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ABSTRACT

Modernizing Smallholder Agriculture and Achieving Food Security: An Exploration in Machinery Services and Labor Reallocation in China*

Worldwide, most farms are small and family-operated. This study discusses the future of smallholder agriculture in China, where most farms are small, and farms' parcels are fragmented. The study puts forward a framework of vertical division of labor and specialized production in agriculture. We posit that hiring machinery services could be a pathway to connect smallholders with modern agriculture and achieve food security in China. Using household-level data from China, this study examines the impact of hiring machinery services on farm productivity, food security, and rural households' welfare. Findings show that mechanization services increased rural Chinese families' food security and agricultural productivity. Hiring machinery services improves smallholders' income by influencing the input efficiency of maize production. At the same time, increased mechanization implied greater participation in off-farm work. In other words, more family labor and time are allocated to off-farm work, which results in higher total income and increased consumption expenditures. Our findings highlight the importance of technology to improve smallholder agriculture and food security, not only in China but also in other South and Southeast Asian countries.

JEL Classification: Q12, C36, J22

Keywords: production efficiency, machinery services, household welfare, food security

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INTRODUCTION

There are more than 570 million farms worldwide, most of which are small and family-operated. In developing and transition countries, small farms (less than 2 hectares) operate about 12 percent of the world's agricultural land, and family farms operate about 75 percent of such land. Similarly, most farms in China are small and parcels are fragmented. Small family farms are still fundamental to Chinese agrarian production. For example, China's 2016 national agricultural census found that about 207 million rural households operate farms and cultivate about 140 million hectares.[2] With increased urbanization, labor migration, and opportunities to participate in land rental arrangements, Chinese agriculture is at a pivotal point. Technological progress and economic development in rural China require Chinese agriculture to modernize. Smallholder agriculture's development relates directly to food security, which is vital for China, a country with a large population, and influences global food security (Huang and Yang, 2017). Thus, modernizing traditional smallholder agriculture is paramount in improving agricultural productivity and maintaining food security.

In 2019, the Chinese government issued opinions on promoting small farmers' connection and Chinese agriculture's modernization. The modernization of Chinese agriculture has opened the debate on large-size farm production and small family farms' survival and continuity. The continuity and survivability of small farms in China are challenging because of limited land and other productive resources. Mainstream studies advocate modern industrial agriculture based on a large-scale farm through farmland rental and capital investment (Du, 2013; Guo et al., 2019;

[2] Source: http://www.stats.gov.cn/tjsj/tjgb/nypcgb/qgnypcgb/201712/t20171214_1562740.html

Lu et al., 2018). To this end, the government has promoted farmland transfer to encourage farm size expansion (Wang et al., 2017). Expanding farm size has been argued to be necessary to help small-farm households increase food security and survivability (Fan and Chan-Kang, 2005; Van den Berg et al., 2007). However, given the inverse relationship between farm size and agricultural productivity, some scholars suggest a moderate scale of production agriculture.

Previous studies have neglected China's unique rural land system and farmland market (Zhou et al., 2020b), which may exaggerate the notion of increasing farm size. Recall that under the household contract responsibility system popularized throughout China in 1984, farmland is distributed for social equity rather than efficiency. This leads to the fragmentation of farmland, which increases the cost of forming. In contrast, large-scale operations and the substitution of capital for labor may be detrimental to smallholders' employment security and well-being and rural Chinese households' social stability. Moreover, Liu and Wang (2019) found that large-scale Chinese farm households' farmland is far less productive than small-scale farm households. Therefore, suggesting that it would be impossible to achieve impressive agricultural returns by merely expanding the scale of farmland. Thus, the role of small family-based agricultural production in China deserves a closer look and examination if we aim to increase efficiency and food security[3] in the country, while promoting the modernization of its agricultural sector.

In this study, we explore the path to modernizing agriculture in China and its relation to

[3] Food security is a broad concept. It is a multidimensional function of food availability, food access, food utilization and food stability. Food availability comprises of food production (total output or yield) and crop diversity. See Barrett (2010), Gregory et al. (2005), and Jenkins and Scanlan (2001) for different measures and dimensions of food security.

increases in efficiency and food security. We specifically look at the impact of hiring machinery services on farm productivity, food security, and rural households' welfare. To do so, we use a nationally representative household-level dataset, with heterogeneous regions and maize as the main grain crop analyzed. We find that mechanization services increased food security and agricultural productivity among rural Chinese families. Our analysis shows that hiring machinery services improves smallholders' income by influencing the input efficiency of maize production. At the same time, increased mechanization influences greater participation in off-farm work, that is, more family labor and time are allocated to off-farm work, which results in higher total income and increased consumption expenditures. These findings highlight the importance of technology to improve smallholder agriculture and food security.

This paper contributes to the literature investigating the role of modernization in the process of agricultural development and makes two significant contributions. First, we examine the impact of hiring machinery services on maize productivity from the aspects of output (a measure of food security) and input (farming efficiency). Second, we provide explanations for the path of agricultural modernization in China and verify its validity with empirical analysis.

