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Impact of production outsourcing on the adoption of low-carbon agricultural technologies in China

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Abstract: Adopting low-carbon agricultural technologies (LCATs) is fundamental to reducing carbon emissions in agriculture. Our study explores the factors influencing the adoption of LCATs and the roles of production outsourcing and specialised farming within the framework of off-farm employment. In this regard, survey data were collected from 1 040 farmers in the Yellow River region of China in 2020 to examine the effect of production outsourcing on the farmers' adoption of LCATs. Potential mechanisms associated with specialised farming and off-farm employment are considered to comprehend this relationship. We also investigate the heterogeneous effects of production outsourcing on adopting LCATs, taking different education levels and arable land areas into account. The results show a positive association between production outsourcing and farmers' LCATs adoption behaviour, even after considering self-selection bias. Specifically, outsourcing production can significantly increase the likelihood of farmers adopting low-carbon tillage, low-carbon irrigation, and low-carbon fertilisation technologies by 7.2%, 8.1%, and 7.3%, respectively. This effect is more pronounced among farmers with higher levels of education and smaller areas of arable land. Furthermore, production outsourcing increases the LCATs adoption by promoting specialised farming. The findings suggest that outsourcing is vital to alleviating the lack of LCATs adoption resulting from off-farm employment.

Keywords: agricultural social services; carbon mitigation measures; mediating effect model; propensity score matching; specialised farming; off-farm employment

Global warming has recently become a serious threat to human health and ecological balance due to the growth of greenhouse gas (GHG) emissions. According to the fifth the United Nations Intergovernmental Panel on Climate Change (IPCC) assessment report, agricultural production has become the world's second-largest source of GHG emissions (IPCC 2014). Measures promoting LCATs are being implemented to mitigate GHG emissions from agriculture, which offers a potential solution for mitigating agricultural carbon emissions by reducing agrochemical inputs and conserving the soil layer structure (FAO 1995). Nevertheless, despite the advantages of LCATs and the ongoing efforts of numerous local organisations, the adop-

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tion rate of LCATs by farmers remains low (Kassie et al. 2015; Mao et al. 2022).

To tackle these challenges, exploring innovative solutions that can empower farmers and enhance their adoption of LCATs is imperative. Significant knowledge, capital, and labour intensity are the LCATs that can pose challenges for farmers, especially smallholders, who may struggle with independent technology adoption (Yamaguchi et al. 2019). The rise of agricultural production outsourcing provides a way to overcome the labour, capital, and knowledge barriers associated with the LCATs adoption (Lu et al. 2023). As off-farm employment opportunities expand, labour becomes a scarce resource. Production outsourcing optimises the factor allocation, labour resources, and land scale, further promoting specialised farming while reducing the cost of technology adoption. Additionally, production outsourcing expands the information dissemination channels, enabling farmers to understand new and access better technologies. The critical role of production outsourcing in promoting farmers adopting LCATs cannot be ignored. Previous studies have noted the relationship between outsourcing production and the ecological environment (Liang et al. 2020; Chang et al. 2023). For example, Zhang et al. (2023) indicated that outsourcing services could improve agricultural eco-efficiency by agricultural technology substitution. Lu et al. (2023) showed that outsourcing can reduce agricultural carbon emissions by adopting green technology. Therefore, it is reasonable to infer that outsourcing has an important impact on adopting LCATs. However, previous literature has overlooked the direct investigation of the relationship between outsourcing and the adoption of LCATs. Furthermore, they have failed to consider the variations in this relationship across different types of technologies and various groups.

In the literature related to LCATs, most studies focus on exploring the driving factors affecting the adoption of LCATs (Conley and Udry 2010; Pham et al. 2021). These factors can be classified into three main aspects. The fundamental factors include education, farming experience, risk perception, access to credit, household income, and arable land (Acevedo et al. 2020; Chouksey et al. 2021; Adego and Woldie 2022). Social factors mainly revolve around social networks, social trust, and social participation (Yaméogo et al. 2018; Gao et al. 2019; DeDecker et al. 2022). Moreover, factors that influence government policy, such as technology subsidies, penalties, and extensions, on adopting LCATs have also been examined (Cremades et al. 2015; Dar et al. 2020; Sikka et al. 2022). However, no empirical study has scrutinised the influence of production outsourcing on adopting LCATs from the perspectives of off-farm employment and specialised farming.

