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Impacts of work attitude of outsourcing services on food losses: evidence from rice harvest in China

RESEARCH ARTICLE

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Abstract

This study uses survey data from 651 farmers in China to study the impacts of moral hazard on rice harvest losses and we further study the differences of the impacts across farm scales. The results show that large-scale farms have lower harvest losses and the service providers have more serious attitude when harvesting. After addressing the endogeneity of moral hazard using instrumental variable approach, moral hazard increases harvest losses. However, this impact diminishes as farm size increases. These findings demonstrate the need to reduce moral hazard by increasing farm size, introducing intermediaries, and written contracts, etc.

Keywords: farm scale, food losses, moral hazard, outsourcing service, rice harvest
JEL code: Q010, Q150

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1. Introduction

In China, organizations or individuals are engaged in providing agricultural machinery outsourcing services to farmers who do not own such machinery. This enables small-scale farms to use machinery for agricultural production (Ji *et al.*, 2017). Agricultural machinery outsourcing services are considered a way to achieve economies of scale (Cai and Wang, 2021). At certain extent, these services have solved the mechanization problem of small-scale farms by enabling mechanization of certain crop production stages, such as ploughing, planting and harvesting, etc. (Picazo-Tadeo and Reig-Martínez, 2006; Zhang *et al.*, 2017). Moreover, similar habits are observed in various countries characterized by small-scale farms. In the Netherlands, small-scale farmers who lack sufficient labor are more willing to buy machinery outsourcing services (Igata *et al.*, 2008).

Booming agricultural machinery outsourcing services have received considerable attention. The origin and development of agricultural machinery outsourcing services (Yang *et al.*, 2013) and farmers' outsourcing service participation and its influencing factors (Cai and Wang, 2021; Yi, 2018) have been studied. Researchers have also explored the effects of outsourcing services on agricultural production (Deng *et al.*, 2020; Lu and Du, 2020) and farmers' welfare (Mi *et al.*, 2020). Few studies have focused on the impacts of changes in the relationship between farmers and the market caused by agricultural machinery outsourcing services. The essence of agricultural machinery outsourcing services is the division of labor (Yi, 2018). The relationship between farmers and service providers is that of principal and agent (Huan and Hou, 2020). Huan and Hou (2020) argued that the goal of service providers is to maximize their own profits without considering factors such as the yield and quality of crops, the decline of land fertility, and pollution. Therefore, service providers may adopt labor-saving and careless practices, which cause the moral hazard of reducing service quality. Some scholars have elaborated on the possibility of service providers' moral hazard from the perspective of game theory (Cai and Liu, 2019; Huan and Hou, 2020). The farmer survey in China by Cai and Liu (2019) indicated that poor service quality contributed to farmers' low satisfaction with outsourcing services, which impliedly provides evidence of the existence of moral hazard.

Theoretical studies have shown that there is a moral hazard in agricultural machinery outsourcing services (Cai and Liu, 2019; Huan and Hou, 2020). However, there is a lack of empirical evidence on whether moral hazard in agricultural machinery outsourcing services will have a substantial impact on agricultural production. Lu and Du (2020) believed that the positive impacts of outsourcing service specialization are greater than the negative effects. However, they did not directly study the negative impacts of the moral hazard in outsourcing services on agricultural production.

This study provides empirical evidence of moral hazard. To collect the empirical evidence, the selection of the stage in the production process that is outsourced is important. This is because certain moral hazards and their consequences may be difficult to be observed well in time due to the seasonality and cyclicality of agricultural production. For example, if, while planting rice, the depth to which the rice seedlings are transplanted by the service provider is too shallow, it may result in a low survival rate of the rice seedlings (Lee *et al.*, 2017). However, the survival rate of rice will be known only at a later stage of the growth of the seedlings. The low survival rate will not be detected within a reasonably short time after transplanting. However, the consequence of moral hazard in harvesting services is easy to be observed, which causes an increase in harvest losses. Service providers' moral hazard behaviors, such as increasing forward speed of machine and leaving some crops in the corner unharvested, will directly increase the harvest losses. These losses are clearly visible after harvesting, or even during the process, by the rice shed in the field and unharvested plants in the turning point of the harvesters. Meanwhile, farmers have a fairly accurate idea of the expected yield by the appearance of the harvest-ready crop based on years of experience. Therefore, the farmer can perceive whether the outsourcing service providers have moral hazard behaviors. This is evidenced by the dissatisfaction that farmers express over the hired harvesting services (Cai and Liu, 2019). Therefore, this study investigates the impacts of moral hazard on the outsourcing harvesting services and further on the harvest losses.