The rest of the paper is organized as follows. Section 2 presents the literature review. Section 3 reviews the theoretical considerations, including the conceptual framework. Section 4 provides details of our estimation strategy. The data and variables used in this paper are introduced in Section 5. Section 6 presents the results and discussion. Section 7 concludes with a summary and policy implications.

LITERATURE REVIEW

Agricultural modernization aims to establish capital-intensive, rationalized, and specialized (Knickel et al., 2017). The main difference between modern agriculture and traditional agriculture lies in technological change. For example, in modern agriculture, farmers adopt modern agricultural technologies, agrochemicals, high-yielding, hybrid crops, and hybrid livestock. Adoption helps reduce production costs and increase labor productivity. Modern farmers tend to maximize yields, feed conversion ratios, and profit. Thus, institutional, university, and/or industry-led research becomes the driving force of agricultural modernization. Modernizing agriculture can be explained by a farming modernization index (dos Santos et al., 2018). Ruttan (1977) summed up five general models of agricultural development: high-payoff input, urban-industrial impact, diffusion, conservation, and frontier models, and highlighted the importance of institutional innovations.

Since agriculture within and across countries has changed significantly during the past few decades and agricultural technology has continued to break new ground, more studies have attempted to understand the development paths of smallholders' agriculture (Borras Jr, 2009). The introduction of new factors, transfer of capital, and the adoption and diffusion of modern technology is appropriate for developing traditional agriculture (Schultz, 1978). In addition to the increased machinery investment in agriculture, many studies have highlighted the importance of hiring machinery services in agriculture. Hiring such services helps smallholders respond to rising labor costs and family labor loss due to migration and off-farm opportunities (Wang et al., 2017; Zhang et al., 2017). A farm-level analysis of the Australian grains industry from 1989 to 2004 demonstrated that capital investment was likely to help farms increase total factor productivity (i.e., increased food security) and help close the productivity gap between small and large farms.

Agricultural modernization has been explored and documented in various countries. For instance, Hayami and Ruttan (1971) found that technological changes overcome resource constraints and improve agricultural output in developed countries. The authors' categorized technological changes into labor-saving technological progress, as represented by the United States, and land-saving technological progress, as defined by Japan. In another study, Sofranko et al. (1976) revealed the agricultural modernization strategies among Ghanaian farmers. In another study, Altieri (2009), using traditional small farms in developing countries and agro-ecological approaches, found that small farms are more productive and resource-conserving than large farms. A reason is that small farms promote healthy plant growth and beneficial organisms while using labor and local resources more efficiently. In a study, Bergius et al. (2018) used the Southern Agricultural Growth Corridor of Tanzania as an example to explain how the green economy promoted agricultural modernization through capital-intensive land investments in Africa.

THEORETICAL CONSIDERATION

A third path for China's agricultural modernization

Two agricultural modernization scenarios are typical: a small population with a large amount of farmland or a large population with small farmland. The first scenario is most common in Western countries, mainly the United States, and labor shortages would promote labor-saving technology in agriculture. Large size is the primary characteristic of farms in the United States.

Therefore, the application of large machinery is nearly always part of agricultural production. Specifically, agricultural development relies mainly on inputs like water (Ali et al., 2017), chemical fertilizer and improved seeds that enhance land productivity (Huang, 2016). East Asian agriculture, especially in Japan, has developed through agricultural modernization in the second scenario.

Transforming smallholder farms into large-scale farms is challenging since the aggravated farmland fragmentation under the household contract responsibility system. However, developing large-scale farms is not an appropriate path for China's agricultural modernization. Its only path is leasing in farmland from numerous farmers who have originally contracted farmland for a limited time. That is because rural Chinese households are assigned and have the original rights to contract for and operate farmland, but not ownership (Wang and Zhang, 2017). Moreover, the farmland lease market's imperfection may increase the risk and farmland leasing cost (Zou and Luo, 2018). Due to China's household registration system, or *hukou*, it is difficult for rural Chinese households to qualify for permanent residency rights and associated social benefits in urban areas (Willmore et al., 2012). This creates instability in the off-farm employment of farming family members, negatively affecting the farmland lease market.

To this end, an increasing number of studies have supported the view that smallholder agriculture would be maintained in China for a long time (He and Yin,2015). Additionally, the farm size distribution in China provides strong evidence of small farms' dominance (Table 1). There are several reasons. First, many traditional small farmers still rely heavily on the farm (Wang et al., 2017). Although rural households have increased opportunities for off-farm activities, still, the peasant family and the circular nature of labor migration make farmland a central and non-substitutable resource in rural China (Van der Ploeg et al., 2014). Second, the migration of middle-aged males from rural to urban areas has led to a shortage of agricultural labor or the feminization and aging of the labor. Third, China still has a significant population that still relies on agriculture. People ages 55 and older (about 106 million) accounted for about 34 percent of total farm operators, suggesting farmland usage was negatively affected by an aging farming population (Zou et al., 2018). Therefore, modern agricultural techniques like farm machinery or agricultural technologies that require a specific scale of operation or are costly cannot be effectively used.

