Received: 20 June 2023 | Revised: 15 February 2024 | Accepted: 1 March 2024

DOI: 10.1002/agr.21934

RESEARCH ARTICLE

Agribusiness An International Journal WILEY

# The effects of agricultural machinery services and land fragmentation on farmers' straw returning behavior

Xin Wang[1] | Yanping Song[1] | Wei Huang[2]

[1]School of Economics and Management, Anhui Agricultural University, Hefei, China

[2]Department of Economics, Swedish University of Agricultural Sciences, Uppsala, Sweden

**Correspondence**
Yanping Song
Email: syp@ahau.edu.cn

Wei Huang
Email: wei.huang@slu.se

**Funding information**
Swedish Foundation for International Cooperation in Research and Higher Education (STINT) for the funding support on Joint China-Sweden Mobility program, Grant/Award Number: CH2017-7302; Key Project of Philosophy and Social Sciences in Anhui Province, China, Grant/Award Number: AHSKZ2020D03; The Soft Science Project of Anhui Province, China, Grant/Award Number: 202106f01050060; The Major Project of Humanities and Social Sciences in Anhui Province, China, Grant/Award Number: SK2020ZD12

## Abstract

Straw returning is important for rural ecological management and sustainable agricultural development. Using farm survey data for Anhui Province, China, in 2020, we applied the double-hurdle model to investigate the impact of agricultural machinery services and land fragmentation on farmers' straw-returning behavior, and to explore the relationship between agricultural machinery self-service and outsourced service. Self-service had a significant positive effect on farmers' straw-returning behavior, while outsourced service had a significant positive effect only on degree of adoption. Land fragmentation had a significant negative effect on farmers' straw-returning behavior, and significantly inhibited the effect of self-service on adoption decision. Complementarity existed between self-service and outsourced service in farmers' straw-returning adoption decision, and the effect was more pronounced among smaller-scale farmers. There was significant substitutability between self-service and outsourced service in degree of adoption among larger-scale farmers. Transfer and integration of rural land, increasing agricultural machinery purchase subsidy, upgrading farmers' self-service capability,

**Abbreviations:** 2SLS, two-stage least squares; DWH, durbin-wu-hausman; HCRS, household contract responsibility system; IV-Probit, instrumental variable probit; OLS, ordinary least square.

and promoting development of socialized agricultural machinery services should be implemented to promote crop straw returning. EconLit Citations: Q01, Q16.

**KEYWORDS**

crop straw returning, double-hurdle model, extension service, outsourced service

## 1 | INTRODUCTION

Open-field straw burning can be widely observed in developing countries (Jiang et al., 2021; Seglah et al., 2020). Burning is an economical and convenient method of converting straw into usable nutrients, combined with rapid disposal of agricultural waste and elimination of many pathogens, but it has disadvantages from an environmental perspective (Lai et al., 2022). Straw burning emits large amounts of harmful substances, including particulate matter, carbon monoxide, nonmethane volatile organic compounds, and polycyclic aromatic hydrocarbons, which cause air pollution and endanger human health (Guo, 2021; Liu et al., 2020). Open-field straw burning also contributes an estimated 12%–14% to global warming potential (Andini et al., 2018). Although the practice of straw burning is declining globally because of bans in some countries, it remains a serious problem in developing countries (Ahmed et al., 2015; Kaur et al., 2022; Zheng & Luo, 2022).

Straw returning is a management method that returns straw to the soil as organic fertilizer (Zhang et al., 2019) and is the most cost-effective alternative to burning (Jiang et al., 2021). It avoids ecological damage, increases soil fertility and crop yields, and improves soil carbon sequestration, but also has some drawbacks, such as stimulating emissions of nitrous oxide and methane, which are important greenhouse gases (Li et al., 2018; Liu et al., 2023). Overall, straw returning is an important strategy to improve the greening of agriculture and farmers' welfare (Liu et al., 2023). However, studies have found a clear contradiction between farmers' stated willingness to adopt straw returning and their actual behavior (Chen, Wang, et al., 2023; He et al., 2023). Many countries have made numerous efforts to promote straw returning, but with limited results (Jiang et al., 2021; Seglah et al., 2020). Identifying the reasons for the low adoption rate of straw returning remains an important empirical issue in agriculture.

China is the world's largest developing and agricultural country, with the highest straw production in the world and repeated open burning (Liu et al., 2020). To promote straw returning, China has developed a variety of straw returning modes. The specific mode considered in this study was crushing and returning to the field, which is currently the most popular practice among Chinese farmers (Li et al., 2018). In this approach, the crushed straw is distributed evenly and buried in the tillage layer through multiple operations with tractor-drawn machinery (Tang et al., 2023; Zhao et al., 2018). A better understanding of China's experience with straw returning could help facilitate diffusion of the practice in other developing countries and improve economic development.

The availability of agricultural machinery has been found to be an important factor influencing farmers' decision to adopt straw returning (Tang et al., 2023). The Green Revolution placed mechanization at the heart of agricultural development (Belton et al., 2021; Rigg et al., 2016; Zhang et al., 2017), as a driver of agricultural transformation (Zhou, Ma, et al., 2020). The introduction of technological change depends not only on relative factor prices, but also on the difficulty of factor substitution (Zheng & Xu, 2017). Insufficient supply of tractors and other related agricultural machinery will constrain induced change in straw returning (Liao et al., 2023), while studies by for example, Mano et al. (2020) and Fang et al. (2020) have found that availability of agricultural machinery is positively associated with widespread implementation of improved agronomic practices such as straw returning. Investment in agricultural machinery is a sizable expense and involves high sunk costs that are beyond the means of most farmers in developing countries (Guo, 2021). Purchasing external services is another option by which farmers can achieve mechanization (Houssou et al., 2013; Qian et al., 2022). In Ghana, most farmers access mechanized land preparation services by hiring private tractor services (Houssou et al., 2013). Using field survey data from Sichuan, China, Chen, Zhou, et al. (2023) confirmed that outsourced machinery services have a significant impact on adoption of straw returning by farmers. However, this does not mean that household agricultural machinery can be completely replaced, and in fact household agricultural machinery is indispensable for farmers (Aryal et al., 2019). Thus the literature shows that agricultural machinery plays an important role in straw returning, but no previous study has examined how different sources of machinery affect farmers' straw-returning behavior.

Land fragmentation is a common agricultural characteristic in many developing countries and is defined by McPherson (1982) as the existence of multiple spatially independent plots that are farmed as individual units. Land fragmentation has existed in China since implementation of the Household Contract Responsibility System (HCRS) in the 1980s (Wang, Zang, et al., 2020). Land is divided into different categories based on fertility, proximity, irrigation, and so on, and tenure is distributed according to egalitarianism, so that a family owns several noncontiguous plots of land (Tan et al., 2006). Nowadays, land fragmentation is considered a major obstacle to agricultural activity (Van Phan & O'Brien, 2022) and is a problem that is further exacerbated by frequent land redistribution (Qiu et al., 2022). Survey data show that the average number of land plots owned by Chinese farm households is 4.2 and the average plot size is 0.11 ha (Wang et al., 2022). The impact of land fragmentation on farmers' straw-returning behavior has triggered extensive discussions, and it is generally agreed that there is a negative correlation between land fragmentation and farmers' straw-returning behavior. In a comprehensive review of 77 empirical studies, Xie and Huang (2021) found that farmers are often reluctant to implement pro-environmental farming techniques, including straw returning, on highly fragmented farmland. In addition, numerous studies have revealed a negative impact of land fragmentation on agricultural mechanization (Nguyen & Warr, 2020; Tran & Vu, 2019). Despite farmers' strong desire to use machinery, land fragmentation hinders agricultural mechanization (Huo et al., 2022). Therefore, it is necessary to consider the agricultural characteristics of land fragmentation when studying the impact of agricultural machinery services on farmers' straw-returning behavior, but to our knowledge no such studies have been conducted.

In this study, a comprehensive framework was built to explore the effects of agricultural machinery services (self-service, outsourced service) and land fragmentation on Chinese farmers' straw-returning behavior. The data used in the study were from a survey in 2020 of 426 grain farmers at a fixed observation site in rural Anhui Province, which is one of the important agricultural production areas in China. Statistically, straw residues from annual grain crops (rice, wheat, and corn) account for more than 75% of total crop residues (Chen et al., 2019). Because of the complexity of farmers' decision-making process and the integrated nature of contemporary agricultural technologies, we used a double-hurdle model to divide farmers' behavior into two nonindependent decision processes: adoption decision and degree of adoption.

The contributions of this study are twofold: (1) it attempts to integrate agricultural machinery services, land fragmentation, and farmers' straw-returning behavior into a unified framework to help identify constraints to straw returning to fields, and (2) it assesses the impact of different sources of agricultural machinery services, that is, self-service by purchasing machinery or outsourced service by leasing machinery (Qian et al., 2022; Qiu & Luo, 2021), on straw returning behavior. Considering only one of these may lead to biased estimates, by ignoring potential differences associated with each. Considering self-service and outsourced service together in this study better reflected the actual agricultural mechanization situation of farmers and enabled more comprehensive analysis of the intrinsic links between land fragmentation and farmers' straw-returning behavior in different agricultural machinery service approaches.

The remainder of this paper is organized as follows: Section 2 introduces the theoretical background and research hypotheses. Section 3 presents the model framework, data, variables, and the empirical model. Section 4 discusses the results of the empirical model. Section 5 considers policy implications and Section 6 presents the main conclusions of the work.