Considering the preceding discussion, our research makes several noteworthy contributions. First, our study employs production outsourcing as an agricultural social service in the LCATs adoption behaviour, with specialised farming as a mediator. While the previous literature has focused on ways to encourage farmers to adopt LCATs (Zhao et al. 2022), the role of production outsourcing and specialised farming on the farmers' LCATs adoption behaviour has received limited attention. Second, we examine the mechanism moderating off-farm employment on the effect of production outsourcing. Although the existing studies have discussed the impact of off-farm employment on the LCATs adoption behaviour, their conclusions are inconsistent (Huang et al. 2020). This article presents a theoretical framework to elucidate the influence of off-farm employment on the adoption of LCATs. It proves off-farm employment as a moderating factor that can enhance the positive impact of production outsourcing on the behaviour of adopting LCATs. Thirdly, we perform a series of robust tests to examine the relationship between production outsourcing and the adoption of LCATs. Furthermore, to ensure the reliability of the results, we employ the Propensity Score Matching approach to address the sample self-selection bias. We replace the core explanatory and explained variables with outsourcing levels and other LCATs.

Consequently, this paper aims to address the following questions: will agricultural production outsourcing significantly affect the farmers' LCATs adoption behaviour? If so, what are the specific mechanisms by which production outsourcing influences the farmers' adoption of LCATs? And which groups are more likely to adopt LCATs? Answering these questions can help governments to explore feasible and effective ways to promote low-carbon agriculture. Accordingly, a survey of 1 040 farmers in the Yellow River Basin of China was conducted for the analysis. Then, we explored the relationship between production outsourcing and the farmers' LCATs adoption behaviour and its heterogeneity, considering the moderating role of specialised farming and the mediating effect of off-farm employment.

MATERIAL AND METHODS

We have chosen three representative types of LCATs. These include low-carbon tillage technologies that encompass no-tillage, straw return, and deep ploughing. Low-carbon irrigation technologies include sprinkler,

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drip, and pipe irrigation. Low-carbon fertilisation technologies include soil formula fertilisation, water and fertiliser integration, and slow-release fertiliser applications. The primary regression variable is low-carbon irrigation technology, while the other two are subjected to robustness testing. Whether farmers adopt LCATs is a 0–1 selection choice problem. So, we established a binary probit model to verify the effect of production outsourcing on the farmers' adoption of LCATs. Besides, we use the propensity score matching (PSM) to test the endogeneity of the estimated results of production outsourcing to improve the farmers' LCATs adoption behaviour. The baseline regression model was set up in the following form:

$$Technique_i = \alpha + \beta_1 Outsourcing_i + \theta Control_i + \varepsilon_i \quad (1)$$

where: $Technique_i$ – whether the farmer i adopts LCATs; $Outsourcing_i$ – whether the farmer i outsources production (This outsourcing practice encompasses five stages: land preparation, mulching, harvesting, irrigation, and pest control. To evaluate the reliability of our findings, we also incorporated the 'degree of outsourcing' as an additional independent variable in the robustness test. This variable measures the actual number of production phases that have been outsourced.); $Control_i$ – includes the vector of control variables affecting the technology adoption behaviour of the farmer i, including individual characteristics, family characteristics, social characteristics, policy characteristics, and rural characteristics; α – intercept term; β_1,θ – coefficients to be estimated; ε_i – random error term.

Furthermore, specialised farming is the mediating variable for farmers specialising in producing and operating specific agricultural products. The level of specialisation is determined by the number of different types of operations and the distribution of land area among these operations. To measure the degree of specialised farming, we employed the Herfindahl-Hirschman concentration index (*HHI*) to measure the degree of specialised farming (Bradshaw 2004), as outlined in Equation (2).

$$HHI = \sum_{j=1}^{n} \left(\frac{S_{ij}}{X_i} \right)^2 \quad (2)$$

where: S_{ij} – area planted by farmer i for crop j; X_i – total area planted by farmer i.

$HHI \in [0-1]$, the higher the value, the higher the degree of crop specialisation of the farmer. When $HHI = 1$, it indicates that the farmer grows only one crop.

Then, referring to Baron and Kenny (1986), we carry on mediating the effect analysis. Equations (3–5) can be written as:

$$Technique_i = \alpha + \beta_1 Outsourcing_i + \theta Control_i + \varepsilon_i \quad (3)$$

$$Special_i = \gamma + \beta_2 Outsourcing_i + \delta Control_i + \sigma_i \quad (4)$$

$$Technique_i = \phi + \beta_3 Outsourcing_i + \beta_4 Special_i + \omega Control_i + \mu_i \quad (5)$$

where: $Special_i$ – degree of specialisation of the farmer i cultivation as the mediating variable; γ, β_2, δ, φ, β_3, β_4, ω – parameters or parameter matrices to be estimated; σ_i, μ_i – random disturbance terms; the remaining variables and signs remain consistent with Equation (1).

