Effects of Renting-in Cropland on Machinery Use Intensity and Land Productivity: Evidence from Rural China

by Hongyun Zheng, Wanglin Ma, and Xiaoshi Zhou

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Abstract

This study examines the impacts of renting-in cropland on machinery use intensity, utilizing an innovative endogenous-treatment Poisson regression (ETPR) model and survey data from wheat farmers in China. We also analyze how machinery use intensity affects land productivity, reflected by wheat yields and net returns, using a two-stage residual inclusion (2SRI) model. Unlike previous studies that consider general machinery use, this study considers self-owned machinery use intensity and purchased machinery service use intensity. The ETPR model results reveal that renting-in cropland significantly increases self-owned machinery use intensity. However, it has a negative and insignificant impact on purchased machinery service use intensity. The 2SRI model estimates show that increasing self-owned machinery use intensity and purchased machinery service use intensity significantly increases wheat yields and net returns. Our findings suggest that it is essential to take stakeholders' land transfer status into account when designing policies to promote agricultural mechanization and enhance land productivity.

Keywords: Renting-in cropland; Machinery use intensity; Land productivity; Wheat production; China

JEL Codes: R14; Q15; O33

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[1] College of Economics and Management, Huazhong Agricultural University, Wuhan, China, Email: Hongyun.Zheng@outlook.com;
[2]Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand, Email: Wanglin.Ma@lincoln.ac.nz;
[3]School of Economics and Management, Nanjing University of Science and Technology, Nanjing, China. Email: Xiaoshi.Zhou@outlook.com

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1. Introduction

Farm machinery use plays an increasingly important role in promoting sustainable agricultural production in developing countries. The existing studies have confirmed that farm machinery use can generate various benefits for smallholder agriculture and rural development (Justice & Biggs, 2020; Ma et al., 2018; Mano et al., 2020; Mueller et al., 2019; Paudel et al., 2019; Sims et al., 2016; Takeshima et al., 2020; Van Loon et al., 2020; Zhou et al., 2020). For example, farm machinery use can substantially save farm labor, improve production efficiency and crop productivity, relieve rising real wage issues caused by agricultural labor shortages, and accelerate economic structural transformation. Farm machinery use can also empower rural women in farm management when men migrate to urban regions for better off-farm work opportunities (Ma et al., 2018; Sigh, 2013). Notably, promoting agricultural mechanization increases farm productivity and food security and generates gender equality, building blocks to the United Nations to achieve Goal 2 (zero hunger) and Goal 5 (gender equality) within the 17 Sustainable Development Goals.

Smallholder farmers usually access farm machines through three channels, including renting machines, buying machines, and purchasing machinery services (Ji et al., 2012; Ma et al., 2018; Paudel et al., 2019; Yang et al., 2013; Zhou et al., 2020). Among them, renting machines is the least popular to smallholder farmers as it requires technical know-how on the machinery operation. In comparison, buying machines and purchasing machinery services are two commonly used channels among smallholder farmers as they are more manageable (Binswanger & Singh, 2018; Daum & Birner, 2020; Van Loon et al., 2020; Yang et al., 2013).

An increasing number of studies have investigated the factors affecting farmers' decisions to use self-owned machinery or purchased machinery services (Aryal et al., 2019; Daum & Birner, 2020; Ma et al., 2018; Mottaleb et al., 2017; Mottaleb et al., 2016; Nxumalo et al., 2020; Paudel et al., 2020; Qiu & Luo, 2021; Wang et al., 2020; Yagi & Hayashi, 2020; Yi, 2018). Aryal et al. (2019) reported that economic condition, market access, and off-farm work participation are the main factors determining farmers' machinery use decisions in Bangladesh. Wang et al. (2020) found that farm size and land fragmentation are two essential factors affecting mechanization service use in China. Nxumalo et al. (2020) showed that land tenure, financial assistance, and access to loans mainly influence farmers' mechanization service use in South Africa. A study on China by Qiu & Luo (2021) shows an inverse U-shaped relationship between farm size and the usage of agricultural mechanization services, and households with larger farms are more likely to purchase self-owned machinery assets.

Moreover, some empirical evidence highlights that land transfers play a significant role in affecting farm machinery use (Akram et al., 2020; Deaton et al., 2018; Nguyen & Warr, 2020; Qiu et al., 2020; Yamauchi, 2016). For example, Deaton et al. (2018) showed that farmers are likely to use machinery-related practices such as conservation practices on the rented land in Canada. Akram et al. (2020) found that an increase in the leased land size tends to increase the probability of harvester/thresher ownership in Pakistan. Using rural survey data from China, Qiu et al. (2020) indicated that land rented-in tends to increase machinery use in grain production. These findings can be attributed to the fact that land transfer promotes land consolidation and enlargement, providing a key prerequisite for mechanized agricultural production.

This study extends the previous studies and investigates the associations between renting-in cropland, machinery use intensity, and land productivity. We aim to achieve two analytical objectives: (1) investigating the impacts of renting-in cropland on machinery use intensity; and (2) examining how machinery use intensity affects land productivity. Designing appropriate policies that promote rural land transfers and agricultural mechanization requires a comprehensive understanding of the relationship between farmers' land rental market participation and farm machinery use. Our findings would provide valuable insights for rural development policy design, not only for China but also for other countries promoting rural land transfers and mechanized agricultural production. We analyze data collected from 558 households in three major wheat-producing provinces (i.e., Shandong, Henan, and Anhui) in China.