Furthermore, although farms with different farming scales may have access to harvesting outsourcing services, providing services to farms of different scales means different profits for the outsourcing service providers. The higher profits that service providers earn from large-scale farms may affect the occurrence of moral hazard. Therefore, we also take the farm scale into account to study whether it affects the impacts of moral hazard on rice harvest losses.

To explore the impacts of moral hazard posed by outsourcing services on harvest losses, we use the detailed information on rice harvest losses and agricultural production collected in 2016 from 651 Chinese farm households who hired outsourcing services to harvest rice. The work attitudes of service providers (whether seriously or not) are used to quantify moral hazards. The instrumental variable approach, which considers the endogeneity of moral hazard, is used to estimate its impacts on rice harvest losses. Overall, we find evidence of negative impacts of moral hazards on rice harvest losses. The farm scale is a key factor that influences the effects of moral hazard. For small-scale farms, moral hazard is a crucial factor that increases rice harvest losses. As the scale increases, service providers gradually have the scale effects and earn more profits. This acts as an income incentive which reduces moral hazard. Therefore, with the increase in scale, the impacts on rice harvest losses decline. Our findings suggest that with the further expansion of agricultural machinery outsourcing services, policies should be formulated to mitigate the negative impacts of moral hazard, such as regulating the outsourcing service market and steadily promoting scale operations.

The remaining parts of this paper is organized as follows: Section 2 introduces the model design and data. Section 3 presents the empirical results and the corresponding discussion. Section 4 is the conclusion and policy implications.

2. Methods and data

2.1 Model specification

To investigate the relationship between rice harvest losses and moral hazard, we consider a farm household model with the following relationship:

$$L = f(M,P,H) + e \tag{1}$$

where L is the rice harvest losses, M captures the moral hazard of the service providers, and P is a vector of production and harvesting condition variables. Further, H is a vector of household and individual characteristics, and e is the error term.

The first task in estimating the rice harvest losses is to clarify the specific stages of the losses. Existing studies have not unified the start- and end-points of the harvest losses when estimating the rice harvest losses and have considered various estimated stages, including reaping, threshing, winnowing, and transportation (Qu *et al.*, 2021a). The use of combine harvesters consolidates inseparably the reaping, threshing, and winnowing operations. Therefore, the start- and end-points of harvest losses in this study are defined as the field and storage. The stages during which losses occur are reaping, threshing, winnowing, and field transportation (Qu *et al.*, 2021b). To facilitate the comparison between farms of different scales, the harvest losses rate is used to measure harvest loss. The specific estimation formula is as follows:

$$HLR = (L_1+L_2+L_3+L_4) / ((L_1+L_2+L_3+L_4)+PRO) \times 100\% \tag{2}$$

where HLR is the rice harvest loss rate; L_1, L_2, L_3, and L_4 represent losses at the reaping, threshing, winnowing, and field transportation stages, respectively; PRO is the final production quantity.

We use operators work attitudes (Att) to capture their moral hazard. In the questionnaire, there is a three-point scale (fine, general, rough) for 'working attitude when reaping'. Att will be 0 if the answer is general or rough, which means service provider does not take the harvesting service seriously, otherwise it will be 1. That's to say, if service providers exhibit moral hazard, they will not treat the harvesting seriously (Att=0). The evaluation of service providers' work attitudes is given by farmers based on their observations during harvesting and years of experience, which make them credible. Similar subjective variables are widely used when there is a lack of objective variables, such as happiness and satisfaction (Jin *et al.*, 2020). One concern in the estimation through this model is reverse causality. Work attitudes can be endogenous in Equation 1. High harvest losses may increase the probability of moral hazard. The harvest losses are usually high in rugged or irregularly shaped plots, which provide conditions for service providers to inadvertently create moral hazard or to their inherent moral hazard. Because it is difficult to distinguish whether a high loss rate is due to the topography of plots or moral hazard, which creates conditions for service providers to implement moral hazard.