# 2 | THEORETICAL BACKGROUND AND HYPOTHESES

## 2.1 | Agricultural machinery services and farmers' straw returning behavior

Most previous research on technology adoption has focused on the demand side, but technology supply plays a critical and often overlooked role in facilitating adoption of new technologies (Aker et al., 2023). According to Davis (1989), perceived ease of use is one of the major antecedents of technology acceptance by users. Ease of technology adoption has a significant impact on straw returning (Liao et al., 2023), and perceived ease of technology contributes the most in influencing farmers' willingness to return straw to the field (Gai et al., 2021). Since straw returning depends on use of agricultural machinery such as tractors, farmers' perceived ease of use of the technology is directly related to their ease of access to the relevant machinery. Studies have shown that agricultural mechanization can effectively promote the diffusion of agricultural technologies (Belton et al., 2021; Takeshima et al., 2013; Yang et al., 2013), and that insufficient supply of machinery is an important constraint to technological change. In China, there are two ways for farmers to access agricultural machinery services: purchasing agricultural machinery for self-service and purchasing outsourced service (Qian et al., 2022). Both self-service and outsourced service have a facilitating effect on farmers' straw-returning behavior (Chen, Zhou, et al., 2023; Jiang et al., 2018). Hou et al. (2019) showed that the likelihood of straw returning by farmers increases when agricultural machinery can meet the demands imposed by straw. Therefore, the following hypotheses were tested in this study:

**H1.** Agricultural machinery services have a positive effect on farmers' straw-returning behavior (H1a. For machinery self-service; H1b. For machinery outsourced service).

## 2.2 | Agricultural machinery self-service and outsourced service

Rational smallholder theory holds that farmers, as rational economic beings who seek to maximize their own interests, can rationally allocate and effectively utilize the resources they possess (Schultz, 1964). In terms of choice of farm service, some scholars believe that the self-service and outsourced service approaches are complementary in agricultural production (Qian et al., 2022). This is confirmed by data showing that 52% of family farms in China purchase outsourced service and also use self-service (Li et al., 2019). However, others report a substitution effect between self-service and outsourced service. Choosing outsourced service may be costly (Hu et al., 2022; Wang et al., 2016), for example, Takeshima et al. (2018) found that switching from rented to owned tractors can increase returns to scale. Larger farms are more likely to invest in owned machinery assets (Qiu & Luo, 2021). For smallholder farmers, purchasing agricultural machinery is not cost-effective and they face high sunk costs (Zhou, Ma, et al., 2020). Outsourcing services can help such farmers avoid risks, reduce transaction costs, and improve roundabout economics (Belton et al., 2021; Zhang et al., 2017). Adu-Baffour et al. (2019) point out that outsourced service can overcome problems with access to machinery and the limitations of mechanization at farm scale. In a study of farm mechanization in Ghana, Diao et al. (2014) found that many smallholder farmers were willing to pay for rental services at market prices and unlikely to pay for full ownership of tractors. There may be a relationship between agricultural machinery self-service and outsourced service, but the nature of this relationship has not yet been identified and it could be either complementary or substitution. Therefore, there may be a substitution or complementary effect between agricultural machinery self-service and outsourced service in straw returning. The following hypothesis was tested in this study:

**H2.** There is a substitution or complementary effect between agricultural machinery self-service and outsourced service in straw returning.

### 2.3 | Land fragmentation and farmers' straw-returning behavior

Land fragmentation is considered an important constraint to technological change (Li et al., 2022). Some studies suggest that land fragmentation prevents a shift in farmers' production behavior through increased labor intensity and higher cost of technology adoption (Bradfield et al., 2021; Jia & Petrick, 2014). As rational economic agents, farmers are often reluctant to invest more in highly fragmented farmland (Xie & Huang, 2021). Increased technology adoption costs reduce farmers' willingness to return straw to the field (Gao et al., 2018). Land fragmentation increases the time and difficulty of agricultural machinery operations, and reduces productivity while increasing the material cost of machinery (Lu et al., 2020; Veljanoska, 2018). When plot size is relatively small, machinery cannot be effectively operated or turned around, which leads to an increase in the cost of straw returning to the field, difficulty in obtaining effects of scale, and lower probability of farmers being willing to implement straw returning (Lu et al., 2020). Despite successful rural land restructuring in China, land fragmentation is still a very serious problem. Fragmented land means that farmers operate at a scale below the threshold for involvement in agricultural machinery services, limiting their adoption decision and degree of adoption of straw returning technology. Therefore, the following hypotheses were tested:

**H3.** Land fragmentation has a negative effect on farmers' straw-returning behavior.

**H4.** Land fragmentation plays a negative moderating role between agricultural machinery services and farmers' straw-returning behavior (H4a. For machinery self-service; H4b. For machinery outsourced service).

## 3 | DATA AND EMPIRICAL MODEL SPECIFICATION

### 3.1 | Data and description of variables

The survey data used in the analysis originated from the Fixed Observation Points of the Ministry of Agriculture and Rural Affairs of China in Anhui Province in 2020. These data are used to capture changes in rural productivity, production relations, and so on, and to understand the dynamics and requirements of different villages and farm households. The sample involved a total of 17 villages, covering different areas such as plains, hills, and mountains, with some villages located on the outskirts of cities. Rural fixed observation data have been used in many previous studies and are recognized as being of high quality (Adamopoulos et al., 2022; Chari et al., 2021). Anhui Province, located in the central region of China, has excellent natural conditions for crop cultivation and was the birthplace of rural reform in China. Crop production in the province is dominated by rice, wheat, and corn, making it an important commodity grain base. In response to the straw disposal problem, the province has developed a 3-year action plan and a 5-year enhancement action for comprehensive utilization of crop straw. Therefore, growers of grain crops in the survey data were selected as the study sample and their straw returning behavior was analyzed. The original survey involved a total of 1298 rural households, collecting basic economic and land information on multiple types of farmers and their villages. The total sample included 483 households growing grain crops, and valid data for 426 of these were retained for analysis after excluding samples with missing relevant variables. The survey data on farmers' straw returning behavior included both mechanical crushing and returning to the field after rotting, of which crushing and returning to the field accounted for an estimated 89.04%[1] of total straw production. This statistical result confirms the

[1]Value calculated by the authors by organizing the data.

appropriateness of the straw returning mode selected for analysis in this study. Definitions of all variables used in this study and the corresponding descriptive analysis are provided in Table 1.

*Farmers' adoption decision on straw returning*: The dependent variable was farmers' straw returning decision making behavior, which comprised two steps: "adoption decision" and "adoption degree." Referring to Mao et al. (2021) and Thompson et al. (2021), for the measure of adoption decision we assigned a value of 1 to adoption of straw returning and a value of 0 to nonreturning, while we used the proportion of total straw output returned to the field to measure degree of adoption. As can be seen in Table 1, the farmers who adopted straw returning comprised 60.1% of the total sample and the returned amount comprised 51.5% of total straw output. Table A1 shows the ratio of seed to straw conversion for grain crops (rice, wheat, and corn) and its sources.

*Agricultural machinery services and land fragmentation*: Agricultural machinery services consisted of two variables, self-service and outsourced service (Qian et al., 2022; Takeshima, 2017). In measuring agricultural machinery services, "whether the household owns a tractor" was used to indicate self-service on a farm.

**TABLE 1** Definitions and descriptive statistics on variables used in the analysis.

| Variables | Definition | Mean | SD |
|---|---|---|---|
| Dependent variables | | | |
| Adoption decision | Whether the farm implements straw returning: yes = 1; no = 0 | 0.601 | 0.490 |
| Adoption degree | Proportion of total straw output returned to land (%) | 0.515 | 0.459 |
| Independent variables | | | |
| Self-service | Whether the household owns a tractor: yes = 1; no = 0 | 0.338 | 0.474 |
| Outsourced service | Number of agricultural machinery service providers/Total number of farm households | 0.011 | 0.012 |
| Land fragmentation | Number of plots per unit area (plots/ha) | 22.128 | 41.392 |
| Control variables | | | |
| Gender | Gender of household head: male = 1; female = 0 | 0.934 | 0.248 |
| Age | Actual age of household head in 2020 (years) | 59.615 | 11.390 |
| Education | Education level of household head (years) | 6.242 | 2.624 |
| Health | Self-evaluated health status: excellent = 1; good = 2; moderate = 3; poor = 4; incapacitated = 5 | 1.718 | 0.978 |
| Total household income | Total household income (10,000 EUR) | 1.185 | 1.102 |
| Cadre households | Yes = 1; no = 0 | 0.031 | 0.172 |
| Labor | Number of laborers (people) | 2.725 | 1.325 |
| Land scale | Total land area of the rural holding (ha) | 0.753 | 1.960 |
| Rented-in land | Whether land is rented-in by the family | 0.131 | 0.338 |
| Cooperative member | Yes = 1; no = 0 | 0.009 | 0.097 |
| Internet access | Whether the family has internet access: yes = 1; no = 0 | 0.826 | 0.379 |
| Village terrain | Village terrain: plains = 1; hills = 2; mountains = 3 | 1.657 | 0.761 |
| Village economic level | Whether the village is more economically developed than the medium level of the county (city) in which it is located: yes = 1; no = 0 | 0.411 | 0.493 |
| No. of observations | | 426 | |

The tractor is one of the most commonly used machines in agricultural production and can be equipped to perform different agricultural production tasks by changing tillage tools (Grabowski et al., 2014; Zhou, Zhang, et al., 2020). Therefore, farms with tractors have an advantage in accessing self-service. “Ratio of number of farm machinery service providers in the village to total number of farm households” was used to indicate outsourced service (the larger the ratio, the easier for farmers to access outsourced service). In the sample, 33.8% of farmers reported owning a tractor and the ratio of farm machinery service providers to total farm households was 0.011, that is, on average, each farm machinery service provider needed to serve around 91 farmers. In measuring degree of land fragmentation, previous studies have generally used number of plots, number of plots per unit area, and Simpson's index (Bradfield et al., 2021; Cao et al., 2022; Rao, 2019; Veljanoska, 2018). However, since the survey data did not cover plot level and since a single measure of land fragmentation such as number of plots would ignore the influence of scale of operations, we used “number of plots per unit area” as the measure of land fragmentation and its mean value was 22.1 (the higher value, the higher the degree of land fragmentation). Average number of plots per household and average plot size were also calculated, with the results showing that the average household in the dataset owned 5.944 plots and the average plot size was 0.129 ha (Table B1).