We attempt to contribute to the literature on rural land rental market development and agricultural mechanization from three aspects. First, we take into account both self-owned machinery use intensity and purchased machinery service use intensity. This differs from previous studies considering binary machinery use decisions (Qiu et al., 2020; Takeshima et al., 2020; Zhou et al., 2020) and general machinery use intensity (Kuwornu et al., 2017; Ma et al., 2018). The usage of machinery use intensity variables can provide a better indication as they consider different production stages. Second, we employ an endogenous-treatment Poisson regression (ETPR) model to address the selection bias issue associated with the renting-in cropland. Farmers choose to rent-in cropland by themselves, and this fact leads to a potential self-selection issue. Ignoring such a self-selection issue in empirical estimation would produce biased estimates. The ETPR model addresses selection bias originating from both observed factors (e.g., age, gender, farm size) and unobserved factors (e.g., farmers' motivation to enlarge cultivated land). Third, we examine the joint impacts of self-owned machinery use intensity and purchased machinery service use intensity on land productivity. A two-stage residual inclusion (2SRI) model is utilized to facilitate the estimation. The findings help us understand whether changes in farm machinery use patterns induced by renting-in cropland would generate productivity gains or losses.

Wheat production in China is an interesting case. According to the data released by FAO, China is the largest wheat producer globally, and wheat production plays an essential role in improving rural households' livelihoods. To boost sustainable production, wheat farmers have used various machines (e.g., rotary cultivator, fertilizer distributor, and harvester) at different production stages (e.g., land preparation, fertilizer application, and harvesting). In recent years, the Chinese government has implemented policy instruments to ensure rural land rights' confirmation, registration, and certification, aiming to promote land transfer and consolidation in rural areas (Luo, 2018). The policy support has provided farmers with an unprecedented opportunity to participate in land rental markets. It is reported that the land transfer rate in

China has increased from 3% in 2004 to 37% in 2018 (NBSC, 2020). The well-developed land rental markets enable farmers to rent-in cropland to achieve economies of scale and improve production efficiency by using farm machines to substitute labor, eventually maximizing land productivity.

The rest of this paper is structured as follows: Section 2 introduces the estimation strategies, and it is followed by Section 3 that presents the data, key variable measurements, and descriptive statistics. The empirical results are presented and discussed in Section 4. The final section concludes with policy implications.

2. Estimation strategies

2.1 Endogenous-treatment Poisson regression (ETPR) model

The first objective of this study is to estimate the impact of renting-in cropland on machinery use intensity. The propensity score matching (PSM) approach and inverse probability weighted regression adjustment (IPWRA) estimator have been employed to eliminate the selection bias issue in previous studies (Liu et al., 2019; Mano et al., 2020; Singha, 2019). However, they can only address observed selection bias but not unobserved selection bias. Therefore, this study employs the ETPR model, which can address observed and unobserved selection bias issues, to conduct the empirical analysis.

The ETPR model estimation involves two stages. The first stage models farmers' renting-in cropland decisions. Following previous studies on land transfers (Zhang et al., 2021; Zou et al., 2020), this study employs a random utility maximization framework to model farmers' renting-in cropland decisions. Let U_{iR}^* and U_{iN}^* be the expected utilities obtained from renting-in and not renting-in cropland, respectively. As farmers are assumed to be risk-neutral and utility-maximizing, they would compare the utility difference (R_i^*) received from renting-in and not renting-in cropland. They choose to rent in the cropland if R_i^* is greater than zero, i.e., $R_i^* = U_{iR}^* - U_{iN}^* > 0$. The unobservable R_i^* can be expressed as a function of observed variables in a latent variable model:

$$R_i^* = \alpha_i X_i + \vartheta_i IV_i + \varepsilon_i;\ R_i = \begin{cases} 1, & if\ R_i^* > 0 \\ 0, & otherwise \end{cases} \tag{1}$$

where R_i^* is a latent variable indicating the probability of renting-in cropland and the observed dichotomous variable R_i determines it. In particular, R_i represents farmers' land transfer status (R_i=1 for households with renting-in cropland and $R_i = 0$ for households without renting-in cropland). X_i is a vector of exogenous variables (e.g., age, gender, family size, and soil types) affecting farmers' decisions to rent in cropland. IV_i refers to an instrumental variable (IV). α_i and ϑ_i refer to vectors of parameters to be estimated. and ε_i is an error term, which is assumed to be normally distributed with zero means. We employ a land certificate variable capturing whether a household obtains land certificates to serve as the IV in Equation (1). In essence, land certificate ownership influences farmers' renting-in land decisions, but it does not directly impact machinery use intensity. A falsification test helps justify the validity and effectiveness of the IV (see the upper part of Table A1 in the Appendix).

The second stage of the ETPR model estimates the impact of renting-in cropland on machinery use intensity. For simplicity, we assume that machinery use intensity (i.e., self-owned machinery use intensity or purchased machinery service use intensity in this study) is a linear function of renting-in cropland variable (R_i) and a vector of explanatory variables (X_i). Formally, we express the functions as follows:

$$S_i = \beta_i R_i + \gamma_i X_i + \mu_i \tag{2}$$

$$M_i = \delta_i R_i + \varphi_i X_i + \upsilon_i \tag{3}$$

where S_i and M_i are two count variables, representing self-owned machinery use intensity and purchased machinery service use intensity, respectively. R_i is a binary variable indicating farmer i' s renting-in cropland status. X_i is a vector of control variables. β_i, γ_i, δ_i, and φ_i are parameters to be estimated. μ_i and v_i are two error terms.