To address the endogeneity of work attitudes, we introduce instrumental variable: the distance from the homestead to the nearest paved road (Htor). We believe that the distance from the homestead to the nearest paved road is a credible instrumental variable because the greater the distance, the longer the distance to be traveled on an unpaved road, which requires careful driving. Further, farmers who live in areas far from paved roads are more likely to be economically disadvantaged (Dercon, 2009), and their attitude of conserving food (Greeley and Martin, 1986) can influence service providers' work attitudes toward harvesting. Moreover, homesteads and paved roads, which are planned by the village communities, determine the instrumental variable. The variable is unlikely to affect harvest losses in the fields. Therefore, we estimate the model in an instrumental variable framework:

$$HLR = \alpha_0 + \alpha_1(\widehat{Att}) + \alpha_2(P) + \alpha_3(H) + v \tag{3}$$

$$Att = \beta_0 + \beta_1(Htor) + \beta_2(P) + \beta_3(H) + u \tag{4}$$

where Htor is the instrumental variable that is correlated with work attitudes but influences the rice harvest loss rate only through work attitudes. Here, v and u are random errors. Two-stage least squares (2SLS) is used for the estimation.

Since the farm scale explored in this study is a relative concept, we follow the approach of Li *et al.* (2019) and classify the farm scale based on the statistical characteristics of the sample. Specifically, we use the median of planting area (0.267 ha) to classify farms into small-scale farms and large-scale farms. Farms with planting area less than 0.267 ha are classified as small-scale farms, while farms with planting area greater than or equal to 0.267 ha are classified as large-scale farms.

2.2 Covariates

Based on existing studies, we add the following two types of control variables (Qu *et al.*, 2021b). The production and harvesting conditions include combine harvesting (Com), winnowing machinery (Win), transportation machinery (Tra), weather conditions (Wea), pest disease conditions (Pest), planting area (Area), yield (Yield), land terrain (Flat), distance from the field to storage locations (Dis), labor shortages (Lab), food saving consciousness (Sav), rice maturity status (Mat), and the selling price of rice (Price). Household and individual characteristic variables include the gender (Gen), age (Age), and education (Edu) of the head of the household, agricultural training experience (Train), total family income (T-inc), and the share of income from rice in total income (R-incs). The specific definitions of the variables are listed in Table 1.

2.3 Data

The data are derived from the rice harvest loss survey conducted in 2016 by the China Agricultural University (CAU) and the Rural Fixed Observatory Point Office of the Research Center for Rural Economy (RCRE) of China's Ministry of Agriculture and Rural Affairs (CAU and RCRE, unpublished data). Using the stratified sampling method, the villages in the top 10 rice-producing provinces (Autonomous Regions and Municipalities) were identified to be surveyed. The households were then selected from the household registration list of each village using a systematic sampling method. The rice losses in the four harvest stages were estimated by the farmers based on their years of experience (Affognon *et al.*, 2015; Kaminski and Christiaensen, 2014). The work attitudes of service providers were also reported by the farmers based on their observations while the service providers supplied the harvesting services. Other information, including production conditions and household characteristics, is collected.

The samples used in this study are 651 households that bought harvesting outsourcing services. The samples cover most provinces in three advantageous regions of rice production, the Yangtze River basin, the northeast plain, and the southeast coast, which are defined in the 'Regional Layout Planning for Advantageous Agricultural Products' (China Ministry of Agriculture and Rural Affairs, 2008) (Figure 1). For some sample provinces that do not belong to any of the advantageous regions, they are classified into the corresponding advantageous regions according to their natural resources, cultivation characteristics, and geographical locations. The division of advantageous regions is based on regional resource endowment, market conditions, and ecological environment, which can well represent the rice production situation and the key development areas of rice planting in the future. The corresponding regional dummy variables are introduced in the model.

3. Results and discussion

3.1 Descriptive analysis

Table 1 presents the definitions and means of the variables. Overall, the average rice harvest loss rate for farmers are 3.54%. The percentage of service providers who were serious about their work was only 17%. Combine harvesters were used by 76%, mechanical winnowing by 53%, and mechanical transportation by 71% of the surveyed farmers.

The rice harvest loss rate was 4.33% for small-scale farms, which was higher than that of large-scale farms (2.72%). The possible reason is that the small plot area brings difficulties for machinery operation, which increases harvest lossess. The difficulties for machinery operation on small plots may also make a clear difference in service providers' attitudes toward small-scale and large-scale farms. Only 11% of service providers to small-scale farms take the harvesting operation with due seriousness, while 24% of service providers to large-scale farms take harvesting seriously.

