adoption areas, physical input quantities, and longitudinal county-farmer data.

6. Conclusions

This study examined the association between county-level urban–rural integration and farmers' self-rated green production capability from the perspective of local opportunity structures. In the study areas, the baseline CURI was positively associated with self-rated capability after accounting for observed individual, farm, and provincial characteristics. The estimated association was stronger for small-scale operations within the analytical sample. Pesticide-expenditure categories and urban end-market sales displayed more consistent associations with the baseline CURI or capability measure than did fertilizer expenditure and order- or contract-based sales.

Taken together, the economic, public-service, spatial, and agricultural-production conditions represented by CURI described a county-level opportunity structure that was associated with farmers' reported green production capability in the sampled areas. The cross-sectional analysis does not establish that changes in these conditions enhance capability or input outcomes, and the sensitivity of the association to indicator coverage reinforces this limitation. The study therefore provides a bounded county-farmer framework for formulating and evaluating hypotheses about service access, market linkages, and scale-related constraints. Future interventions should be tested with designs that measure service exposure, verified practices, and distributional consequences across farm sizes.

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Abbreviations

The following abbreviations are used in this manuscript:

CURI	County-level urban–rural integration

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