The ETPR model utilizes the maximum likelihood estimator to jointly estimate Equations (1) and (2), and Equations (1) and (3), respectively. Without losing generality, the error term ε_i in Equation (1) and the error term μ_i in Equation (2) are assumed to be bivariate normal with zero mean and covariance matrix:

$$\begin{pmatrix}\varepsilon_i\\ \mu_i\end{pmatrix} \sim \begin{bmatrix}\sigma^2 & \sigma_{\varepsilon\mu}\rho_{\varepsilon\mu}\\ \sigma_{\varepsilon\mu}\rho_{\varepsilon\mu} & 1\end{bmatrix} \tag{4}$$

where σ^2 is the variance of the error term μ_i. $\sigma_{\varepsilon\mu}$ refers to the covariance of error terms ε_i and μ_i. $\rho_{\varepsilon\mu}$ is the correlation coefficient between error terms ε_i and μ_i. Similarly, the joint estimation of Equations (1) and (3) would also generate a correlation coefficient $\rho_{\varepsilon v}$ between error terms ε_i and v_i. If either $\rho_{\varepsilon\mu}$ or $\rho_{\varepsilon v}$ is statistically significant, this would suggest the presence of selection bias arising from unobserved factors (Li et al., 2020; Ma et al., 2020).

2.2 Two-stage residual inclusion (2SRI) model

The second objective of this study is to estimate the impact of self-owned machinery use intensity and purchased machinery service use intensity on land productivity, reflected by crop yields and net returns. To achieve this goal, we follow previous studies (Kumar et al., 2020; Ma & Zhu, 2020; Tesfaye & Tirivayi, 2020; Ying et al., 2019; Zhu et al., 2020) and employ the two-stage residual inclusion (2SRI) model to estimate the impacts of machinery use intensity on land productivity. The 2SRI approach helps address the potential endogeneity issues of machinery use intensity variables (S_i and M_i) and reverse causality between machinery use intensity and land productivity. This is important since better-performing farmers with higher productivity levels may be more likely to use farm machines intensively, which generates potential reverse causality issues that should be addressed.

In the first stage of the 2SRI framework, we specify two models for farmers' decisions on self-owned machinery use intensity and purchased machinery service use intensity, respectively. The models can be written as:

$$S_i = \zeta_i IV_{Si} + \eta_i X_i + \tau_i \tag{5}$$

$$M_i = \theta_i IV_{Mi} + \kappa_i X_i + \sigma_i \tag{6}$$

where S_i, M_i and X_i have been defined defined earlier. IV_{Si} and IV_{Mi} are two additional instrumental variables for model identification purposes; ζ_i, η_i, θ_i, and κ_i refer to parameters to be estimated; τ_i and σ_i represent two error terms. For the usage of IV_{Si} and IV_{Mi}, we construct two variables representing the average self-owned machinery use intensity and average purchased machinery service use intensity of other households (except the sample household) within the same village. Excluding the sampled households when constructing the IVs helps eliminate the potential reverse influence issues in peer effects. Theoretically, the two synthesized IVs directly affect individuals' decisions on machinery use intensity via peer effects but do not affect their land productivity directly. Econometrically, we employ a falsification test to check the validity of IV_{Si} and IV_{Mi}. The results (see the lower part of Table A1 in the Appendix) suggest the synthesized IVs affect machinery use intensity significantly at the 1% level but do not affect land productivity variables (wheat yields and net returns), even at the 10% significance level. The findings justify the validity of the synthesized IVs.

We rely on the conditional mixed process (CMP) model to jointly estimate Equations (5) and (6). Afterward, two residual terms ($Residual_{Si}$ and $Residual_{Mi}$) are predicted. The second stage estimates the land productivity equation. In particular, the residual terms generated from the first stage estimation are included in the land productivity equation as additional regressors. Specifically, the function of the second-stage estimation can be expressed as:

$$Y_i = \lambda_i S_i + \pi_i M_i + \varsigma_i X_i + \xi_i Residual_{Si} + \varrho_i Residual_{Mi} + \omega_i \tag{7}$$

where Y_i refers to land productivity indicator (i.e., wheat yields or net returns in this study). S_i,

M_i and X_i are defined earlier. λ_i, π_i, ς_i, ξ_i, and ϱ_i represent vectors of parameters to be estimated. ω_i refers to an error term. The inclusion of $Residual_{Si}$ and $Residual_{Mi}$ helps account for the endogeneity issues of the variables representing self-owned machinery use intensity and purchased machinery service use intensity, arising from unobserved heterogeneities (Ma & Zhu, 2020; Zhu et al., 2020).

3. Data, key variable measurements, and descriptive statistics

3.1 Data

The data used for the empirical analysis were obtained from a rural household survey that was conducted between June and July 2019 in China. We utilized a stratified sampling technique to select samples. In the first stage, Shandong, Henan, and Anhui provinces were purposely selected as they are the top three major wheat-producing provinces in China. In 2018, Shandong, Henan, and Anhui provinces had wheat sown areas of 4.06, 5.74, and 2.88 million hectares, respectively, accounting for 52.33% of the total sown areas in China. The statistics show that 4.03, 5.62, and 2.57 million hectares of wheat were sown by agricultural mechanization in Shandong, Henan, and Anhui, respectively, and land transfer rates reached 38.69% in Shandong, 38.50% in Henan, and 45.50% in Anhui at the end of 2018 (CAAMM, 2019; CRSY, 2019). In the second stage, two cities were randomly chosen in each selected province, including Linyi and Zaozhuang in Shandong, Xinyang and Zhumadian in Henan, and Suzhou and Huaibei in Anhui. In the next stage, we randomly selected two to three towns in each city and then two to three villages in the selected towns. In the final stage, we randomly selected 10 to 30 households in each selected village. The data collection procedure results in 558 sample households, comprising 84 households with rented-in cropland in 2018, and the rest 474 without renting-in cropland.