*Other variables of interest*: We controlled for individual characteristics, household characteristics, and village characteristics. Studies have found that individual characteristics of farmers, such as gender, age and so on, play an important role in technology adoption behavior (Cai et al., 2022; Marescotti et al., 2021). The individual characteristics we considered were gender, age, education, and health of the household head (Table 1). We found that 93.4% of household heads in the sample were male (and thus only 6.6% were female) and that their average age was 59.6 years, with 6.2 years of education. A 5-point scale (*excellent* = 1, *good* = 2, *moderate* = 3, *poor* = 4, *incapacitated* = 5) was used to measure the health status of the household heads, of which 55.1% had excellent status, 26.7% had good status, 10.8% had moderate status, and the remaining 6.3% had poor or incapacitated status (Table C1).

The household characteristics we considered were total household income, cadre households, labor, land scale, rented-in land, membership of cooperative, and internet access. Numerous studies have shown that technology adoption is closely related to farmers' economic power and identity, and that external organization and political identity can increase farmers' sense of responsibility for green production (Gao et al., 2020; Hu et al., 2022; Zheng & Luo, 2022). Number of household laborers, land scale, and the source of land influence farmers' technology adoption behavior (Cao et al., 2020; Gao et al., 2018; Ma et al., 2018; Marescotti et al., 2021; Townsend et al., 2018). Lack of information is an important barrier to technology adoption among farmers, while internet access can facilitate the flow of information (Cai et al., 2022; Michels et al., 2020). We found that the average total income of the farm households in the dataset was 11,850 EUR, with 3.1% of the total sample having a member of the household who was a village leader, only 0.9% of farmers were members of cooperatives, and each household had an average of 2.7 laborers (Table 1). In terms of land, the average size of household operation was 0.75 ha, with around 13.1% of the households renting land. Around 83% of the farmers reported using the internet (Table 1).

The village characteristics we controlled for were terrain and economic level. It has been shown that in villages with differing terrain and economic levels, differences in labor employment opportunities and difficulty in farming due to adverse terrain can result in differences in farmers' production decisions (Qiu & Luo, 2018; Tang & Luo, 2021). For the measure of village terrain, we assigned plains a value of 1, hills a value of 2, and mountains a value of 3. We found that 51.9% of farmers' villages were on plains, 30.5% were on hills, and 17.6% were on mountains (Table C1). We categorized the economic level of the village depending on whether the village was more economically developed than the medium level of the county (city) in which it was located. The results showed that 41.1% of the villages were above the medium economic level (Table 1).

## 3.2 | Empirical model specification

### 3.2.1 | Double-hurdle model

According to the statistics in Table 1, only 60.1% of farmers in the sample returned straw to the field in 2020, which means that 39.9% of farmers did not adopt strawing returning and were assigned a value of zero. Failure to select appropriate econometric methods to deal with these zero values can lead to biased results (Adusah-Poku & Takeuchi, 2019). Econometric models to deal with censoring in latent variables have been developed, such as the Tobit model, double-hurdle model, and Heckman selection model (Makate et al., 2023). Compared with the Tobit model, the double-hurdle model and Heckman selection model provide greater flexibility, make weaker assumptions, and treat individual behavior as a two-stage process (Cragg, 1971; Heckman, 1979), advantages that have been exploited in previous studies. For example, Jafari et al. (2023) explored the export behavior of firms using the double-hurdle model, while Yang et al. (2023) used the Heckman selection model to study adoption by farmers of rice and fish cocultivation technology. However, the double-hurdle model and Heckman selection model treat values of zero in the dataset differently. Humphreys (2013) summarized the key elements when deciding on the appropriate estimator in the presence of zeros and concluded that when zero is a genuine zero, that is, it represents a choice of corner solution, the double-hurdle model is more appropriate. When zeros represent nonobservable responses, that is, true missingness, such as in wage rate models where the sample includes unemployed people, the Heckman selection model is more appropriate (Humphreys, 2013; Lenaerts et al., 2022).

For the purposes of the present study, the double-hurdle model was deemed more appropriate than the Heckman selection model because the Chinese National Development and Reform Commission and Ministry of Agriculture implemented a comprehensive utilization policy for straw, including straw returning, as early as 2009, and strengthened it in 2019 (Liang et al., 2023). It is certain that almost all farmers are aware of straw-returning technology, but still almost 40% of the farmers in the sample did not apply it. Therefore the zeros in the data are genuine zeros, reflecting the farmers' optimal choice rather than representing missing values. The double-hurdle model has been widely used in technology adoption research, for example, Zhang et al. (2023) used it to examine how rural social networks facilitate farmers' participation in water environment management, while Makate et al. (2023) examined farmers' seed purchasing decisions in East Africa with the help of a double-hurdle model. Balana et al. (2022) applied a double-hurdle model to estimate farmers' adoption decisions and intensity of use of inorganic fertilizer and improved seed. Based on this, we constructed a double-hurdle model to analyze the main factors affecting farmers' straw-returning behavior.

In the first hurdle, we used a Probit model to estimate the adoption decision of farmers, constructed as follows:

$$D_i{}^* = \alpha Z_i + u_i,\ u_i \sim N(0, 1), \begin{cases} D_i = 1, \text{ if } D_i{}^* > 0 \\ D_i = 0, \text{ if } D_i{}^* \le 0, \end{cases} \tag{1}$$

where $D_i^*$ is the potential variable ($D_i = 1$ indicates that farmers have adopted the straw returning technology, $D_i = 0$ means they have not); $Z_i$ is a variable affecting the adoption decision of farmers (including independent and control variables); $\alpha$ is a parameter to be estimated; and $u_i$ is a random error term assumed to follow a standard normal distribution.

In the second hurdle, we estimated the degree of adoption using truncated regression and written as:

$$A_i{}^* = \beta X_i + \varepsilon_i,\ \varepsilon_i \sim N(0, \sigma^2), \begin{cases} A_i = A_i{}^*, \text{ if } A_i{}^* > 0, D_i = 1 \\ A_i = 0, \text{ otherise}, \end{cases} \tag{2}$$

where $A_i^*$ is the potential adoption degree variable ($D_i^* > 1$ and $A_i^* > 1$ indicates that the degree of adoption of straw returning by farmers is $A_i = A_i{}^*$); $Z_i$ is a variable affecting the adoption degree of farmers (including independent and control variables); $\beta$ is a parameter to be estimated; and ε is an random error term, which obeys a normal distribution.

The log-likelihood function for the double-hurdle model is:

$$\mathrm{LnL} = \sum_{0} \ln\left[1 - \Phi(\alpha Z_i)\Phi\left(\frac{\beta X_i}{\sigma}\right)\right] + \sum_{+} \ln\left[\Phi(\alpha Z_i)\frac{1}{\sigma}\phi\left(\frac{A_i - \beta X_i}{\sigma}\right)\right]. \tag{3}$$

### 3.2.2 | Moderating effect model

In our initial theoretical Section 2, we established the hypothesis that land fragmentation plays a negative moderating role between agricultural machinery services and farmers' straw-returning behavior (hypothesis H4). To verify whether this effect exists, we referred to existing studies (Zhang et al., 2023), drew on the moderating effect test of Wen et al. (1999), and introduced two interaction terms, land fragmentation and self-service, and land fragmentation and outsourced service, into the model. The model was extended as follows:

$$Y_i = \alpha + \beta_1 \mathrm{MS}_i + \beta_2 \mathrm{LF}_i + \beta_3 \mathrm{MS}_i \times \mathrm{LF}_i + \beta_4 C_i + \mu_i. \tag{4}$$

where $Y_i$ is the dependent variable; $\mathrm{MS}_i$ is agricultural machinery service (including self-service and outsourced service); $\mathrm{LF}_i$ is the moderating variable (land fragmentation); $\mathrm{MS}_i \times \mathrm{LF}$ is the interaction term including land fragmentation and self-service, and land fragmentation and outsourced service; $C_i$ is the control variable; $\alpha$ and $\beta$ are parameters to be estimated; and $\mu_i$ is random error.

## 4 | RESULTS AND DISCUSSION

### 4.1 | Agricultural machinery services, land fragmentation, and farmers' straw returning decision

Table 2 shows the results obtained in the first hurdle with the Probit model (which explained the decision of farmers to return straw), where columns (1), (2), and (3) show the variables self-service of farm machinery, outsourced service, and land fragmentation, respectively. The coefficient of self-service was positive and statistically significant at 1% level, indicating that farm households owning tractors have a higher probability of adopting straw returning. This is similar to findings by Abdulai and Huffman (2014) that mechanization is a driver of agricultural transformation and that farm ownership of tractors can motivate farmers to adopt soil conservation practices. The coefficient of outsourced service was positive, but not significant, indicating that ease of access to outsourced services does not significantly contribute to adoption of straw returning by farmers. A possible explanation is that the Chinese government has issued a ban on open straw burning and provides various support measures for straw returning, actions that have greatly influenced farmers' decision to return straw to the fields (Gao et al., 2018; Zheng & Luo, 2022). The coefficient of land fragmentation was negative and significant at 10% level (Table 2), implying that a higher degree of land fragmentation makes straw returning by farmers less likely, which is similar to findings by Gao et al. (2018). A possible explanation is that fragmented land increases the cost of straw returning, which leads to a decrease in farmers' willingness to adopt. Land fragmentation leads to a decline in agricultural labor productivity and constrains the decision to mechanize, while efficiency can be improved through land consolidation (Jia & Petrick, 2014; Wang, Yamauchi, et al., 2020).