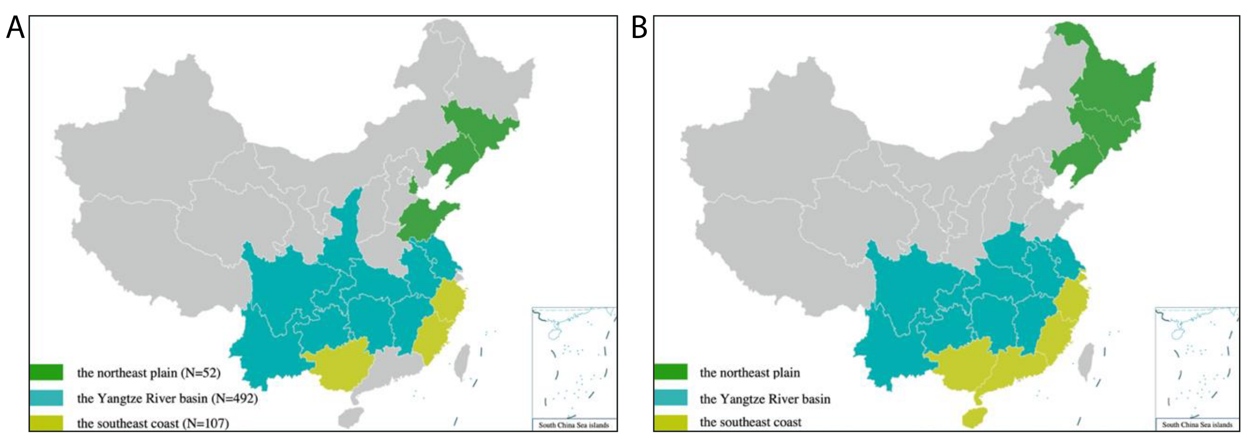

Figure 1. Sample distribution. (A) study area; (B) three advantageous regions of rice production.

Table 1. Descriptive statistics.[1]

Variable	Definition	All farms	Small-scale farms	Large-scale farms
Dependent variable				
HLR	Harvest loss rate (%)	3.54	4.33	2.72
Core independent variable				
Att	1 if operators treat harvesting seriously, 0 otherwise	0.17	0.11	0.24
Instrumental variable				
Htor	Distance from the homestead to the nearest paved road	0.30	0.33	0.28
Production and harvesting condition variables				
Com	1 if using a combine harvester, 0 otherwise	0.76	0.76	0.75
Win	1 if the grains are winnowed by a machine, 0 otherwise	0.53	0.62	0.45
Tra	1 if the grains are transported by a machine, 0 otherwise	0.71	0.61	0.82
Wea	Weather condition: 1 if the weather is bad, 0 if it is normal	0.14	0.08	0.20
Pest	No pest = 1, slight pests = 2, serious pests = 3	1.79	1.70	1.89
Area	Planting area of rice (ha)	0.40	0.15	0.66
Yield	Yield (quintal/ha)	84.81	86.00	83.60
Flat	1 if the terrain is flat, 0 otherwise	0.81	0.86	0.75
Dis	Distance from the field to storage locations (km)	0.58	0.54	0.63
Lab	1 if farmers report a lack of manpower, 0 otherwise	0.23	0.28	0.18
Sav	1 if farmers pick up rice after harvest, 0 otherwise	0.18	0.19	0.17
Mat	1 if rice is harvested on maturity, 0 otherwise	0.93	0.96	0.91
Price	The price of rice (yuan/kg)	2.88	2.90	2.86
Household and individual characteristics				
Gen	Gender of the household head (male = 1, female = 0)	0.87	0.86	0.89
Age	Age of the household head	54.33	55.86	52.76
Edu	Schooling years of the household head	7.33	7.28	7.38
Train	1 if the household head received agricultural training, 0 otherwise	0.10	0.12	0.07
T-inc	Household income (10,000 yuan)	7.21	6.57	7.87
R-incs	Rice income as a percentage of total income (%)	19.42	9.29	29.77
n	Number of observations	651	329	322

[1] The investigators asked farmers about the weather conditions, such as normal weather, strong winds, and heavy rain. If farmers reported conditions other than normal weather, we assumed that the weather was bad during harvest. Farmers also reported other variables related to production and harvest based on their observations, such as labor (the options were lack, fair, and adequate).

To further understand the variation in service providers' work attitudes and rice harvest loss rates at different farm scales, we divide the samples into 10 groups according to the deciles of the rice planting area. From Figure 1, it is observed that, generally, the rice harvest loss rates decreased with the increase in farm scale. For service providers, their service fees are proportional to the service area, and in many cases, they face increasing return to scale. Thus, as the farm scale increases, service providers may become more serious with the incentives of increased income. On the other hand, farmers' management will become difficult, and labor will become scarce as scale increases, causing their work attitudes decline as scale increases. When the farm scale was small, the average work attitude of farmers was more serious than that of service providers. As the scale of the farm expanded, the gap between the average work attitudes of farmers and service providers gradually became smaller (Figure 2).