We employed a pretest and structured questionnaire to collect comprehensive information on the individual, demographic, household- and farm-level characteristics (e.g., age, gender, and education of household heads, family size and dependency ratio, farm size, and soil types). We also gather information on the inputs (e.g., types and patterns of self-owned machinery use and purchased machinery service use) and outputs (yields and sales prices) of wheat production in the 2018 cropping season. The enumerators who spoke both Mandarin and local dialects conducted a face-to-face interview with sample farmers.

3.2 Key variable measurements

3.2.1 Machinery use intensity

We focus on self-owned machinery use intensity and purchased machinery service use intensity in this study. Each of them is measured as a count variable, capturing the number of production stages using farm machines. We have considered ten stages of wheat production based on our preliminary survey results. They include: (1) land plowing; (2) sowing; (3) fertilizer use; (4) irrigation; (5) pesticide use; (6) weeding; (7) harvesting; (8) transport; (9) threshing; and (10) drying. We prepared ten binary-choice questions in our questionnaire to collect information regarding farmers' self-owned machinery use status at different stages. Likewise, another ten binary-choice questions were prepared to gather information regarding farmers' purchased machinery service use status at different stages. Each question records a value of one if a household has used a farm machine in a particular production stage and zero otherwise. We then aggregated the machinery use information to construct two count variables (0-10) that reflect self-owned machinery use intensity and purchased machinery service use intensity.

Table A2 in the Appendix presents the descriptive statistics of the variables representing the ten production stages. It shows that around 85% of farm households use self-owned machines for pesticide spraying and weeding purposes. Approximately 97% of them purchase machinery services for harvesting and threshing activities. Only 0.9% of farm households use drying machines. Table A3 in the Appendix demonstrates the distributions of the frequencies and cumulative percentages for self-owned machinery use intensity and purchased machinery service use intensity. It shows that 8.24% of farm households did not have any self-owned machines for wheat production, and only 1.79% did not purchase any machinery services. Farm households using self-owned machines at three stages occupy the largest proportion (30%), while those using purchased machinery services at five stages account for the largest proportion (33%) in our surveyed samples. None of the households use self-owned machines or purchased machinery services at all ten stages.

Table A2 Descriptive statistics of machinery use choices by production stages

Production stages	Definition	Self-owned machinery use (%)	Purchased machinery service use (%)
Land plowing	1 if rotary cultivator is used, 0 otherwise	12.37	85.48
Sowing	1 if grain seeder is used, 0 otherwise	18.28	78.67
Fertilizer use	1 if fertilizer distributor is used, 0 otherwise	21.33	59.86
Irrigation	1 if irrigation machine is used, 0 otherwise	41.94	7.89
Pesticide use	1 if power sprayer is used, 0 otherwise	85.13	4.12
Weeding	1 if weeding machine is used, 0 otherwise	84.59	3.58
Harvesting	1 if the harvester is used, 0 otherwise	3.05	96.77
Transport	1 if farming vehicle such as tractor is used, 0 otherwise	49.64	48.03
Threshing	1 if grain thresher is used, 0 otherwise	3.05	96.77
Drying	1 if grain dryer is used, 0 otherwise	0.90	0.90

Table A3 Distributions of the number of production stages using self-owned machinery or purchased machinery services

Number of production stages	Self-owned machinery use intensity			Purchased machinery service use intensity		
	Frequency	Percentage	Cumulative percentage	Frequency	Percentage	Cumulative percentage
0	46	8.24	8.24	10	1.79	1.79
1	27	4.84	13.08	2	0.36	2.15
2	103	18.46	31.54	35	6.27	8.42
3	165	29.57	61.11	63	11.29	19.71
4	117	20.97	82.08	66	11.83	31.54
5	43	7.71	89.78	186	33.33	64.87
6	37	6.63	96.42	155	27.78	92.65
7	12	2.15	98.57	28	5.02	97.67
8	2	0.36	98.92	8	1.43	99.10
9	6	1.08	100.00	5	0.90	100.00
10[a]	0	0	100.00	0	0	100.00
Total	558	100.00		558	100.00	

[a] As shown in Table A2, we have considered ten stages of wheat production in this study. However, our survey shows that none of the households uses machines in all ten stages.

3.2.2 Renting-in cropland

Renting-in cropland is defined as a dichotomous variable, which equals one if a household has rented in cropland for wheat production and zero otherwise. This definition is consistent with the definition used in previous studies (Qiu et al., 2020; Zhang et al., 2020). To enrich our understanding regarding the relationship between land rental market participation and farm machinery use, we also estimate the impact of renting-out cropland on machinery use intensity. As the definition for renting-in cropland variable, renting-out cropland is a dichotomous variable, which has a value of one if a household has rented out cropland and zero otherwise.

3.2.3 Land productivity

We employ two variables, wheat yields and net returns, to reflect land productivity (Zheng et al., 2020). In particular, wheat yields are defined as wheat yields per unit of land (i.e., kg/mu; 1mu=1/15 hectare). Net returns refer to the differences between the total revenue of wheat production and variable costs, which is also measured per unit of land, i.e., yuan/mu. The variable costs include expenditure on seeds, pesticides, fertilizer, machinery (self-owned machinery and purchased machinery services), irrigation, and hired labor.