Among the control variables (Table 2), the coefficient of health was negative and significant at 5% level, meaning that farmers with poorer physical health are less likely to adopt straw-returning technology in a context of self-service or land fragmentation. A possible explanation is that although farm machinery can act as a substitute for labor and draft livestock, operators still need to have sufficient energy to operate the machinery (Mano et al., 2020).

**TABLE 2** Estimated coefficient (standard error in brackets) of factors influencing farmers' straw returning decision.

| | Double-hurdle model, first hurdle | | |
|---|---|---|---|
| **Variables** | **(1)** | **(2)** | **(3)** |
| Self-service | 0.512*** | | |
| | (0.171) | | |
| Outsourced service | | 0.048 | |
| | | (0.061) | |
| Land fragmentation | | | −0.004* |
| | | | (0.002) |
| Gender | 0.241 | 0.297 | 0.210 |
| | (0.275) | (0.273) | (0.278) |
| Age | 0.011 | 0.011 | 0.011 |
| | (0.007) | (0.007) | (0.007) |
| Education | −0.010 | −0.016 | −0.010 |
| | (0.029) | (0.028) | (0.029) |
| Health | −0.180** | -0.177** | −0.174** |
| | (0.086) | (0.086) | (0.086) |
| Total household income | −0.065 | -0.071 | −0.076 |
| | (0.080) | (0.083) | (0.084) |
| Cadre households | 0.359 | 0.399 | 0.370 |
| | (0.400) | (0.407) | (0.410) |
| Labor | −0.039 | −0.056 | −0.059 |
| | (0.059) | (0.059) | (0.059) |
| Land scale | 0.789*** | 1.047*** | 1.054*** |
| | (0.199) | (0.184) | (0.183) |
| Rented-in land | 0.346 | 0.367* | 0.341 |
| | (0.211) | (0.212) | (0.213) |
| Cooperative member | −0.162 | −0.296 | −0.380 |
| | (0.603) | (0.602) | (0.601) |
| Internet access | −0.296 | −0.253 | −0.272 |
| | (0.204) | (0.204) | (0.203) |
| Village terrain | 0.098 | 0.083 | 0.184 |
| | (0.108) | (0.111) | (0.124) |
| Village economic level | 0.939*** | 0.912*** | 1.022*** |
| | (0.151) | (0.151) | (0.162) |
| Constant | −1.032 | −0.707 | −1.082* |
| | (0.644) | (0.716) | (0.646) |

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Fragmented land requires more energy from the farmer to adopt straw returning, and energy is lacking in farmers in poorer physical condition. The coefficient of land scale and that of rented-in land (column 2) were both positive and significant at 1% statistical level, indicating that farmers with larger holdings are more likely to adopt straw returning. This is in line with findings by Townsend et al. (2018) in a survey of farmers in the East of England that farm scale is an important factor influencing farmers' willingness to adopt incorporation of straw into the soil, with an increase in farm scale positively influencing their willingness. Large-scale farmers, who are more focused on long-term benefits and more likely to achieve economies of scale, tend to adopt technologies that contribute to sustainable agriculture (Mao et al., 2021). As with the land scale variable, the coefficient of village economic level was positive and statistically significant at 1% level (Table 2). Thus the higher the economic level of a village, the higher the likelihood of farmers adopting straw returning. A possible explanation is that agricultural machinery sets certain financial requirements for the purchaser, and villages at a higher economic level are better able to meet these financial requirements and secure a supply of agricultural machinery (Zheng et al., 2022).

## 4.2 | Agricultural machinery services, land fragmentation, and degree of straw returning

Table 3 shows the results obtained using truncated regression in the second hurdle (which explained the degree of adoption of straw returning by farmers). The coefficients of self-service and outsourced service were positive and significant, at 5% and 1% level, respectively, indicating that both self-service and outsourced service access can significantly improve farmers' straw returning level. Pan et al. (2021) reached similar conclusions in a study of farmers' pesticide use behavior, where advanced farm equipment increased the efficiency of chemical input use and thus achieved a reduction in overall use.

The coefficient of land fragmentation (column [3] in Table 3) was negative and significant at 1% level, implying that land fragmentation inhibits degree of adoption of straw returning by farmers. Similarly, Gao et al. (2020) found that the higher the degree of fragmentation of cultivated land, the lower the incentive for farmers to adopt new agricultural extension methods and the more often they opted for crude farming operations. It has been estimated that the intensity of organic fertilizer application by farmers would increase by 0.19% if plot size were to increase by 1 ha (Li & Shen, 2021). Based on the results in Tables 2 and 3, hypotheses H1 and H3 were confirmed.

Among the control variables, health, land scale, and village economic level all had significant effects on degree of adoption of straw returning by farmers, as found for their adoption decisions in the first hurdle. To some extent, this confirmed that the results obtained in the first hurdle are robust. In addition, gender, age, total household income, and village terrain had a significant effect on the degree of adoption of straw returning by farmers. Males tended to implement straw returning on more land compared with females. This is similar to findings by Liu et al. (2019) that female farmers prefer to adhere to traditional agricultural practices more than males. The coefficient of age was negatively significant at 5% level (Table 3), indicating that age reduces the degree of adoption of straw-returning technology by farmers. Older farmers tend more to discard or burn straw in open fields (Huang et al., 2019). As seen for age, the coefficients of both household income and village topography were negatively significant, indicating that the higher the total annual household income and the more uneven the village terrain, the lower the degree of straw returning by farmers. A possible explanation is that growth in Chinese farmers' household income comes mainly from nonfarm income (Huang & Shi, 2021), and an increase in the proportion of nonfarm income makes farmers less dependent on agriculture and reduces agricultural inputs (Li et al., 2022). Farmland in hilly and mountainous areas of Anhui Province is seriously fragmented, which is not conducive to operation of agricultural machinery (Li et al., 2022).

The coefficients of education, cadre households, labor, cooperative membership, and internet were not statistically significant (Tables 2 and 3), which was an unexpected finding. However, on reviewing the available literature and taking the technical characteristics of straw returning into account, we concluded that these results were reasonable. In terms of socioeconomic factors influencing farmers' straw retention behavior, some previous

**TABLE 3** Estimated coefficient (standard error in brackets) of factors influencing degree of adoption of straw returning by farmers.

| Variables | Double-hurdle model, second hurdle (1) | (2) | (3) |
|---|---|---|---|
| Self-service | 0.068** | | |
| | (0.031) | | |
| Outsourced service | | 0.095*** | |
| | | (0.011) | |
| land fragmentation | | | −0.001*** |
| | | | (0.000) |
| Gender | 0.123** | 0.058 | 0.087 |
| | (0.062) | (0.055) | (0.063) |
| Age | −0.003** | −0.003** | −0.003** |
| | (0.001) | (0.001) | (0.001) |
| Education | −0.007 | −0.002 | −0.002 |
| | (0.006) | (0.005) | (0.006) |
| Health | −0.047*** | −0.011 | −0.039** |
| | (0.017) | (0.015) | (0.017) |
| Total household income | −0.047*** | −0.039** | −0.064*** |
| | (0.018) | (0.018) | (0.021) |
| Cadre households | 0.040 | 0.048 | 0.009 |
| | (0.080) | (0.070) | (0.080) |
| Labor | −0.020 | −0.005 | −0.018 |
| | (0.013) | (0.012) | (0.013) |
| Land scale | 0.021** | 0.011 | 0.022** |
| | (0.009) | (0.008) | (0.009) |
| Rented-in land | 0.010 | −0.004 | −0.010 |
| | (0.039) | (0.034) | (0.039) |
| Cooperative member | 0.099 | 0.017 | 0.056 |
| | (0.167) | (0.146) | (0.165) |
| Internet access | −0.012 | −0.003 | −0.022 |
| | (0.040) | (0.035) | (0.040) |
| Village terrain | −0.022 | −0.121*** | 0.018 |
| | (0.024) | (0.024) | (0.029) |
| Village economic level | 0.114*** | 0.054** | 0.118*** |
| | (0.031) | (0.025) | (0.030) |
| Constant | 1.113*** | 1.697*** | 1.113*** |
| | (0.132) | (0.128) | (0.130) |

***$p < 0.01$; **$p < 0.05$.

studies have found that factors such as education have a negligible effect (He et al., 2023; Martey & Kuwornu, 2021). For example, Xie and Huang (2021) found no effect of household size, farm population, or village cadres on farmers' pro-environmental agricultural technology adoption behavior. Hu et al. (2022) suggest that there are two reasons why labor numbers have a negligible impact on the willingness of farm households to adopt new technologies. First, the main technologies promoted are labor-saving technologies, which may weaken the role of labor. Second, well-developed agricultural services can compensate for shortage of labor in some household agriculture.

We tested the robustness of the above results by replacing the model used (Table D1). The results confirmed that the results in Tables 2 and 3 are robust.