If β_2, β_4, and $\beta_2 \times \beta_4$ are significantly unequal to 0, it indicates that there is a mediating effect, i.e. production outsourcing can influence the farmers' LCATs through specialised farming.

To explore the moderating effect of off-farm employment on the impact of production outsourcing, we referred to the study of Aiken and West (1991). Specifically, we used the proportion of off-farm income relative to the total household income to indicate the extent of the off-farm employment. As the moderating variable in this paper is continuous, the independent variable is a pseudo-variable, thus the hierarchical regression analysis method is adopted to construct the following moderating effect model (Xu et al. 2021):

$$Technique_i = \omega + \beta_5 Outsourcing_i + \beta_6 Employ_i + \beta_7 Outsourcing_i \times Employ_i + \vartheta Control_i + u_i \quad (6)$$

where: $Employ_i$ – off-farm employment of family i; $Outsourcing_i \times Employ_i$ – cross term of production outsourcing and off-farm employment; ω – constant term; β_5, β_6, β_7, ϑ – parameters to be estimated or the parameter matrix; u_i – random disturbance term.

The other variables and symbols are consistent with Equation (1). When both β_7 and β_1 are significantly nonzero, it indicates the existence of the moderating effect.

The data for the study were collected through a field survey conducted by Northwest Agricultural and Forestry Science and Technology (A&F) University in August 2020 in the middle and upper parts of the Yellow River Basin. The survey employed stratified random

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sampling and structured interviews. Thirteen counties in six provinces, such as Qinghai, Ningxia, Inner Mongolia, Shaanxi, Shanxi, and Henan were selected as the research regions based on the terrain and the level of agricultural economic development. Three to four townships, three to four administrative villages, and 12 to 15 peasant households were randomly selected from each county, resulting in 2 362 peasant households from 44 townships and 182 villages. After excluding missing samples, 1 040 households provided complete information. The distribution of the Yellow River in the study area is depicted in Figure 1.

Table 1 provides a clear overview of variable definitions and summary statistics. In the sample, 22.2% of the respondents adopted low-carbon irrigation technologies, 7.2% adopted low-carbon tillage technologies, and 17.7% adopted low-carbon fertilisation technologies. The overall adoption rate of LCATs appears to be low, likely due to their capital-intensive nature, making them less accessible to individual farmers. A significant 47.6% of the respondents opted for outsourcing production, indicating a well-developed outsourcing service market in recent years. The average specialisation in farming, with a mean value of 0.734, suggests an increasing trend among farmers to focus on specific production areas. Furthermore, off-farm income contributed significantly to the total household income, with an average proportion of 36.9%, highlighting the prevalence of part-time work among farmer households. The demographic data show that the average age of farmer household heads is 57 years, with an average of 7 years of schooling, indicating an ageing and less educated farmer population in China. The proportion of labourers within the total household size is 73.3%, showing the significance of labour within these households. Approximately 60% of farmer households participated in the agricultural insurance programme, demonstrating the proactive approach of farmers in the middle and upper Yellow River regions in mitigating potential risks to agricultural production. In addition, 44.2% of the farmers believe that green production can bring higher returns, indicating that farmers have a positive market awareness of green and low-carbon agricultural products, which will become an important driving force for farmers to adopt LCATs.

Figure 2 illustrates the differences in the choice of production outsourcing and various LCATs among