3.3 Descriptive statistics

The definitions and descriptive statistics of variables used in the empirical analysis are presented in Table 1. We follow the existing literature on land transfer and agricultural mechanization to select the control variables (Akram et al., 2020; Aryal et al., 2019; Benin, 2015; Ma et al., 2018; Qiu et al., 2020; Zhang et al., 2021; Zhou et al., 2020). On average, the total numbers of production stages using self-owned machinery and purchased machinery services were 3.20 and 4.82 (out of 10), respectively. This observation indicates that farmers may prefer the latter to the former in wheat production. Around 15% of sampled households had renting-in cropland for wheat production. The average yields and net returns were 412 kg/mu and 340 yuan/mu, respectively. Table 1 also reveals that the mean age of sample farmers was 56.5 years, and 60% were male. They averagely received 4.73 years of education. The mean farm size for wheat production is 9.07 mu.

Table 2 reports the mean differences in the characteristics between households with and without renting-in cropland. It shows significant differences in self-owned machinery use intensity and purchased machinery service use intensity between the two groups of farmers. Specifically, the intensity of self-owned machinery use is significantly higher for households with renting-in cropland than those without renting-in cropland. However, the intensity of purchased machinery service use is significantly higher for households without renting-in cropland than those with renting-in cropland. The mean comparisons appear to suggest that renting-in cropland increases self-owned machinery use but decreases purchased machinery service use. However, this is not a solid conclusion as confounding factors such as demographic and farm-level characteristics have not been considered in simple mean difference comparison. In fact, we show in Table 2 that households with renting-in cropland differ from those without renting-in cropland in terms of some observed characteristics such as age, education, farm size, and asset ownership. For example, the heads of households with renting-in cropland are younger and better-educated than their counterparts without renting-in cropland. Households with renting-in cropland are more likely to own a larger farm size and air conditioner than those without renting-in cropland. Thus, it is essential to use a rigorous econometric model such as the ETPR model to estimate the impact of renting-in cropland on machinery use intensity.

Table 1 Variable definitions and descriptive statistics

Variables	Definition	Mean (S.D.)
Dependent variables		
Self-owned machinery use intensity	Total number of production stages using self-owned machinery (0-10)	3.20 (1.74)
Purchased machinery	Total number of production stages using purchased	4.82 (1.54)

service use intensity	machinery services (0-10)	
Renting-in cropland	1 if household has rented in cropland for wheat production, 0 otherwise	0.15 (0.36)
Wheat yields	Wheat yields per unit of land (100 kg/mu) [a]	4.12 (1.18)
Net returns	Gross revenue of wheat production minus variable costs (100 yuan/mu) [b]	3.40 (3.52)
Independent variables		
Age	Age of household head (years)	56.50 (11.22)
Gender	1 if household head is male, 0 otherwise	0.60 (0.49)
Education	Schooling years of household head (years)	4.73 (3.84)
Family size	Number of family members (persons)	4.70 (2.45)
Dependency ratio	Ratio of the number of children (15 years or younger) and elder (65 years or older) to the number of family members between 16-64 years old	0.50 (0.59)
Farm size	Size of land used for wheat production (mu)	9.07 (11.31)
Clay soil	1 if cropland has clay soil, 0 otherwise	0.20 (0.40)
Loam soil	1 if cropland has loam soil, 0 otherwise	0.60 (0.49)
Sandy soil	1 if cropland has sandy soil, 0 otherwise	0.20 (0.40)
Asset ownership	1 if household owns an air conditioner, 0 otherwise	0.70 (0.46)
Distance to market	Distance to the nearest input market (km)	2.59 (3.84)
Shandong	1 if household resides in Shandong province, 0 otherwise	0.48 (0.50)
Henan	1 if household resides in Henan province, 0 otherwise	0.26 (0.44)
Anhui	1 if household resides in Anhui province, 0 otherwise	0.26 (0.44)
Instrumental variables		
Land certificate	1 if household obtains land certificates, 0 otherwise	0.75 (0.43)
IV_S	Average use intensity of self-owned machinery of other households within the same village	3.20 (0.86)
IV_M	Average use intensity of purchased machinery services of other households within the same village	4.82 (0.84)
Sample size		558

Note: [a] 1 mu = 1/15 hectare. [b] Yuan is Chinese currency (1USD= 6.90 yuan in 2019). S.D. refers to the standard deviation.

Table 2 Mean differences of the selected variables between households with and without renting-in cropland

Variables	With renting-in cropland	Without renting-in cropland	Mean differences
Self-owned machinery use intensity	3.85 (2.11)	3.09 (1.64)	0.76***
Purchased machinery service use intensity	4.24 (1.88)	4.92 (1.45)	-0.69***
Wheat yields	3.99 (1.35)	4.15 (1.15)	-0.16
Net returns	3.77 (3.38)	3.34 (3.55)	4.28
Age	53.35 (9.03)	57.06 (11.48)	-3.72***
Gender	0.62 (0.49)	0.60 (0.49)	0.02
Education	5.69 (3.73)	4.56 (3.84)	1.13**
Family size	5.00 (2.29)	4.65 (2.48)	0.35
Dependency ratio	0.59 (0.54)	0.49 (0.60)	0.10

Farm size	19.66 (23.58)	7.19 (5.44)	12.47***
Clay soil	0.24 (0.43)	0.19 (0.39)	0.05
Loam soil	0.56 (0.50)	0.61 (0.49)	-0.05
Sandy soil	0.20 (0.40)	0.20 (0.40)	-0.00
Asset ownership	0.80 (0.40)	0.69 (0.46)	0.11**
Distance to market	2.64 (4.12)	2.58 (3.80)	0.06
Shandong	0.58 (0.50)	0.46 (0.50)	0.12**
Henan	0.27 (0.45)	0.25 (0.44)	0.02
Anhui	0.14 (0.35)	0.29 (0.45)	-0.14***
Land certificate	0.71 (0.45)	0.76 (0.43)	-0.04
IV_S	3.09 (0.87)	3.22 (0.85)	-0.14
IV_M	4.81 (0.99)	4.82 (0.81)	-0.01
Sample size	84	474	

Note: *** < 0.01, ** < 0.05. Standard deviation is presented in parentheses.