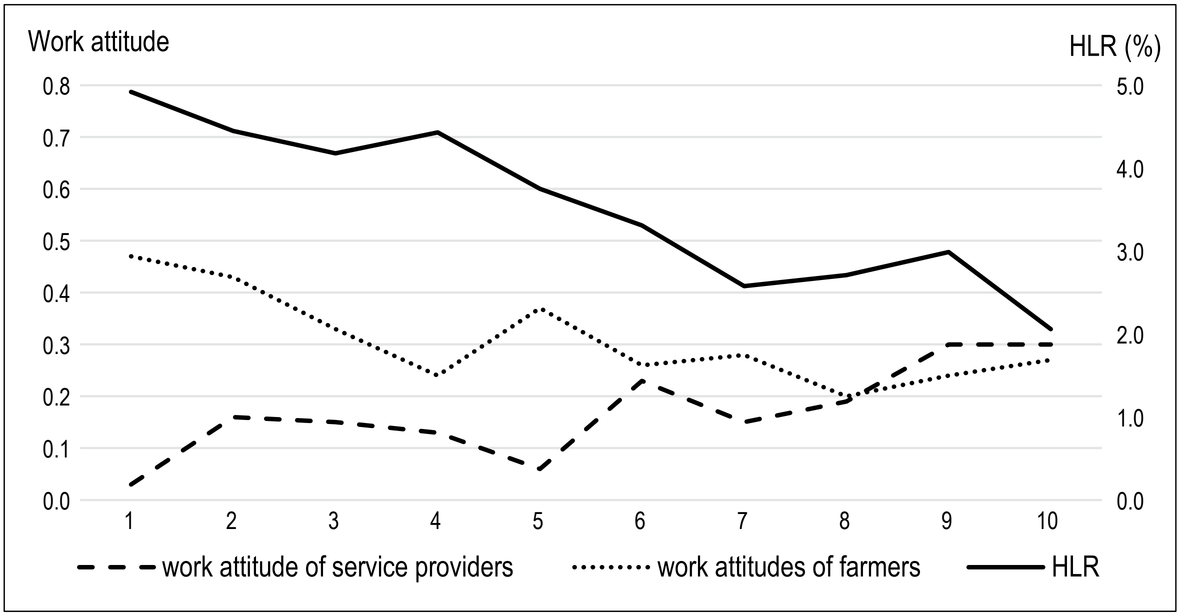

Figure 2. Average work attitudes of service providers and farmers in different farm scales. HLR = harvest loss rate.

3.2 Estimation

Table 2 displays the ordinary least squares (OLS) and 2SLS estimates of the effects of moral hazard on the rice harvest loss rates of all farms. The OLS results show that serious work attitude has a negative coefficient, which means that the moral hazard of service providers will increase the rice harvest loss rates. If the endogeneity of work attitudes does not exist, the 2SLS regression need not be used because the OLS regression would provide consistent and more efficient estimations (Kaufmann *et al.*, 2019). The endogeneity test indicates that it is necessary to address the endogeneity of work attitudes. We reject the weakness of the instrument because the Kleibergen-Paap rk Wald F statistic (Kleibergen and Paap, 2006) is above the 10% critical value. Moreover, Wuepper *et al.* (2018) indicated that the more the instrumental variable correlates with other control variables, the higher the possibility of failing the exclusion restriction. Therefore, we test whether our instrumental variable correlates with plot terrain and planting area. The results in Table 3 show that the instrumental variable is not significantly correlated with them.

Serious work attitude in 2SLS regression also has a negative and significant coefficient. However, its significance level and absolute value are both higher than the results from the OLS regression; this indicates that failing to account for the endogeneity of work attitudes leads to an underestimation of the true effect of moral hazard. Moreover, machinery winnowing, bad weather, pests, flat terrain, shortage of labor, food saving consciousness, and training have the positive effects on harvest losses, while yield, sale price, and the percentage of rice income have the negative effects on harvest losses.