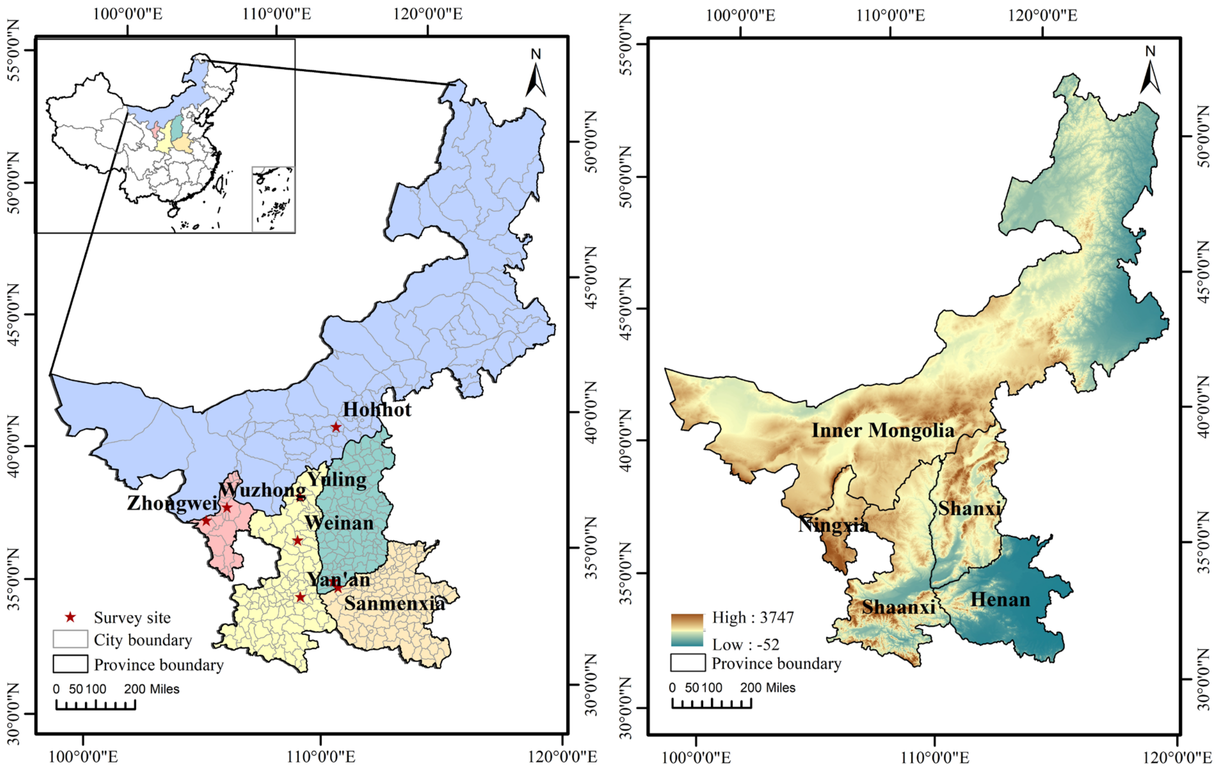

Figure 1. Study area and respondents' distribution

Source: Authors' own processing

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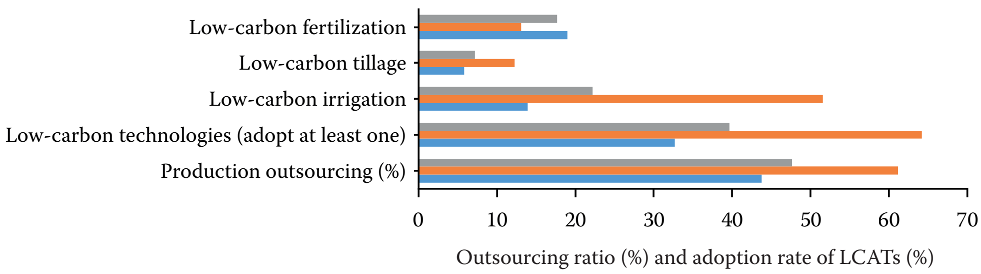
Table 1. Definitions and descriptions of the variables

Variables	Definitions	Mean	SD
Dependent variables			
Low-carbon irrigation	1 if the respondent adopted a low-carbon irrigation technology, 0 if otherwise	0.222	0.416
Low-carbon tillage	1 if the respondent adopted a low-carbon tillage technology, 0 if otherwise	0.072	0.259
Low-carbon fertilization	1 if the respondent adopted a low-carbon fertilization technology, 0 if otherwise	0.177	0.382
Independent variables			
Production outsourcing	1 if the respondent outsourced more than one type of production process, 0 if otherwise	0.476	0.500
Outsourcing level	number of outsourced production processes, including five aspects of land preparation, mulching, harvesting, irrigation, and pest control	0.815	1.121
Mediating variable			
Specialized farming	Herfindahl-Hirschman Index (0–1)	0.734	0.316
Moderating variable			
Off-farm employment	the proportion of off-farm income in total household income	0.369	0.400
Control variables			
Gender	gender of householder's head: male = 1, female = 0	0.958	0.201
Age	age of householder's head (year)	56.901	11.019
Education	educational years of householder's head	6.913	3.627
Health	health level of householder head: unhealthy = 1, in general = 2, health = 3	2.618	0.688
Household size	number of people in a family (person)	3.586	1.548
Labour share	the proportion of household labour in the total household size	0.733	0.301
Social network	number of visitors during Spring Festival (person)	10.488	11.164
Agricultural insurance	1 if the respondent bought agricultural insurance in 2019, and 0 if otherwise	0.591	0.492
Village terrain	village terrain: mountain = 1; hill = 2; plain = 3	2.637	0.724
Production preference	If you pay attention to green production, can you sell it at a good price? 1 = yes, 0 = no	0.442	0.497