## 4.3 | Relationship between self-service and outsourced service of agricultural machinery

To test whether there is a complementary or substitution relationship between self-service and outsourced service, we introduced an interaction term between farmer self-service and outsourced service into the model. The results are shown in Table 4. The coefficient of the interaction term between farmers' self-service and outsourced service (column [1] in Table 4) was positive and significant at 5% level. This indicates that there is a complementary effect between farm machinery self-service and outsourced service in farmers' straw-returning technology adoption decision, as also found by Qian et al. (2022).

In some developing countries there are great differences between farmers of different scales, which implies that the sample may need to be segmented (Deininger & Byerlee, 2012; Llewellyn & Brown, 2020). Therefore, we subdivided the sample of 426 grain-growing households in this study and assessed differences in the relationship between self-service and outsourced service at different scales of operation. Since there were fewer scale operators in the sample data, we divided the sample into two groups, smaller-scale and larger-scale farmers, based on the mean land operation area of the full sample (0.75 ha).

For smaller-scale farmers, the coefficient of the interaction term between self-service and outsourced service (column (3) in Table 4) was positive and statistically significant at 1% level. This indicates that for smaller-scale farmers, the presence of both self-service and outsourced service can promote adoption of straw returning, i.e., there is a complementary effect between self-service and outsourced service. A possible explanation is that after straw shredding, farmers need to hire higher horsepower machinery for tillage and, for cost reasons, smaller-scale farmers may use their own small machinery to level the land in subsequent steps, rather than continuing to hire machinery.

For larger-scale farmers, the coefficient of the interaction term between self-service and outsourced service (column [6] in Table 4) was negative and statistically significant at 10% statistical level, suggesting that for these farms there is a significant substitution effect between self-service and outsourced service in the degree of straw returning adoption. To achieve greater economies of scale, farmers are more likely to invest in their own machinery and equipment, thereby reducing their purchases of outsourced service (Qiu & Luo, 2021). Therefore, as the scale of land operation increases, the complementary effect between self-service and outsourced service gradually becomes a substitution effect.

## 4.4 | Moderating effect of land fragmentation

Table 5 shows the moderating effect of land fragmentation on the effect of agricultural machinery services on farmers' straw-returning behavior. The results showed that the coefficient of the interaction term between land fragmentation and self-service was always negative, but significant only in the first??? (column [1] in

**TABLE 4** Interaction effects (standard error in brackets) of self-service and outsourced service on adoption of straw returning by farmers.

| | All | | Smaller-scale farmers | | Larger-scale farmers | |
|---|---|---|---|---|---|---|
| | First | Second | First | Second | First | Second |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Self-service | 2.129*** | 0.092 | 3.236*** | 0.134 | 2.781 | −0.327 |
| | (0.723) | (0.101) | (0.957) | (0.134) | (1.741) | (0.225) |
| Outsourced service | −0.053 | 0.086*** | −0.003 | 0.061*** | −0.068 | 0.177*** |
| | (0.080) | (0.014) | (0.091) | (0.018) | (0.325) | (0.036) |
| Self-service × outsourced service | 0.303** | 0.016 | 0.594*** | 0.034 | 0.241 | −0.074* |
| | (0.132) | (0.019) | (0.176) | (0.026) | (0.329) | (0.041) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | −1.082 | 1.668*** | -0.715 | 1.260*** | −1.121 | 2.531*** |
| | (0.737) | (0.134) | (0.897) | (0.186) | (2.490) | (0.272) |

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

**TABLE 5** Moderating influence of land fragmentation (standard error in brackets) on effects of self-service and outsourced service adoption of straw returning by farmers.

| | First | Second | First | Second |
|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) |
| Self-service | 1.546*** | 0.106* | | |
| | (0.296) | (0.056) | | |
| Outsourced service | | | 0.032 | 0.096*** |
| | | | (0.063) | (0.012) |
| Land fragmentation | −0.005** | −0.001*** | −0.000 | −0.001 |
| | (0.002) | (0.000) | (0.004) | (0.001) |
| Self-service × land fragmentation | −0.102*** | −0.005 | | |
| | (0.024) | (0.005) | | |
| Outsourced service × land fragmentation | | | −0.001 | −0.000 |
| | | | (0.001) | (0.000) |
| Control variables | Yes | Yes | Yes | Yes |
| Constant | −1.258* | 1.023*** | −0.868 | 1.690*** |
| | (0.656) | (0.138) | (0.723) | (0.134) |

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 5). This indicates that land fragmentation negatively moderates the effect of agricultural machinery self-service on the adoption decision and degree of straw returning behavior, but has a weaker effect on the degree of adoption, i.e., hypotheses H4a was confirmed. Although farmers who own machinery are more likely to invest more time in agriculture (Ji et al., 2012), land fragmentation increases the human and economic costs to farmers of using their own farm machinery. Most farmers are rational and will choose the most cost-effective way of straw disposal (Fang et al., 2020). On small plots, disposal by burning straw and piling straw randomly seem to be more attractive options to farmers.

The coefficient of the interaction term between land fragmentation and outsourced service was negative, but not statistically significant (Table 5). This indicates that land fragmentation has a negligible negative moderating role in the effect of outsourced service on the adoption decision and degree of straw returning by farmers, that is, hypotheses H4b was confirmed. This differs from previous findings by Wang, Yamauchi, et al. (2020) that land fragmentation severely limits the ability to mechanize agriculture in China. A possible explanation is that increasing supply of outsourced services stabilizes or reduces the price of mechanical hiring. In addition, a previous study has found that hiring tractor services can significantly increase the returns to scale in agricultural production, by about 0.2-0.3%, for farms without tractors (Takeshima, 2017).

## 5 | POLICY IMPLICATIONS

Improper crop straw disposal is an important barrier to sustainable agriculture in developing countries. This study demonstrated the role of agricultural machinery services and land fragmentation in farmers' straw-returning adoption behavior. Based on the results, we identified several policy interventions that can promote straw returning to the field by farmers.

It is important to recognize the important role of agricultural machinery services in farmers' straw-returning behavior. In developing countries, agricultural mechanization is still at a relatively low level and machinery is often inaccessible to small farmers. Agricultural machinery services should be vigorously promoted, so that small farmers can also obtain the benefits enjoyed by large-scale operators.

Small plot size and fragmentation are common features of the land system in China and many developing countries, and are underlying reasons why labor-saving technologies such as machinery have failed to spread (Rada & Fuglie, 2019; Wang, Yamauchi, et al., 2020). Land consolidation projects are needed to encourage land transfer and restructuring of plots to achieve land concentration and expand the scale of operations. However, caution is required in designing and implementing policies to reduce land fragmentation, since in some smallholder contexts land fragmentation can reduce food insecurity (Knippenberg et al., 2020).

## 6 | CONCLUSIONS

Using micro-survey data from 2020 on 426 grain crop-producing farms in Anhui Province, China, we explored the impact of farm machinery services on farmers' straw-returning behavior under land fragmentation and analyzed the relationship between different farm machinery service sources.

We found that access to agricultural machinery services had a positive effect on farmers' straw-returning behavior. Self-service capability in machinery services significantly improved adoption rate and degree of straw returning by farmers, while outsourced service only affected degree of adoption. Land fragmentation inhibited farmers' straw-returning behavior and weakened the positive impact of agricultural machinery services. Interestingly, the inhibitory effect of land fragmentation differed between the two forms of agricultural machinery service studied, with self-service being more effective. Exploration of the relationship between these forms of service revealed a significant complementary effect in adoption decision among smaller-scale farmers, and a significant substitution effect in degree of adoption among large-scale farmers. In addition to agricultural machinery service source and land fragmentation, we found that other important socioeconomic factors, such as farmer health status, land scale, and village economic level, influenced farmers' straw-returning behavior.

Several limitations in this study need to be highlighted. First, it was conducted on a relatively small sample of farmers ($N = 426$), it lacked sufficient survey data on large-scale operators, and all farms were located in Anhui Province, China. Second, to measure outsourced service we had to use responses obtained in the village-level survey, which were provided by village cadres and may not reflect farmers' real access to outsourced service. Additionally, some factors that influence farmers' straw-returning behavior, such as social capital, cost perceptions, and soil fertility (Abdulai, 2016; D'Emden et al., 2008; Teklewold et al., 2013), could not be introduced as control variables. Third, we only assessed the straw shredding behavior of farmers and did not consider other straw utilization modes. Future studies should seek to overcome these limitations.

## AUTHOR CONTRIBUTIONS

**Xin Wang**: Data curation; modeling and simulation; original draft preparation. **Yanping Song**: Idea and conceptualization; supervising. **Wei Huang**: Idea and conceptualization; supervising and investigation; revise and editing.

## ACKNOWLEDGMENTS

The authors highly appreciated the Swedish Foundation for International Cooperation in Research and Higher Education (STINT) for the funding support on Joint China-Sweden Mobility program (CH2017-7302). The study was also supported by the Key Project of Philosophy and Social Sciences in Anhui Province, China (Grant Number: AHSKZ2020D03), the Soft Science Project of Anhui Province, China (Grant Number: 202106f01050060), and the Major Project of Humanities and Social Sciences in Anhui Province, China (Grant Number: SK2020ZD12).

## CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

## ORCID

*Wei Huang* http://orcid.org/0000-0002-6652-8268

## PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/agr.21934.

## REFERENCES

Abdulai, A., & Huffman, W. (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, *90*(1), 26–43.

Abdulai, A. N. (2016). Impact of conservation agriculture technology on household welfare in Zambia. *Agricultural Economics*, *47*(6), 729–741.