The previous section provides evidence that farm scale may affect the work attitudes of service providers, which, in turn, may influence the rice harvest loss rates. Therefore, in this section, we examine whether the impacts of moral hazard decrease with the expansion of the farm scale. Table 4 presents the results of the OLS and 2SLS regressions for small-scale and large-scale farms. The OLS results show that serious work attitude has a significantly negative effect on the harvest losses for small-scale farms, but not for large-scale farms. Further, the endogeneity tests show that the 2SLS regressions would have better results than the OLS regressions. Kleibergen-Paap rk Wald F statistic (Kleibergen and Paap, 2006) is above the 15% critical value for small-scale farms, whereas it is above the 10% critical value for large-scale farms. Overall, we reject the weakness of the instrument, but the evidence is not overwhelming. After dealing with endogeneity, the 2SLS

Table 2. Regression results of all farms.[1,2,3]

	OLS	(Robust std. error)	2SLS	(Robust std. error)
Core independent variable				
Att	-0.629*	(0.33)	-3.082***	(1.07)
Production and harvesting condition variables				
Com	0.236	(0.33)	0.567	(0.37)
Win	1.253***	(0.27)	1.302***	(0.27)
Tra	-0.550*	(0.30)	-0.423	(0.30)
Wea	0.684	(0.49)	0.867*	(0.52)
Pest = 2	0.544**	(0.27)	0.398	(0.29)
Pest = 3	1.201***	(0.37)	0.862**	(0.40)
Area	-1.119***	(0.38)	-0.665	(0.43)
Yield	-0.014**	(0.01)	-0.015***	(0.01)
Flat	0.772**	(0.35)	0.791**	(0.36)
Dis	-0.238	(0.19)	-0.212	(0.19)
Lab	0.862***	(0.29)	0.610*	(0.32)
Sav	1.125***	(0.33)	1.200***	(0.33)
Mat	0.030	(0.45)	0.189	(0.48)
Price	-1.468**	(0.61)	-1.756***	(0.63)
Household and individual characteristics				
Gen	0.614**	(0.31)	0.521	(0.33)
Age	0.018	(0.01)	0.017	(0.01)
Edu	-0.051	(0.06)	-0.054	(0.06)
Train	1.209**	(0.49)	1.197**	(0.51)
T-inc	0.025	(0.03)	0.018	(0.03)
R-incs	-0.016**	(0.01)	-0.018**	(0.01)
Cons	8.170***	(2.17)	8.694***	(2.23)
Region control	Yes		Yes	
R^2	0.23		–	
Kleibergen-Paap rk Wald F statistic	–		25.311	
Endogeneity test	–		*P*=0.021	
n	651		651	

1 **P*<0.10, ***P*<0.05, ****P*<0.01.

2 Stock-Yogo critical values for weak identification tests (used for Kleibergen-Paap rk Wald F statistics) are 16.38 for 10% maximal IV bias; 8.96 for 15% maximal IV bias; 6.66 for 20% maximal IV bias; and 5.53 for 25% maximal IV bias (Stock and Yogo, 2005).

3 OLS = ordinary least squares; 2SLS = two-stage least squares.

Table 3. Test of instrumental variable.[1,2,3]

Variable	(1) flat	(2) area
Htor	0.279 (0.21)	0.003 (0.02)
Cons	3.662*** (0.99)	0.394*** (0.11)
Pseudo R^2/R^2	0.03	0.47
n	651	651

1 Robust standard errors are reported in parentheses.

2 ****P*<0.01.

3 Logit regression and ordinary least square are used for estimation of column 1 and 2, respectively. We control for region and household and individual characteristic variables.

Table 4. Regression results of small-scale and large-scale farms.[1,2,3]