Source: Authors' estimates from survey data, 2020



	Production outsourcing	Low-carbon technologies (adopt at least one)	Low-carbon irrigation	Low-carbon tillage	Low-carbon fertilization
Total sample	47.60%	39.62%	22.21%	7.21%	17.69%
Large farmers	61.14%	64.19%	51.53%	12.23%	13.10%
Small farmers	43.77%	32.68%	13.93%	5.80%	18.99%

Figure 2. Distribution of the LCATs adoptions and outsourcing among different farmers

LCATs – low-carbon agricultural technology

Source: Authors' own processing

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the different groups. Based on the mean of the arable land area, we divided the farmers into two groups: small-scale farmers with less than 24 acres and large-scale farmers with more than 24 acres. In the total sample, 47.60% of the farmers realised outsourced production. 39.62% adopted at least one type of LCATs. Specifically, 64.19% of large-scale farmers adopted LCATs, and 32.68% of small-scale farmers adopted LCATs. In addition, a comparison of different LCATs shows that farmers have the highest adoption rate for low-carbon irrigation and the lowest for low-carbon tillage. For smallholders limited by production assets, the adoption rates of capital-intensive technologies, such as low-carbon irrigation (13.93%) and low-carbon tillage (5.80%) are low, while the adoption rate of low-carbon fertilisers (18.99%) is relatively high.

RESULTS AND DISCUSSION

Baseline regression results. This paper used Stata15 to estimate the effect of production outsourcing on the adoption on LCATs. Before estimating, a multicollinearity diagnosis was performed at first, and all the variables passed the multicollinearity diagnosis with a variance inflation factor (*VIF*) of less than 2.5. The regression results of the baseline model are reported in Table 2. In columns (3) and (4), the estimation results show that production outsourcing is statistically significant at the 1% level with positive coefficient signs. The estimated mean marginal effects in column (4) indicate that production outsourcing increases the likelihood of adopting LCATs by 7.2% compared with farmers who do not outsource production. In addition, one of the exciting variables is agricultural insurance, which is statistically significant at the 5% level and has a positive sign of the corresponding marginal effect, implying that purchasing agricultural insurance increases the likelihood of adopting LCATs by 5.6%.

Table 2. Effects of production outsourcing on the LCATs adoption behaviour

Variables	Probit (1)	Probit (2)	Probit (3)	Margins (4)
Production outsourcing	0.299*** (0.087)	0.335*** (0.090)	0.262*** (0.094)	0.072*** (0.026)
Gender	–	0.612** (0.281)	0.645** (0.289)	0.177** (0.079)
Age	–	–0.014*** (0.005)	–0.011** (0.005)	–0.003** (0.001)
Education	–	0.021 (0.013)	0.023 (0.014)	0.006 (0.004)
Health	–	–0.053 (0.071)	–0.090 (0.074)	–0.025 (0.020)
Household size	–	0.017 (0.033)	0.009 (0.034)	0.002 (0.009)
Labour share	–	–0.040 (0.158)	0.043 (0.164)	0.012 (0.045)
Social network	–	–	–0.002 (0.004)	–0.001 (0.001)
Agricultural insurance	–	–	0.205** (0.104)	0.056** (0.028)
Village terrain	–	–	0.492*** (0.097)	0.135*** (0.026)
Constant	–0.916*** (0.063)	–0.772 (0.496)	–2.327*** (0.575)	–
N	1 040	1 040	1 040	1 040
Pseudo R^2	0.011	0.079	0.157	0.157

**, ***significance at the 5% and 1% levels, respectively; LCATs – low-carbon agricultural technology

Source: Authors' own results obtained using Stata15

Endogeneity test. Considering that the farmers' behaviour of production outsourcing is essentially the farmers' self-selection, the self-selection bias will cause endogeneity problems. Then, this paper uses the propensity score matching (PSM) to test the endogeneity of the estimated results of the production outsourcing to improve the farmers' LCATs adoption behaviour. Table 3 reports the estimation results of four mainstream matching methods: the k-nearest neighbour matching method (k = 4), caliper matching method, kernel matching method, and local linear regression matching. The results showed that the average treatment effects (ATT) of production outsourcing under the four matching methods are all statistically significant. After correcting the endogenous bias, the impact of the production outsourcing on the adoption of LCATs is still significantly positive, consistent with the baseline regression results.