4. Empirical results

4.1 ETPR model estimates

Table 3 presents the empirical results. We present the results for the impact of renting-in cropland on self-owned machinery use intensity in columns 2-3 of Table 3, and the results for the impact of renting-in cropland on purchased machinery service use intensity in the last two columns of the same table. The results presented in the lower parts of Table 3 show that the coefficients of the correlation terms ($\rho_{\varepsilon\mu}$ and $\rho_{\varepsilon v}$) are statistically significant at the 1% level. The findings suggest the presence of selection bias stemming from unobserved factors and justify the appropriateness of using the ETPR model in this study (Ma & Wang, 2020).

The first-stage estimations of the ETPR model (columns 2 and 4 of Table 3) reveal the determinants of renting-in cropland. They report similar results. In general, we show that farmers' decisions to rent in cropland are significantly associated with farm size, soil types of the cultivated cropland, location-fixed characteristics, and land certificate ownership, which are largely consistent with the findings in the literature (Feng et al., 2010; Jin & Deininger, 2009; Qiu et al., 2020).

In the next section, we will first discuss the impact of renting-in cropland on machinery use intensity. This is followed by the discussion regarding the impact of control variables on machinery use intensity.

4.1.1 Impact of renting-in cropland on machinery use intensity

We show that the renting-in cropland variable's coefficient is positive and statistically significant in the third column of Table 3, while its coefficient is negative but insignificant in the last column of the same table. The results suggest that renting-in cropland significantly increases self-owned machinery use intensity, but it does not affect purchased machinery service use intensity significantly. To some extent, our findings are in line with the findings of Qiu & Luo (2021), who reported that large farms tend to invest in self-owned machinery equipment in China. Several facts help explain the relationship between renting-in cropland and machinery use intensity, and we discuss the potential reasons from two major aspects for simplicity. First, the expansion of land scale achieved by renting-in cropland helps farmers achieve economies of scale, reducing the unit cost of using self-owned machinery in wheat production (Peng et al., 2020; Wang et al., 2020). In comparison, smallholder farmers face price uncertainties when purchasing machinery services as they are price-takers in the machinery service markets. Thus, when expanding cropland size by renting-in cropland, using self-owned machines becomes a cost-saving strategy for smallholder farmers in wheat production. Although purchased machines are initially expensive, they, as fixed household assets, can be reused yearly, reducing production costs in the long run.

Table 3 Impacts of renting-in cropland on machinery use intensity: ETPR model estimations

Variables	ETPR model		ETPR model	
	Renting-in cropland (Coefficients)	Self-owned machinery use intensity (Coefficients)	Renting-in cropland (Coefficients)	Purchased machinery service use intensity (Coefficients)
Renting-in cropland		0.230 (0.067)***		-0.054 (0.045)
Age	-0.011 (0.007)	-0.005 (0.002)**	-0.010 (0.007)	0.002 (0.001)
Gender	-0.082 (0.182)	0.002 (0.047)	-0.084 (0.180)	-0.017 (0.027)
Education	0.005 (0.026)	-0.001 (0.006)	0.005 (0.026)	0.005 (0.004)
Family size	-0.003 (0.037)	0.018 (0.010)*	-0.003 (0.037)	0.0001 (0.006)
Dependency ratio	0.089 (0.123)	-0.011 (0.039)	0.083 (0.121)	0.002 (0.022)
Farm size	0.124 (0.016)***	0.004 (0.001)***	0.122 (0.016)***	-0.011 (0.003)***
Clay soil	-0.506 (0.300)*	0.271 (0.070)***	-0.505 (0.295)*	-0.145 (0.045)***
Loam soil	-0.364 (0.209)*	0.221 (0.058)***	-0.360 (0.209)*	-0.040 (0.031)
Asset ownership	0.111 (0.212)	0.170 (0.050)***	0.118 (0.211)	-0.098 (0.027)***
Distance to market	-0.033 (0.031)	-0.005 (0.005)	-0.031 (0.029)	0.003 (0.002)
Shandong	0.968 (0.235)***	-0.404 (0.053)***	0.977 (0.231)***	0.181 (0.032)***
Henan	-0.232 (0.326)	-0.188 (0.058)***	-0.214 (0.315)	0.031 (0.042)
Constant	-1.650 (0.544)***	1.203 (0.144)***	-1.668 (0.537)***	1.569 (0.091)***
Land certificate	-0.363 (0.182)**		-0.364 (0.180)**	
$\rho_{\varepsilon\mu}$	-0.941 (0.021)***			
Wald test ($\rho_{\varepsilon\mu}$=0)	$Chi^2(1)$=88.75***, Prob>chi^2 =0.001			
$\rho_{\varepsilon v}$			0.884 (0.068)***	
Wald test ($\rho_{\varepsilon v}$=0)			$Chi^2(1)$=20.32***, Prob>chi^2 =0.001	
Sample size	558		558	

Note: *** < 0.01, ** < 0.05, * < 0.10. Robust standard errors are presented in parentheses. The reference region is Anhui. The reference soil is sandy soil.

We have conducted a variance inflation factor (VIF) test to check the potential multicollinearity issue of the control variables. The results show that the estimated mean VIF is 1.44, which is smaller than the critical value of 10. This finding suggests that the selected explanatory variables have no multicollinearity issues (Zheng & Ma, 2021).