	Small-scale farms				Large-scale farms			
	OLS	**(Robust std. error)**	**2SLS**	**(Robust std. error)**	**OLS**	**(Robust std. error)**	**2SLS**	**(Robust std. error)**
Core independent variable								
Att	-1.494***	(0.45)	-7.968***	(2.51)	0.159	(0.44)	-1.746*	(0.93)
Production and harvesting condition variables								
Com	0.815*	(0.49)	1.147**	(0.55)	-0.487	(0.43)	-0.109	(0.48)
Win	1.662***	(0.38)	1.270***	(0.44)	0.863**	(0.35)	1.045***	(0.36)
Tra	-0.507	(0.40)	-0.331	(0.44)	-0.049	(0.44)	0.027	(0.45)
Wea	0.793	(0.74)	0.731	(0.77)	0.903	(0.66)	1.054	(0.67)
Pest = 2	0.588	(0.41)	0.182	(0.49)	0.637*	(0.35)	0.487	(0.36)
Pest = 3	1.738***	(0.55)	1.251*	(0.64)	1.045**	(0.51)	0.589	(0.55)
Area	-8.876***	(2.93)	-8.099**	(3.28)	-0.614*	(0.35)	-0.324	(0.36)
Yield	-0.027***	(0.01)	-0.023**	(0.01)	-0.012*	(0.01)	-0.014*	(0.01)
Flat	-0.154	(0.61)	0.290	(0.65)	0.888**	(0.44)	0.871*	(0.45)
Dis	-0.087	(0.37)	0.231	(0.53)	0.033	(0.23)	0.001	(0.22)
Lab	1.352***	(0.41)	0.649	(0.55)	0.033	(0.32)	-0.126	(0.34)
Sav	1.358***	(0.49)	1.792***	(0.59)	0.310	(0.40)	0.282	(0.40)
Mat	-1.234	(0.77)	-1.018	(0.97)	-0.252	(0.54)	0.048	(0.55)
Price	-1.236	(0.89)	-2.093*	(1.08)	-2.416***	(0.89)	-2.362***	(0.92)
Household and individual characteristics								
Gen	0.912*	(0.47)	0.699	(0.67)	0.361	(0.34)	0.297	(0.33)
Age	0.030	(0.02)	0.031	(0.02)	0.004	(0.02)	0.003	(0.02)
Edu	0.021	(0.08)	-0.006	(0.09)	-0.107	(0.07)	-0.109	(0.08)
Train	1.286*	(0.72)	1.646**	(0.82)	-0.246	(0.50)	-0.305	(0.58)
T-inc	0.021	(0.05)	-0.007	(0.05)	0.047	(0.03)	0.037	(0.03)
R-incs	-0.002	(0.02)	-0.016	(0.03)	-0.022***	(0.01)	-0.024***	(0.01)
Cons	7.462**	(3.12)	9.348**	(3.71)	13.237***	(3.10)	12.811***	(3.18)
Region control	Yes		Yes		Yes		Yes	
R^2	0.31		–		0.22		–	
Kleibergen-Paap rk Wald F statistic	–		11.745		–		23.467	
Endogeneity test	–		P=0.002		–		P=0.045	
n	329		329		322		322	

[1] *P<0.10, **P<0.05, ***P<0.01.

[2] Stock-Yogo critical values for weak identification tests (used for Kleibergen-Paap rk Wald F statistics) are 16.38 for 10% maximal IV bias; 8.96 for 15% maximal IV bias; 6.66 for 20% maximal IV bias; and 5.53 for 25% maximal IV bias (Stock and Yogo, 2005).

[3] OLS = ordinary least squares; 2SLS = two-stage least squares.

regression results demonstrate that serious work attitude has a significantly negative effect on rice harvest losses on both small-scale and large-scale farms. The OLS results greatly underestimate the true effect of moral hazard. Its second largest coefficient indicates that it is impossible to ignore its effect.

Moreover, the coefficient of work attitude on small-scale farms is larger than that on large-scale farms, which means that moral hazard is more severe among small-scale farmers than among large-scale farmers. This proves our initial conjecture that the effects of moral hazard decrease as the farm scale increases. Usually, harvesting outsourcing services are paid in proportion to the area to be harvested. The larger the area to be harvested, the higher the service fee. One way to reduce moral hazard is to provide certain incentives to agents (service providers). The high profits from large-scale farms may translate into income incentives for service providers, making them more serious in providing services to large-scale farms than to small-scale farms. Therefore, as farm size increases, the occurrence of moral hazard of the service providers decreases, and, therefore, the impacts on the rice harvest loss rates decrease. This presumption can also be supported by the negative coefficient of the planted area on small-scale farms, which is the only variable that has a greater impact on harvest losses than moral hazard. The larger the area of small-scale farms, the smaller the rice harvest loss rates. This is also reflected in the coefficients of combine harvesting, which is positive in small-scale farms but not significant in large-scale farms. This is because small-scale farms are not convenient for the operation of combine harvesters (Otsuka *et al.*, 2016).

Based on the above discussion, we assume that when the farm scale is further expanded, the negative impact of moral hazard on rice harvest losses may disappear. To verify this conjecture, we conduct a regression analysis on the largest one-tenth of the farms. The OLS and 2SLS results are listed in Table 5. Both the

Table 5. Regression results of the largest one-tenth of the farms.[1,2,3]