Influence mechanism. First, we verified the mediating effect of specialised farming. The regression results are shown in Table 4. Column (1) shows the ordinary least squares regression results for the impact of production outsourcing on specialised farming. The results show that production outsourcing is statistically significant at the 1% level with positive coefficients, which indicates that production outsourcing significantly increases the farmers' specialised farming. The regressions in column (2) include production

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Table 3. Consider the endogeneity of production outsourcing (PSM)

Variable	Matching methods	Treated	Controls	ATT	SE	*T*-stat
Production outsourcing	*k*-nearest neighbor matching	0.269	0.184	0.085***	0.031	2.76
	caliper matching	0.269	0.182	0.087***	0.029	2.96
	kernel matching	0.269	0.189	0.079***	0.028	2.82
	local linear regression matching	0.269	0.188	0.080**	0.037	2.19
	Mahalanobis matching	0.269	0.194	0.074**	0.031	2.42

**, ***significance at the 5% and 1% levels, respectively; ATT – average treatment effect on the treated
Source: Authors' own results obtained using Stata15

Table 4. Analysis of the influence mechanism of production outsourcing

Variables	Specialized farming	Low-carbon technology adoption	
	OLS (1)	Probit (2)	Margins (3)
Production outsourcing	0.060*** (0.020)	0.239*** (0.095)	0.065** (0.026)
Specialized farming	–	0.489*** (0.157)	0.133*** (0.042)
Controls	yes	yes	yes
Constant	0.608*** (0.108)	–2.591*** (0.582)	–
N	1 040	1 040	1 040
R^2	0.076	–	–
Pseudo R^2	–	0.088	0.088

, * significance at the 5% and 1% levels, respectively; OLS – ordinary least squares
Source: Authors' own results obtained using Stata15

outsourcing and specialised farming. The results show that production outsourcing and specialised farming are significant at the 1% level with positive coefficients, indicating that specialised farming partially mediates the effect of production outsourcing on whether farmers implement LCATs. Column (3) shows the regression results of the mean marginal effect in column (2). The marginal effect of production outsourcing is still significant.

Second, we verified the moderating effect of off-farm employment. The results are shown in Table 5. Column (2) shows that the positive impact of the production outsourcing on the LCATs adoption is statistically significant at the 1% level. The estimated coefficient of off-farm employment is statistically significant at the 1% level. In an economic sense, with the increase in off-farm employment, the adoption of LCATs will be hindered. Furthermore, we added the interaction item of production outsourcing and off-farm employment in columns (3) and (4). It is worth noting that the interaction item is significant and positive, which means off-farm employment improves the effect of production outsourcing in promoting the adoption of LCATs. In other words, production outsourcing can alleviate the obstacles to off-farm employment adopting the LCATs. The reason is that off-farm employment leads to the scarcity of the family agricultural labour force. By outsourcing production, farmers can replace labour and machinery and introduce LCATs.

Heterogeneity analysis. It is acknowledged that internal factors, besides production outsourcing, may impact the farmers' LCATs adoption behaviour. As noted in prior research (Chouksey et al. 2021; Acevedo et al. 2020), the varying characteristics of household heads and different planting practices can result in heterogeneity in the farmers' investment decisions for agriculture. Thus, to gain a deeper understanding of the effect of production outsourcing on the farmers' LCATs adoption behaviour in diverse situations, Table 6 presents the results of the heterogeneity regression estimates.

First, considering the influence of the farmers' education level difference on the technology effect of outsourcing, farmers are divided into two groups: those without a secondary education (Education < 9) and those with a secondary education (Education ≥ 9). The results show that the estimation coefficients in columns (1) and (2) are statistically significant. It is worth noting that the marginal effect regression coefficient in column (2)

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Table 5. Moderating the effect estimation results of off-farm employment