Adamopoulos, T., Brandt, L., Leight, J., & Restuccia, D. (2022). Misallocation, selection, and productivity: A quantitative analysis with panel data from China. *Econometrica*, *90*, 1261–1282.

Adu-Baffour, F., Daum, T., & Birner, R. (2019). Can small farms benefit from big companies' initiatives to promote mechanization in Africa? A case study from Zambia. *Food Policy*, *84*, 133–145.

Adusah-Poku, F., & Takeuchi, K. (2019). Household energy expenditure in Ghana: A double-hurdle model approach. *World Development*, *117*, 266–277.

Ahmed, T., Ahmad, B., & Ahmad, W. (2015). Why do farmers burn rice residue? Examining farmers' choices in Punjab, Pakistan. *Land Use Policy*, *47*, 448–458.

Aker, J. C., Dillon, B., & Welch, C. J. (2023). Demand, supply and long-term adoption: Evidence from a storage technology in West Africa. *Journal of Development Economics*, *165*, 103129.

Andini, A., Bonnet, S., Rousset, P., & Hasanudin, U. (2018). Impact of open burning of crop residues on air pollution and climate change in Indonesia. *Current Science*, *115*(12), 2259–2266.

Aryal, J. P., Rahut, D. B., Maharjan, S., & Erenstein, O. (2019). Understanding factors associated with agricultural mechanization: A Bangladesh case. *World Development Perspectives*, *13*, 1–9.

Balana, B. B., Mekonnen, D., Haile, B., Hagos, F., Yimam, S., & Ringler, C. (2022). Demand and supply constraints of credit in smallholder farming: Evidence from Ethiopia and Tanzania. *World Development*, *159*, 106033.

Belton, B., Win, M. T., Zhang, X., & Filipski, M. (2021). The rapid rise of agricultural mechanization in Myanmar. *Food Policy*, *101*, 102095.

Bradfield, T., Butler, R., Dillon, E., Hennessy, T., & Kilgarriff, P. (2021). The effect of land fragmentation on the technical inefficiency of dairy farms. *Journal of Agricultural Economics*, *72*(2), 486–499.

Cai, Y., Qi, W., & Yi, F. (2022). Mobile Internet adoption and technology adoption extensity: Evidence from litchi growers in Southern China. *China Agricultural Economic Review*, *14*(1), 106–121.

Cao, A., Guo, L., & Li, H. (2022). How does land renting-in affect chemical fertilizer use? The mediating role of land scale and land fragmentation. *Journal of Cleaner Production*, *379*, 134791.

Cao, H., Zhu, X. Q., Heijman, W., & Zhao, K. (2020). The impact of land transfer and farmers' knowledge of farmland protection policy on pro–environmental agricultural practices: The case of straw return to fields in Ningxia, China. *Journal of Cleaner Production*, *277*, 123701.

Chari, A., Liu, E. M., Wang, S. Y., & Wang, Y. (2021). Property rights, land misallocation, and agricultural efficiency in China. *The Review of Economic Studies*, *88*(4), 1831–1862.

Chen, H., Wang, H., & Li, Y. (2023). Research on government regulations, cognition and farmers' willingness of straw-to-field. *Sustain*, *15*, 9823.

Chen, J., Gong, Y., Wang, S., Guan, B., Balkovic, J., & Kraxner, F. (2019). To burn or retain crop residues on croplands? An integrated analysis of crop residue management in China. *Science of the Total Environment*, *662*, 141–150.

Chen, Q., Zhou, W., Song, J., Deng, X., & Xu, D. (2023). Impact of outsourced machinery services on farmers' green production behavior: Evidence from Chinese rice farmers. *Journal of Environmental Management*, *327*, 116843.

Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica*, *39*(5), 829–844.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.

Deininger, K., & Byerlee, D. (2012). The rise of large farms in land abundant countries: Do they have a future? *World Development*, *40*, 701–714.

D'Emden, F. H., Llewellyn, R. S., & Burton, M. P. (2008). Factors influencing adoption of conservation tillage in Australian cropping regions. *Australian Journal of Agricultural and Resource Economics*, *52*(2), 169–182.

Diao, X., Cossar, F., Houssou, N., & Kolavalli, S. (2014). Mechanization in Ghana: Emerging demand, and the search for alternative supply models. *Food Policy*, *48*, 168–181.

Fang, Y., Xu, K., Guo, X., & Hong, Y. (2020). Identifying determinants of straw open field burning in northeast China: Toward greening agriculture base in newly industrializing countries. *Journal of Rural Studies*, *74*, 111–123.

Gai, H., Yan, T., Zhang, A., Batchelor, W. D., & Tian, Y. (2021). Exploring factors influencing farmers' continuance intention to crop residue retention: Evidence from rural China. *International Journal of Environmental Research and Public Health*, *18*, 7412.

Gao, L., Zhang, W., Mei, Y., Sam, A. G., Song, Y., & Jin, S. (2018). Do farmers adopt fewer conservation practices on rented land? Evidence from straw retention in China. *Land Use Policy*, *79*, 609–621.

Gao, Y., Zhao, D., Yu, L., & Yang, H. (2020). Influence of a new agricultural technology extension mode on farmers' technology adoption behavior in China. *Journal of Rural Studies*, *76*, 173–183.

Grabowski, P. P., Haggblade, S., Kabwe, S., & Tembo, G. (2014). Minimum tillage adoption among commercial smallholder cotton farmers in Zambia, 2002 to 2011. *Agricultural Systems*, *131*, 34–44.

Guo, S. (2021). How does straw burning affect urban air quality in China? *American Journal of Agricultural Economics*, *103*(3), 1122–1140.

He, J., Zhou, W., Qing, C., & Xu, D. (2023). Learning from parents and friends: The influence of intergenerational effect and peer effect on farmers' straw return. *Journal of Cleaner Production*, *393*, 136143.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*, 153–161.

Hong, W., Luo, B., & Hu, X. (2020). Land titling, land reallocation experience and investment incentives: Evidence from rural China. *Land Use Policy*, *90*, 104271.

Hou, L., Chen, X., Kuhn, L., & Huang, J. (2019). The effectiveness of regulations and technologies on sustainable use of crop residue in northeast China. *Energy Economics*, *81*, 519–527.

Houssou, N., Diao, X., Cossar, F., Kolavalli, S., Jimah, K., & Aboagye, P. O. (2013). Agricultural mechanization in Ghana: Is specialized agricultural mechanization service provision a viable business model? *American Journal of Agricultural Economics*, *95*(5), 1237–1244.

Hu, Y., Li, B., Zhang, Z., & Wang, J. (2022). Farm size and agricultural technology progress: Evidence from China. *Journal of Rural Studies*, *93*, 417–429.
Huang, J., & Shi, P. (2021). Regional rural and structural transformations and farmer's income in the past four decades in China. *China Agricultural Economic Review*, *13*(2), 278–301.
Huang, X., Cheng, L., Chien, H., Jiang, H., Yang, X., & Yin, C. (2019). Sustainability of returning wheat straw to field in Hebei, Shandong and Jiangsu provinces: A contingent valuation method. *Journal of Cleaner Production*, *213*, 1290–1298.
Humphreys, B. R. (2013). *Dealing with zeros in economic data* (Vol. 1, pp. 1–27). University Alberta, Department of Economics.
Huo, Y., Ye, S., Wu, Z., Zhang, F., & Mi, G. (2022). Barriers to the development of agricultural mechanization in the north and northeast China Plains: A farmer survey. *Agric*, *12*(2), 287.
Jafari, Y., Koppenberg, M., Hirsch, S., & Heckelei, T. (2023). Markups and export behavior: Firm-level evidence from the French food processing industry. *American Journal of Agricultural Economics*, *105*(1), 174–194.
Ji, Y., Yu, X., & Zhong, F. (2012). Machinery investment decision and off-farm employment in rural China. *China Economic Review*, *23*(1), 71–80.
Jia, L., & Petrick, M. (2014). How does land fragmentation affect off-farm labor supply: Panel data evidence from China. *Agricultural Economics*, *45*(3), 369–380.
Jiang, W., Yan, T., & Chen, B. (2021). Impact of media channels and social interactions on the adoption of straw return by Chinese farmers. *Science of the Total Environment*, *756*(20), 144078.
Jiang, X., Yan, T. W., Shang, Y., & Zhang, J. B. (2018). Land scale and straw recycling technology adoption: A micro survey based on the four provinces of Hebei, Shandong, Anhui and Hubei. *China Land Science*, *32*(12), 42–49.
Kaur, M., Malik, D. P., Malhi, G. S., Sardana, V., Bolan, N. S., Lal, R., & Siddique, K. H. M. (2022). Rice residue management in the Indo-Gangetic Plains for climate and food security. A review. *Agronomy for Sustainable Development*, *42*, 92.
Knippenberg, E., Jolliffe, D., & Hoddinott, J. (2020). Land fragmentation and food insecurity in Ethiopia. *American Journal of Agricultural Economics*, *102*(5), 1557–1577.
Knuck, J., & Hess, S. (2023). Who buys regional fresh milk brands? An analysis of German household data. *Agribusiness International Journal*, *39*(2), 473–493.
Lai, W., Li, S., Li, Y., & Tian, X. (2022). Air pollution and cognitive functions: Evidence from straw burning in China. *American Journal of Agricultural Economics*, *104*(1), 190–208.
Lenaerts, B., de Mey, Y., & Demont, M. (2022). Revisiting multi-stage models for upstream technology adoption: Evidence from rapid generation advance in rice breeding. *Journal of Agricultural Economics*, *73*(1), 277–300.
Li, B., & Shen, Y. (2021). Effects of land transfer quality on the application of organic fertilizer by large-scale farmers in China. *Land Use Policy*, *100*, 105124.
Li, H., Dai, M., Dai, S., & Dong, X. (2018). Current status and environment impact of direct straw return in China's cropland—A review. *Ecotoxicology and Environmental Safety*, *159*, 293–300.
Li, L., Khan, S. U., Guo, C., Huang, Y., & Xia, X. (2022). Non-agricultural labor transfer, factor allocation and farmland yield: Evidence from the part-time peasants in Loess Plateau region of Northwest China. *Land Use Policy*, *120*, 106289.
Li, N., Wang, X. S., Wang, S. J., & Li, G. S. (2019). Self-purchasing or outsourcing: How does farmland right confirmation affect farmers' choice of agricultural mechanization? *Chinese Rural Economics*, *6*, 54–75.
Liang, F., Li, B., Vogt, R. D., Mulder, J., Song, H., Chen, J., & Guo, J. (2023). Straw return exacerbates soil acidification in major Chinese croplands. *Resources*, *Conservation and Recycling*, *198*, 107176.
Liao, X. J., Zhang, J. Y., & Ning, K. (2023). The selection logic and intervention effect difference of compelled changes of mechanized straw returning technology. *Journal of Jiangxi University of Finance and Economics*, *3*, 107–120.
Liu, D., Song, C., Xin, Z., Fang, C., Liu, Z., & Xu, Y. (2023). Agricultural management strategies for balancing yield increase, carbon sequestration, and emission reduction after straw return for three major grain crops in China: A meta-analysis. *Journal of Environmental Management*, *340*, 117965.
Liu, T., He, G., & Lau, A. K. H. (2020). Statistical evidence on the impact of agricultural straw burning on urban air quality in China. *Science of the Total Environment*, *711*, 134633.
Liu, Y., Ruiz-Menjivar, J., Zhang, L., Zhang, J., & Swisher, M. E. (2019). Technical training and rice farmers' adoption of low-carbon management practices: The case of soil testing and formulated fertilization technologies in Hubei, China. *Journal of Cleaner Production*, *226*, 454–462.
Llewellyn, R. S., & Brown, B. (2020). Predicting adoption of innovations by farmers: What is different in smallholder agriculture? *Applied Economic Perspectives and Policy*, *42*(1), 100–112.
Lu, H., Hu, L., Zheng, W., Yao, S., & Qian, L. (2020). Impact of household land endowment and environmental cognition on the willingness to implement straw incorporation in China. *Journal of Cleaner Production*, *262*, 121479.
Ma, W., Abdulai, A., & Goetz, R. (2018). Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. *American Journal of Agricultural Economics*, *100*(2), 502–520.