	OLS	**(Robust std. error)**	**2SLS**	**(Robust std. error)**
Core independent variable				
Att	0.155	(0.56)	-1.391	(0.89)
Production and harvesting condition variables				
Com	-1.076	(0.85)	-0.800	(0.77)
Win	3.189***	(0.87)	3.380***	(0.83)
Tra	4.209**	(1.80)	4.964***	(1.65)
Wea	0.763	(0.98)	0.529	(0.96)
Pest = 2	1.410***	(0.51)	1.013**	(0.51)
Pest = 3	2.359***	(0.79)	1.858**	(0.78)
Area	-0.672	(0.55)	-0.837	(0.54)
Yield	-0.002	(0.02)	0.006	(0.02)
Flat	-3.800***	(1.36)	-4.759***	(1.43)
Dis	0.090	(0.56)	0.192	(0.45)
Lab	-2.120**	(0.80)	-2.388***	(0.68)
Sav	-1.168**	(0.54)	-0.948**	(0.47)
Mat	3.222**	(1.52)	3.849***	(1.32)
Price	-0.574	(1.89)	-2.233	(1.89)
Household and individual characteristics				
Gen	0.913	(0.66)	0.923*	(0.52)
Age	-0.000	(0.04)	-0.007	(0.03)
Edu	0.218**	(0.11)	0.182**	(0.08)
Train	-2.450***	(0.81)	-2.146***	(0.74)
T-inc	-0.083	(0.06)	-0.144**	(0.07)
R-incs	-0.034**	(0.01)	-0.028**	(0.01)
Cons	2.135	(7.06)	6.806	(6.81)
Region control	Yes		Yes	
R^2	0.76		–	
Kleibergen-Paap rk Wald F statistic	–		30.452	
Endogeneity test	–		P=0.029	
n	65		65	

[1] *P<0.10, **P<0.05, ***P<0.01.

[2] Stock-Yogo critical values for weak identification tests (used for Kleibergen-Paap rk Wald F statistics) are 16.38 for 10% maximal IV bias; 8.96 for 15% maximal IV bias; 6.66 for 20% maximal IV bias; and 5.53 for 25% maximal IV bias (Stock and and Yogo, 2005).

[3] OLS = ordinary least squares; 2SLS = two-stage least squares.

endogeneity test and Kleibergen-Paap rk Wald F statistic (Kleibergen and Paap, 2006) indicate the greater reliability of the 2SLS results. The 2SLS regression results show that serious work attitude has no impact on the rice harvest loss rates when the farm scale increases further; this means that moral hazard gradually disappears with the expansion of the farm scale. In addition, the changes in the coefficient of the terrain (*Flat*) indicate that moral hazard gradually disappears with the expansion of the farm scale. The coefficient of the terrain changes from positive in Table 3 to negative in Table 4. The moral hazard in large-scale farms with flat terrain arises because the flat terrain facilitates the service providers to speed up harvesting, which enables the moral hazard and leads to increased rice harvest loss rates. With the disappearance of moral hazard in large-scale farms, the flat terrain at this time creates favorable conditions for mechanical harvesting, thereby helping reduce the rice harvest loss rates. Moral hazard is no longer an important factor affecting losses. It is replaced by factors such as means of transportation and terrain.

4. Conclusions

Booming outsourcing services have received much attention from researchers. However, only a few studies have theoretically explored the moral hazard introduced by outsourcing services in the principal-agent relationship between farmers and the market (service providers), and most of them found the negative impacts on agricultural production. This study examines the impacts of the moral hazard in harvesting outsourcing services on agricultural production from the perspective of rice harvest losses, taking into account the effects of farm scale. The findings are as follows. The average impact of the moral hazard of service providers on the rice harvest loss rates decreases as the farm scale increases. With the expansion of the farm scale, the proportion of service providers who work seriously rises gradually to be equal to the proportion of serious farmers. After dealing with the endogeneity of the moral hazard variable, the 2SLS regression results show that moral hazard increases the rice harvest loss rates, and as the farm scale expands, this effect of moral hazard gradually disappears.

This study provides empirical evidence for the moral hazard posed by agricultural machinery outsourcing services and its impacts on rice harvest losses. This is a reminder of the need to intervene to reduce the moral hazard in agricultural machinery outsourcing services to improve efficiency of outsourcing services. The findings of this study suggest that increasing farm scale is one of the means to mitigate moral hazard. This also implies the role of income incentives in reducing moral hazard. However, increasing the farm scale is a slow process (Zhang *et al.*, 2018). Another way is to regulate the machinery outsourcing service market, for example, by signing written service contracts to regulate the behavior of service providers and inducing intermediaries who could ensure satisfactory performance of service.

This study only discusses the moral hazard involved in harvesting outsourcing services. The moral hazard that arises in outsourcing other stages of crop production could be the subject of future studies. Due to the continuous development of agricultural outsourcing services, we should comprehensively evaluate their role in agriculture. While we appreciate the positive role of agricultural outsourcing services in the mechanization of agriculture and scale management, we must be aware of the negative impact of moral hazard on agricultural production. Only in this way can outsourcing services be beneficial to the long-term development of agriculture.

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Conflict of interest

The authors declare there are no conflicts of interest.

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