Variables	Low-carbon technology adoption			
	Probit (1)	Margins (2)	Probit (3)	Margins(4)
Production outsourcing	0.249*** (0.095)	0.067*** (0.025)	0.268*** (0.096)	0.072*** (0.025)
Off-farm employment	–0.543*** (0.127)	–0.146*** (0.033)	–0.550*** (0.127)	–0.147*** (0.033)
Production outsourcing × off-farm employment	–	–	0.405* (0.245)	0.109* (0.066)
Controls	yes	yes	yes	yes
Constant	–2.231*** (0.583)	–	–2.249*** (0.583)	–
N	1 040	1 040	1 040	1 040
Pseudo R^2	0.096	0.096	0.097	0.097

*, **, ***significance at the 10%, 5%, and 1% levels, respectively
Source: Authors' own results obtained using Stata15

is lower than in column (1). In an economic sense, the technology effect of production outsourcing is stronger for farmers with higher levels of education. The possible explanation is that farmers with higher education levels have a more vital information screening ability to master LCATs as soon as possible through outsourcing production. Therefore, paying more attention to farmers with low education levels is necessary, i.e. strengthen the technical training and improve their cognitive ability.

Then, based on the mean of arable land area, we divided the farmers into small-scale and large-scale farmers. The results in columns (3) and (5) show that the estimation coefficient of production outsourcing is statistically significant at the 1% level for small-scale farmers. However, it is not significant for large-scale farmers. That means the impact of production outsourcing on LCATs shows significant heterogeneity among farmers of different scales. Small-scale farmers that outsource production are more likely to implement LCATs. A possible explanation is that production outsourcing can alleviate the smallholders' lack of resource endowment regarding labour, technology, machinery, and information sources. By contrast, large-scale farmers have strong resource endowments and large social networks. They tend to adopt LCATs with their machinery and equipment. To verify this conjecture, we analysed the substantial impact of resource endowment on the adoption of LCATs. In practice, we chose the ownership of productive assets to represent the resource endowment. The regression results are shown in columns (4) and (6) of Table 6. For every unit increase in productive assets, the adoption rate of LCATs for large-scale farmers increases by 8.2%. Though the estimation coefficient of production outsourcing is still not significant for large-scale farmers. In contrast, the coefficient of productive assets is not significant for small-scale farmers, which also reaffirms the robustness of the heterogeneity findings of this paper.

Robustness check. First, we replaced the core explanatory variable. This paper uses the outsourcing

Table 6. Heterogeneity analysis of production outsourcing effect

Variables	Education < 9	Education ≥ 9	Arable land ≤ 24		Arable land > 24	
	Margins (1)	Margins (2)	Margins (3)	Margins (4)	Margins (5)	Margins (6)
Production outsourcing	0.059*** (0.032)	0.082** (0.042)	0.071*** (0.024)	0.116*** (0.032)	–0.037 (0.071)	0.082 (0.069)
Productive assets	–	–	–	–0.012 (0.017)	–	0.082** (0.034)
Controls	yes	yes	yes	yes	yes	yes
N	601	439	811	811	229	229
Pseudo R^2	0.107	0.067	0.071	0.086	0.071	0.081

*, **, *** significance at the 10%, 5%, and 1% levels, respectively
Source: Authors' own results obtained using Stata15

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level to replace the core explanatory variable 'production outsourcing' in the basic regression model. Specifically, the actual number of outsourcing of the production links is used as a substitute variable for the outsourcing level, and the value is between 0 and 5 (0 indicates that agricultural production is not outsourced; 5 means that all the agricultural production links are outsourced). The outsourcing times of the production links can directly reflect whether farmers outsource production and the degree of vertical division of family farming. The marginal effect estimation result of regression (2) further shows that the probability of the LCATs adoption will increase by 3.6% for each additional unit of outsourcing level.

Second, we replaced the explained variable. Considering that a single technology does not fully represent LCATs, we further selected other LCATs to check the technical impact of production outsourcing. The low-carbon tillage technology was initially selected to take the baseline regression. The estimated results in columns (4) of Table 7 indicate that production outsourcing can significantly improve the farmers' adoption of low-carbon tillage technologies. Besides, we replaced the explained variable with low-carbon fertilisation technologies. The estimated results in columns (6) and (7) show that production outsourcing significantly impacts the farmers' adoption of low-carbon fertilisation technologies.

Third, we add control variables. As rational economic people, farmers mainly pay attention to the economic benefits of agricultural production. When farmers think green production can achieve product premiums and bring higher profits, they are more inclined to adopt LCATs. Therefore, we added the control variable of 'production preference' and re-regression. The results are shown in columns (7) and (8) of Table 7. From the marginal effect results in column (8), after increasing the control variables, production outsourcing is still at a significant level of 5%, which positively promotes the adoption of LCATs. In addition, the coefficient of the production preference is significantly positive at the 1% level, indicating that the probability of farmers adopting LCATs will increase by 8.5% for 1 unit increase in the farmers' income expectations for green production.