Makate, C., Angelsen, A., Terje Holden, S., & Tveitereid Westengen, O. (2023). Rainfall shocks and inequality have heterogeneous effects on farmers' seed purchase decisions in East Africa. *Climate Risk Management*, *42*, 100556.
Mano, Y., Takahashi, K., & Otsuka, K. (2020). Mechanization in land preparation and agricultural intensification: The case of rice farming in the Cote d'Ivoire. *Agricultural Economics*, *51*(6), 899–908.
Mao, H., Zhou, L., Ying, R., & Pan, D. (2021). Time preferences and green agricultural technology adoption: Field evidence from rice farmers in China. *Land Use Policy*, *109*, 105627.
Marescotti, M. E., Demartini, E., Filippini, R., & Gaviglio, A. (2021). Smart farming in mountain areas: Investigating livestock farmers' technophobia and technophilia and their perception of innovation. *Journal of Rural Studies*, *86*, 463–472.
Martey, E., & Kuwornu, J. K. M. (2021). Perceptions of climate variability and soil fertility management choices among smallholder farmers in Northern Ghana. *Ecological Economics*, *180*, 106870.
McPherson, M. F. (1982). *Land fragmentation: A selected literature review*. Harvard University, Harvard Institute for International Development.
Michels, M., Fecke, W., Feil, J. H., Musshoff, O., Lülfs-Baden, F., & Krone, S. (2020). "Anytime, anyplace, anywhere"—A sample selection model of mobile internet adoption in German agriculture. *Agribusiness*, *36*(2), 192–207.
Nguyen, H. Q., & Warr, P. (2020). Land consolidation as technical change: economic impacts in rural Vietnam. *World Development*, *127*, 104750.
Pan, Y., Ren, Y., & Luning, P. A. (2021). Factors influencing Chinese farmers' proper pesticide application in agricultural products—A review. *Food Control*, *122*, 107788.
Van Phan, P., & O'Brien, M. (2022). Is small beautiful? An empirical analysis of land characteristics and rural household income in Vietnam. *Australian Journal of Agricultural and Resource Economics*, *66*(3), 561–580.
Qian, L., Lu, H., Gao, Q., & Lu, H. (2022). Household-owned farm machinery vs. outsourced machinery services: The impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. *Land Use Policy*, *115*, 106008.
Qiu, T., & Luo, B. (2021). Do small farms prefer agricultural mechanization services? Evidence from wheat production in China. *Applied Economics*, *53*(26), 2962–2973.
Qiu, T., Ma, X., Luo, B., Choy, S. T. B., & He, Q. (2022). Land defragmentation in China: Does rental transaction inside acquaintance networks matter? *Journal of Applied Economics*, *25*(1), 260–279.
Qiu, T. W., & Luo, B. L. (2018). What leads to a "tendency to plant grains" in agricultural planting structure? An empirical analysis based on the impact factors of land property rights and factors allocation. *Chinese Rural Economics*, *2*, 65–80.
Rada, N. E., & Fuglie, K. O. (2019). New perspectives on farm size and productivity. *Food Policy*, *84*, 147–152.
Rao, X. (2019). Land fragmentation with double dividends—The case of Tanzanian agriculture. *European Review of Agricultural Economics*, *46*(4), 609–635.
Rigg, J., Salamanca, A., & Thompson, E. C. (2016). The puzzle of East and Southeast Asia's persistent smallholder. *Journal of Rural Studies*, *43*, 118–133.
Schultz, T. W. (1964). *Transforming traditional agriculture*. Yale University Press.
Seglah, P. A., Wang, Y., Wang, H., Bi, Y., Zhou, K., Wang, Y., Wang, H., & Feng, X. (2020). Crop straw utilization and field burning in Northern region of Ghana. *Journal of Cleaner Production*, *261*, 121191.
Takeshima, H. (2017). Custom-hired tractor services and returns to scale in smallholder agriculture: A production function approach. *Agricultural Economics*, *48*, 363–372.
Takeshima, H., Houssou, N., & Diao, X. (2018). Effects of tractor ownership on returns-to-scale in agriculture: Evidence from maize in Ghana. *Food Policy*, *77*, 33–49.
Takeshima, H., Nin—Pratt, A., & Diao, X. (2013). Mechanization and agricultural technology evolution, agricultural intensification in sub-Saharan Africa: Typology of agricultural mechanization in Nigeria. *American Journal of Agricultural Economics*, *95*(5), 1230–1236.
Tan, S., Heerink, N., & Qu, F. (2006). Land fragmentation and its driving forces in China. *Land Use Policy*, *23*(3), 272–285.
Tang, H., Wang, D., Zhao, J., Xu, C., & Wang, J. (2023). Mode and experiments of a straw ditch-burying returning and maturing in cold region of Northeast China. *European Journal of Agronomy*, *151*, 127006.
Tang, L., & Luo, X. (2021). Can agricultural insurance encourage farmers to apply biological pesticides? Evidence from rural China. *Food Policy*, *105*, 102174.
Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics*, *64*(3), 597–623.
Thompson, N. M., Reeling, C. J., Fleckenstein, M. R., Prokopy, L. S., & Armstrong, S. D. (2021). Examining intensity of conservation practice adoption: Evidence from cover crop use on U.S. midwest farms. *Food Policy*, *101*, 102054.
Townsend, T. J., Sparkes, D. L., Ramsden, S. J., Glithero, N. J., & Wilson, P. (2018). Wheat straw availability for bioenergy in England. *Energy Policy*, *122*, 349–357.
Tran, T. Q., & Vu, H. V. (2019). Land fragmentation and household income: first evidence from rural Vietnam. *Land Use Policy*, *89*, 104247.

Veljanoska, S. (2018). Can land fragmentation reduce the exposure of rural households to weather variability? *Ecological Economics*, *154*, 42–51.

Wang, J., CAO, Y., Fang, X., Li, G., & Cao, Y. (2022). Does land tenure fragmentation aggravate farmland abandonment? Evidence from big survey data in rural China. *Journal of Rural Studies*, *91*, 126–135.

Wang, X., Yamauchi, F., Otsuka, K., & Huang, J. (2016). Wage growth, landholding, and mechanization in Chinese agriculture. *World Development*, *86*, 30–45.

Wang, X. B., Yamauchi, F., Huang, J. K., & Rozelle, S. (2020). What constrains mechanization in Chinese agriculture? Role of farm size and fragmentation. *China Economic Review 62*, 101221.

Wang, Y. H., Zang, L. Z., & Araral, E. (2020). The impacts of land fragmentation on irrigation collective action: Empirical test of the social-ecological system framework in China. *Journal of Rural Studies*, *78*, 234–244.

Wen, Z., Hou, J., & Zhang, L. (1999). A comparison of moderator and mediator and their applications. *Acta Psychologica Sinica 2*, 268–274.

Xie, H., & Huang, Y. (2021). Influencing factors of farmers' adoption of pro-environmental agricultural technologies in China: Meta-analysis. *Land Use Policy*, *109*, 105622.