Second, agricultural mechanization among smallholder farmers is usually restricted by a high degree of land fragmentation in China (Wang et al., 2020; Yang et al., 2013). Our survey also shows that farmers produce wheat on average four plots. To remove this barrier and achieve efficient mechanization production, farmers may rent in adjacent plots to consolidate fragmented cropland. The consolidated cropland also helps reduce the costs of self-owned machinery use rather than the costs of purchased machinery services. As discussed previously, purchased machines can be reused yearly, while farmers must pay costs once they choose to purchase machinery services. This fact motivates farmers to use self-owned machines to support wheat production. Yi et al. (2019) observed that farmers tend to invest in self-owned capital to substituted mechanization services when land consolidation increases.

Our discussions above have focused on renting-in cropland. To enrich our understanding regarding land transfer and machinery use intensity, we estimate the impact of renting-out cropland on machinery use intensity, using the 2SRI approach. The results are presented in Table A4 in the Appendix. We show that renting-out cropland does not significantly impact self-owned machinery use intensity and machinery service use intensity, even at the 10%

significant level. The impacts are negative. If farmers want to reduce farm size or quit agricultural production for re-allocating family laborers to off-farm activities, they may choose to rent out their cropland. If this is the case, the demand for farm machines will reduce.

Table 4 Impacts of machinery use intensity on land productivity: 2SRI model estimation

	First stage (CMP estimation)		Second stage (OLS estimation)	
Variables	Self-owned machinery use intensity (Coefficients)	Purchased machinery service use intensity (Coefficients)	Wheat yields (Coefficients)	Net returns (Coefficients)
Self-owned machinery use intensity			0.373 (0.120)***	1.386 (0.435)***
Purchased machinery service use intensity			0.522 (0.132)***	1.274 (0.435)***
Age	-0.019 (0.006)***	0.011 (0.005)**	0.001 (0.004)	0.008 (0.013)
Gender	0.048 (0.145)	-0.112 (0.125)	0.036 (0.083)	0.006 (0.280)
Education	-0.002 (0.019)	0.013 (0.017)	0.006 (0.011)	0.050 (0.036)
Family size	0.052 (0.028)*	-0.004 (0.025)	-0.039 (0.018)**	-0.117 (0.054)**
Dependency ratio	-0.049 (0.115)	0.001 (0.100)	-0.027 (0.066)	-0.109 (0.249)
Farm size	0.029 (0.006)***	-0.024 (0.005)***	-0.008 (0.005)	-0.006 (0.012)
Sandy soil	0.254 (0.237)	-0.435 (0.200)**	0.291 (0.163)*	0.703 (0.529)
Loam soil	0.191 (0.186)	-0.017 (0.156)	0.366 (0.127)***	1.024 (0.453)**
Asset ownership	0.465 (0.153)***	-0.374 (0.132)***	-0.024 (0.099)	-0.469 (0.311)
Distance to market	-0.028 (0.018)	0.018 (0.015)	-0.011 (0.010)	0.010 (0.029)
Shandong	-0.457 (0.187)**	0.316 (0.154)**	0.574 (0.148)***	1.212 (0.492)**
Henan	-0.324 (0.212)	0.177 (0.180)	-0.843 (0.154)***	-2.787 (0.488)***
Constant	1.587 (0.502)***	1.313 (0.521)**	0.286 (0.974)	-7.552 (3.485)**
IV_S	0.638 (0.077)***			
IV_M		0.676 (0.069)***		
$\rho_{\tau_i \sigma_{i_o}}$	-0.913 (0.042)***			
$Residual_S$			-0.330 (0.130)**	-1.308 (0.465)***
$Residual_M$			-0.444 (0.143)***	-1.340 (0.488)***
Sample size	558		558	558

Note: *** < 0.01, ** < 0.05, * < 0.10. Robust standard errors are presented in parentheses. The reference region is Anhui. The reference soil is sandy soil. Wheat yields are measured in 100 kg/mu. Net returns are measured in 100 yuan/mu.

4.1.2 Impact of control variables on machinery use intensity

The ETPR model estimation shows that the age of household heads, family size, farm size, soil types, asset ownership, and regional dummies also determine machinery use intensity. The coefficient of age variable is negative and statistically significant in column 3 of Table 3, indicating that older farmers tend to use less self-owned machinery in wheat production. Our findings are in line with the results of Akram et al. (2020), who reported that the probability of owning farm machinery (i.e., tube well/water pump, tractor, farm implements, and harvester/thresher) decreases with the increasing age of farmers in Pakistan. The family size variable has a positive and statistically significant coefficient in column 3 of Table 3. The finding suggests that larger family size is associated with a higher level of self-owned machinery use intensity. The results show that the coefficient of the farm size variable is positive and statistically significant in column 3, while it turns significantly negative in the last column of Table 3. The findings suggest that larger farm size significantly increases self-owned machinery use intensity and reduces purchased machinery service use intensity.

Soil types matter with farmers' decisions of utilizing self-owned machinery and purchased machinery services. Specifically, relative to households cultivating cropland with sandy soil (reference group), those growing wheat on cropland with clay and loam soil are more likely to increase self-owned machinery use intensity. In contrast, wheat farmers growing on cropland with clay soil are less likely to increase purchased machinery service use intensity. Table 3 also shows that the asset ownership variable has a positive and statistically significant coefficient in column 3 and a negative and statistically significant coefficient in the table's last column. The findings indicate that asset ownership tends to increase the self-owned machinery use intensity and decrease purchased machinery service use intensity. Asset ownership is a proxy of household wealth. Wealthier farmers may have sufficient capital to buy machines for long-term usage rather than purchasing one-off machinery services. The significant coefficients of regional dummy variables suggest that compared with farmers in Anhui (reference group), those living in Shandong and Henan are less likely to intensify the usage of self-owned machines in wheat production. By contrast, Shandong farmers are more likely to boost the use of purchased machinery services in wheat production.