Discussion. Our results show that agricultural production outsourcing positively affects the adoption of different LCATs to varying degrees. The results support recent studies on outsourcing production on the frequency and intensity of agrochemical inputs (Liang et al. 2020; Chang et al. 2023). However, they mainly focused on the relationship between production outsourcing and a single technique. Unlike previous studies, we considered the impact difference of three types of technologies (low-carbon tillage, low-carbon irrigation, and low-carbon fertilisation). Additionally, discussions on the mediating role of specialised plating and the moderating role of non-farm employment enrich the existing literature on LCATs (Mao et al. 2023; Zhou et al. 2023). Our findings provide implications

Table 7. Robustness check: replaced the explanatory and explained variables, and added control variables

Variables	Replaced the core explanatory variable		Replaced the explained variable				Added control variables	
	Probit (1)	Margins (2)	Probit (3)	Margins (4)	Probit (5)	Margins (6)	Probit (7)	Margins (8)
Outsourcing level	0.130*** (0.039)	0.036*** (0.010)	–	–	–	–	–	–
Production outsourcing	–	–	0.639*** (0.136)	0.081*** (0.018)	0.356*** (0.108)	0.073*** (0.022)	0.244** (0.095)	0.066** (0.025)
Production preference	–	–	–	–	–	–	0.313*** (0.092)	0.085*** (0.024)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Constant	–2.286*** (0.574)	–	–3.377*** (0.758)	–	0.800 (0.589)	–	–2.564*** (0.587)	–
N	1 040	1 040	1 040	1 040	1 040	1 040	1 040	1 040
Pseudo R^2	0.082	0.082	0.085	0.085	0.205	0.205	0.090	0.090

*, **, ***significance at the 10%, 5%, and 1% levels, respectively

Source: Authors' own results obtained using Stata15

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for policymakers to improve the adoption rates and governance efficiency of LCATs by targeting specialised smallholders and outsourcers. Of course, our work is not exempt from limitations. We exclusively employ cross-sectional data, which restricts our ability to examine the evolving effects of production outsourcing on the farmers' LCATs adoption behaviour over time. Also, we dominantly focus on LCATs adoption within the Yellow River Basin. Future research may benefit from utilising panel data or expanding the geographic coverage of surveys to capture temporal-spatial dynamics more effectively and lead to more precise and broad findings.

CONCLUSION

In the context of addressing climate change, the primary technical approach for achieving low-carbon agricultural development is the widespread adoption of LCATs (Li et al. 2021). This study leverages micro-survey data collected from 1 040 farmers in the Yellow River Basin to investigate the relationship between production outsourcing and the farmers' adoption of LCATs. The study's findings highlight the positive impact of outsourcing production on the farmers' adoption of LCATs. Specifically, outsourcing production can significantly increase the likelihood of farmers adopting low-carbon tillage (by 7.2%), low-carbon irrigation (by 8.1%), and low-carbon fertilisation technologies (by 7.3%). We also examine the role of specialised farming and off-farm employment in shaping this relationship. Specialised farming increases the likelihood of adopting LCATs by a substantial 13.3%. On the other side, off-farm employment tends to decrease the probability of the LCATs adoption by 14.6%. However, outsourcing production can mitigate this negative effect and encourage more LCATs adoption among farmers who are also engaged in off-farm work. Furthermore, the impact of production outsourcing on the farmers' LCATs adoption is heterogeneous across different groups. Farmers with a secondary education who outsource production are more inclined to adopt LCATs. Small-scale farmers are more likely to embrace LCATs than their larger counterparts.

Policymakers should acknowledge the significant impact of production outsourcing on the farmers' adoption of LCATs. To facilitate this, they should actively support the development of a comprehensive agricultural outsourcing system. Promoting outsourcing production processes can help introduce capital-intensive LCATs into the agriculture sector. When providing recommendations for specialised farming practices to encourage LCATs adoption through production outsourcing, it is crucial to consider the specific natural resource conditions and planting advantages within each region. It is also essential to support the growth of organisations that facilitate such practices, particularly for farmers engaged in off-farm employment. Additionally, targeted support should be directed towards small-scale farmers with a higher education level. Moreover, there should be a strong emphasis on enhancing regional education efforts and increasing the farmers' awareness of sustainable agricultural practices.

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