Yang, J., Huang, Z., Zhang, X., & Reardon, T. (2013). The rapid rise of cross-regional agricultural mechanization services in China. *American Journal of Agricultural Economics*, *95*(5), 1245–1251.

Yang, X., Deng, X. Z., & Zhang, A. L. (2023). Does conservation tillage adoption improve farmers' agricultural income? A case study of the rice and fish co-cultivation system in Jianghan Plain, China. *Journal of Rural Studies*, *103*, 103108.

Yang, X. J., Qi, Z. H., Chen, X. T., & Yang, C. Y. (2020). Influence of social capital on farmers' adoption of ecological agriculture technology decision-making behavior: Taking rice and shrimp co-culture technology as an example. *Journal of China Agricultural University*, *25*(6), 1830.

Zhang, S., Deng, M., Shan, M., Zhou, C., Liu, W., Xu, X., & Yang, X. (2019). Energy and environmental impact assessment of straw return and substitution of straw briquettes for heating coal in rural China. *Energy Policy*, *128*, 654–664.

Zhang, X., Yang, J., & Thomas, R. (2017). Mechanization outsourcing clusters and division of labor in Chinese agriculture. *China Economic Review*, *43*, 184–195.

Zhang, Y., Hu, N., Yao, L., Zhu, Y., & Ma, Y. (2023). The role of social network embeddedness and collective efficacy in encouraging farmers' participation in water environmental management. *Journal of Environmental Management*, *340*, 117959.

Zhao, H., Shar, A. G., Li, S., Chen, Y., Shi, J., Zhang, X., & Tian, X. (2018). Effect of straw return mode on soil aggregation and aggregate carbon content in an annual maize-wheat double cropping system. *Soil and Tillage Research*, *175*, 178–186.

Zheng, W., & Luo, B. (2022). Understanding pollution behavior among farmers: Exploring the influence of social networks and political identity on reducing straw burning in China. *Energy Research & Social Science*, *90*, 102553.

Zheng, X. Y., & Xu, Z. G. (2017). Endowment restriction, factor substitution and induced technological innovation: A case research on the grain producing mechanization in China. *China Economic Quality*, *16*(1), 45–66.

Zheng, Y., Zhu, T., & Jia, W. (2022). Does Internet use promote the adoption of agricultural technology? Evidence from 1 449 farm households in 14 Chinese provinces. *Journal of Integrative Agriculture*, *21*(1), 282–292.

Zhou, H., Zhang, C., Zhang, W., Yang, Q., Li, D., Liu, Z., & Xia, J. (2020). Evaluation of straw spatial distribution after straw incorporation into soil for different tillage tools. *Soil Till. Res*. *196*, 104440.

Zhou, X. S., Ma, W. L., Li, G. C., & Qiu, H. G. (2020). Farm machinery use and maize yields in China: An analysis accounting for selection bias and heterogeneity. *The Australian Journal of Agricultural and Resource Economics*, *64*(4), 1282–1307.

**How to cite this article:** Wang, X., Song, Y., & Huang, W. (2026). The effects of agricultural machinery services and land fragmentation on farmers' straw returning behavior. *Agribusiness*, *42*, 104–126. https://doi.org/10.1002/agr.21934

## APPENDIX

### Robustness and endogeneity testing

We explored the robustness of the results in two ways: (i) using an alternative estimation model and (ii) reassigning values to the dependent variable.

(i) Following Adusah-Poku and Takeuchi (2019), we preferred the double-hurdle model with the Heckman selection model. Based on previous studies, we selected "technical training" as an exclusion restriction to improve identification in the Heckman selection model (Yang et al., 2020). The coefficient of λ was not significant, so there

**TABLE A1** Crop seed and straw conversion ratios.[a]

| Name of crop and straw | Seed, straw weight ratio |
|---|---|
| Rice: rice straw | 1:0.90 |
| Corn: cornstalks | 1:1.20 |
| Wheat: wheat straw | 1:1.10 |

[a]Values taken from the training manual for the fixed observation site in rural Anhui Province.

**TABLE B1** Statistics on land ownership situation of farmers in the dataset.

| Variables | Mean | Standard deviation |
|---|---|---|
| No. of land plots | 5.944 | 9.615 |
| Plot size (ha) | 0.129 | 0.093 |

**TABLE C1** Statistics on farmers' health status and village terrain.

| Variables | Category | Number | Percentage |
|---|---|---|---|
| Health | Excellent | 235 | 55.16 |
| | Good | 114 | 26.76 |
| | Moderate | 46 | 10.80 |
| | Poor | 24 | 5.63 |
| | Incapacitated | 7 | 1.64 |
| Village terrain | Plains | 221 | 51.88 |
| | Hills | 130 | 30.52 |
| | Mountains | 75 | 17.61 |

was little evidence of selection bias. We report the estimation results of both the Probit model and OLS model in Table D1 (columns [1]–[3] and [4]–[6], respectively). The coefficients of self-service, outsourced service, and land fragmentation were consistent in direction with those in Tables 2 and 3, and were also statistically significant. This indicates that the findings in Tables 2 and 3 are robust.

(ii) We reassigned values to the degree of adoption by farmers, with 1 for the proportion of straw returning between 0% and 20%, 2 for 20%–40%, 3 for 40%–60%, 4 for 60%–80%, and 5 for >80%. Considering the nonnegative integer nature of the data after reassignment, referring to Knuck and Hess (2023), we estimated again using the negative binomial model. The results are shown in the lower part of Table D1 (columns [7]–[9]). The coefficients of self-service, outsourced service, and land fragmentation were consistent in direction with those in Table 3, and all were similarly statistically significant. This again demonstrates the robustness of the results of the double-hurdle model presented in Tables 2 and 3.

Since there may be a causal relationship between farmers' machinery self-service and their straw-returning behavior, we selected the variable "main source of household income" (agriculture = 1, nonagriculture = 0) as the instrumental variable. It has been confirmed that the larger the share of agricultural income, the higher farmers' willingness to invest, and also that an increase in off-farm employment is more likely to reduce the likelihood of owning small-sized machinery (Hong et al., 2020; Ji et al., 2012). Therefore, the main source of household income

**TABLE D1** Results (mean, standard error in brackets) obtained in robustness and endogeneity testing.

| | Heckman selection model | | | | | |
|---|---|---|---|---|---|---|
| | Probit | | | OLS | | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Self-service | 0.533*** (0.171) | | | 0.257*** (0.044) | | |
| Outsourced service | | 0.040 (0.061) | | | 0.089*** (0.018) | |
| Land fragmentation | | | −0.004* (0.002) | | | −0.002*** (0.001) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| lambda | 0.024 (0.072) | 0.081 (0.055) | −0.044 (0.061) | | | |
| Constant | −0.931 (0.645) | −0.642 (0.719) | −0.974 (0.648) | 0.481*** (0.187) | 1.054*** (0.205) | 0.570*** (0.190) |

| | Negative binomial regression model | | | IV-Probit | 2SLS |
|---|---|---|---|---|---|
| Variables | (7) | (8) | (9) | (10) | (11) |
| Self-service | 0.334*** (0.057) | | | 0.695 (0.807) | 0.486** (0.239) |
| Outsourced service | | 0.138*** (0.027) | | | |
| Land fragmentation | | | −0.003*** (0.001) | | |
| Control variables | Yes | Yes | Yes | Yes | Yes |
| Constant | 1.116*** (0.266) | 1.975*** (0.291) | 1.212*** (0.269) | −1.133 (0.769) | 0.337 (0.247) |
| Wald test of exogeneity | | | | 0.05 | |
| First-stage $F$ statistic | | | | | 14.588 |
| DWH-F statistic | | | | | 0.997 |

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

satisfied the correlation condition. Moreover, straw returning is a technology promoted by the Chinese government, which provides subsidies and bans straw burning, with penalties for violators (Fang et al., 2020; Zheng & Luo, 2022). Household income structure does not have a significant effect on farmers' straw-returning behavior (Cao et al., 2020; Jiang et al., 2021). Therefore, the variable also met the exogeneity condition.

Table D1 also shows the estimated results of the IV-Probit and 2SLS models (columns (10) and (11)). The *F* statistic of the first stage was greater than 10, indicating that the model did not have the problem of weak instrumental variables. The Wald test of exogeneity gave a value is 0.05, which is not significant, and the *F* statistic value of the DWH test was also not significant. Therefore, self-service can be considered an exogenous variable, and the results above are reasonable.

## AUTHOR BIOGRAPHIES

**Xin Wang**, a last-year PhD candidate in the College of Economics and Management, at Anhui Agricultural University.

**Yanping Song**, PhD in agricultural economics. Yanping Song is professor in economics in the College of Economics and Management at Anhui Agricultural University.

**Wei Huang**, PhD in agricultural economics.Wei Huang is a researcher (permanently employed) at the Department of Economics, Swedish University of Agricultural Sciences (SLU). Her research interests include measurement of productivity and efficiency in agricultural economics, evaluation of nonmarket goods in environmental economics, eco-efficiency analysis, and demand system analysis. She obtained a PhD degree in agricultural economics from the University Goettingen, Germany, in 2015. She visited the College of Natural Resources at University of California-Berkeley in 2014. She has published academic research papers as leading author in the journals *Applied Economics Perspective and Policy*, *Ecological Economics*, *Australian Journal of Agricultural and Resource Economics*, *Forest Policy and Economics*, *Land Use Policy*, *German Journal of Agricultural Economics*, *Journal of Rural Studies*, *China Agricultural Economic Review*, *Economics Analysis and Policy*.