4.2 The 2SRI model estimates

Table A4 Impacts of renting-out cropland on machinery use intensity: 2SRI model estimation

	First stage (Probit model)	Second stage (Poisson model)	
Variables	Renting-out cropland (Coefficients)	Self-owned machinery use intensity (Coefficients)	Purchased machinery service use intensity (Coefficients)
Renting-out cropland		-0.247 (0.201)	-0.140 (0.090)
Age	0.004 (0.008)	-0.005 (0.002)**	0.002 (0.001)
Gender	0.010 (0.177)	-0.007 (0.047)	-0.017 (0.027)
Education	0.032 (0.024)	0.001 (0.006)	0.006 (0.004)
Family size	0.055 (0.036)	0.019 (0.010)*	0.001 (0.006)
Dependency ratio	0.050 (0.123)	-0.002 (0.039)	0.003 (0.022)
Farm size	-0.086 (0.031)***	0.006 (0.002)***	-0.013 (0.003)***
Sandy soil	0.119 (0.300)	0.249 (0.072)***	-0.142 (0.044)***
Loam soil	-0.034 (0.225)	0.199 (0.060)***	-0.041 (0.030)
Asset ownership	0.073 (0.210)	0.174 (0.051)***	-0.099 (0.027)***
Distance to market	-0.031 (0.040)	-0.005 (0.005)	0.003 (0.002)
Shandong	0.072 (0.218)	-0.363 (0.053)***	0.181 (0.032)***
Henan	0.197 (0.308)	-0.186 (0.059)***	0.032 (0.042)
Constant	-1.909 (0.578)***	1.244 (0.150)***	1.585 (0.094)***
IV1[a]	2.967 (0.477)***		
Residual (Renting-out cropland)		0.152 (0.217)	0.106 (0.102)
Sample size	558	558	558

Note: *** < 0.01, ** < 0.05, * < 0.10. Robust standard errors are presented in parentheses. The reference region is Anhui. The reference soil is sandy soil.

[a] We construct an instrumental variable, IV1, which is defined as the ratio of the number of households with renting-out cropland to the number of other households within the same village. This instrumental variable (IV1) is expected to affect farmers' decisions on renting-out cropland but not directly influence machinery use intensity.

The results estimated by the ETPR model suggest that households with renting-in cropland are more likely to increase the utilization intensity of self-owned machinery than purchased machinery services in wheat production. A further interesting question is how machinery use intensity induced by renting-in cropland affects land productivity. To find an answer to this question, we estimate the impact of machinery use intensity on land productivity. As indicated earlier, the 2SRI model is used to facilitate the estimation. The results are presented in Table 4. Precisely, the first-stage results shown in columns 2-3 are estimated by Equations (5) and (6), using the CMP model. The results presented in the last two columns of Table 4 are estimated by Equation (7) for two land productivity indicators (i.e., wheat yields and net returns), using an ordinary least squares (OLS) regression model. We include the predicted residual terms in the land productivity equations to account for the endogeneity issues of the two machinery use intensity variables.

The results (lower parts of the last two columns in Table 4) show that the two residual terms are statistically significant, suggesting the presence of endogeneity issues and confirming the appropriateness of using the 2SRI approach (Ma & Zhu, 2020; Zhu et al., 2020). Our estimates in Table 4 show that the coefficients of self-owned machinery use and purchased machinery service use variables are positive and statistically significant after controlling potential endogeneity issues. The findings suggest that intensifying either self-owned machines or purchased machinery services in wheat production would improve land productivity by increasing wheat yields and net returns. Farm machinery use increases the application efficiency of inputs (e.g., pesticides and fertilizers) and adoption of proper agronomic practices, reduces input waste in its application, and saves production costs, contributing to increases in wheat yields and net returns. Our findings that machinery use improves land productivity echo with the results in previous studies (Mano et al., 2020; Zhou et al., 2018, 2020).

5. Conclusions and policy implications

This study examined the impact of renting-in cropland on machinery use intensity by distinguishing self-owned machinery use intensity and purchased machinery service use intensity. The nexus between machinery use intensity and land productivity, reflected by wheat yields and net returns, was also investigated. Both the ETPR model and 2SRI model were applied to address the endogeneity issues. The empirical analyses relied on survey data of 558 wheat farmers from Shandong, Henan, and Anhui provinces in China.

The ETPR estimates showed that renting-in cropland has a positive and statistically significant impact on self-owned machinery use intensity. Its impact on purchased machinery service use intensity is negative and insignificant. Besides, self-owned machinery use intensity is mainly affected by the age of household heads, family size, farm size, cropland soil types, and asset ownership. Farm size, soil types, and asset ownership mainly determine the purchased machinery service use intensity. The 2SRI model estimates revealed that intensifying either self-owned machinery use or purchased machinery service use improves land productivity by increasing wheat yields and net returns.

Our findings that renting-in cropland increases self-owned machinery use intensity underscore the importance of considering stakeholders' land transfer status when designing policy to accelerate agricultural mechanization and increase land productivity. Specifically, for farmers with renting-in cropland, policymakers should provide subsidies when purchasing machinery. The government could collaborate with extension agents to provide farmers with training on operating self-owned machines, such as fertilizer distributors and crop dryers. For farm households without renting-in cropland, providing them with purchased machinery service information via advanced information and communication technologies (ICTs) such as smartphones and computers would be a useful pathway to increase their utilization of purchased machinery services. Generally, a more targeted and precise policy design on mechanization promotion is essential since farmers may have heterogeneous mechanization utilization preferences arising from land transfers.

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