The East Asian model of semi-governmental, integrated co-ops based on peasant communities (Huang, 2018) cannot be replicated in China for the following reasons. First, farmers' cooperatives, confined to villages and subject to government intervention, play a more limited role in practice than market-oriented enterprise organizations would. Seconthethe relatively small cooperatives with small amounts of capital are constrained in providing effective services, especially financing services, for smallholders. Finally, there is increasing availability of small-scale agricultural machinery custom-designed to be suitable for small farmers' use (Mottaleb et al., 2016). However, the small machinery available is limited to self-service, which hinders the development of machinery service markets and leads to low utilization rates for these machines.

In conclusion, neither "big and coarse" industrial manufacturing nor "small but fine" family farming is the best path for modernizing China's agricultural sector. Thereafter, exploring the third path for China's agricultural modernization is necessary and practical. We posit a third path of agricultural modernization in which agricultural services are hired, and smallholders specialize in farm production. We provide several reasons to support this statement. First, China will maintain family farms for a long time. The increasing number of rural households participating in off-farm employment will require a need to employ specialized mechanization (Zhang et al., 2017). Second, mechanization service providers could provide the service at a competitive price under an arrangement of cross-regional services since China is a vast country with several agro-climatic zones. In other words, the same crops are harvested at different times.

Mechanization service providers can travel widely throughout the country, lower the unit cost of operation, and improve productivity and labor division. Hiring machinery services generally requires a sufficient farm size and dedication to a particular production process. Thus, hiring machinery services may lead to farm specialization—adjacent plots may be planted with the same crop instead of farmers having to engage in the cumbersome process of transferring operational rights. In this context, hiring machinery services and specializing in production will promote each other. Agricultural modernization through hiring machinery services should be the most suitable path for China. This path differs from the industrialized agrarian revolution in Western countries and the labor intensity of integrated co-ops in East Asia.

Conceptual and Empirical Framework

Agricultural modernization is vital for improving production efficiency and household welfare. Production efficiency depends on higher yield and lower production costs, and household welfare is reflected in increased household income, increased supplies of safe food, and a healthy environment. Figure 1 shows the connection between hiring machinery services and production efficiency and household welfare. First, the model implies that hiring machinery services helps improve agricultural production by adopting precision agricultural technologies. Several studies in the literature have found the positive effects of (i) farmers' participation in outsourcing agricultural activities in farming (Mano et al., 2020; Xin Deng et al., 2020; Zhang et al., 2017) and of (ii) farmers' adoption of agricultural machinery services in developing economies (Abd Latif and Kadhim, 2018; Ma et al., 2018b; Mottaleb et al., 2017). Yang (2019) found that farm households improved their welfare through resource allocation and farm specialization.

Second, in addition to the increase in farm income resulting from productivity improvement, hiring machinery services can improve farming households' labor allocation. For example, household labor may choose to participate in off-farm employment or business entrepreneurship, thus increasing rural households' total income. Third, hiring machinery services may improve input efficiency, particularly pesticides and fertilizer. For example, automatic sprayers can reduce pesticide use by 37 percent while maintaining the treatment quality (Moltó et al., 2001).

We first consider the impact of hiring machinery services on agricultural productivity (maize yield per unit area), farming costs (costs per unit of output), and rural households' welfare (per capita income). Then we explore the mechanism of the impact of hiring machinery services on rural households' welfare. This study uses two measures of agricultural productivity: yield per mu[4] and costs per unit of output (see Muyanga and Jayne, 2019; Guo et al., 2019). Following

[4] 1 mu =0.165 acres (1/15 hectare).

Muyanga and Jayne (2019), the neo-classical production function approach suggests maize output or profitability depends on farmland, labor, and capital inputs. Thus, the relationship between output and inputs can be estimated by the following equations.

$$LnY_i = \alpha_0 + \alpha_1 M_{Si} + \theta I_{INi} + \delta LnF_{LDi} + \omega H_i + \sigma_i + \varepsilon_i \quad (1)$$

where Y_i, the dependent variable is the yield per mu of maize for the *i*th rural household. M_{Si} is the explanatory variable of interest is the hiring of machinery services. I_{INi} is a vector of other input variables, such as cost of family labor, hired labor, fuel, maintenance and depreciation of agricultural machinery owned by the rural household, seeds, fertilizer, pesticide, and other expenses. F_{LDi} is a vector of farmland characteristics, land area, fragmentation (number of plots), and soil fertility. H_i is a vector of exogenous variables, such as socio-demographic characteristics (gender, age, education attainment of the household head), income, labor structure, and social capital. $\alpha_0, \alpha_1, \theta, \delta,$ and ω are parameters to be estimated. σ_i are indicators representing the location (province) of the rural household *i*. The location variable controls for regional differences in production, environment, and other agricultural output conditions. ε_i is the random error term. Let us turn our attention to the cost of production. Specifically, the cost of production can be expressed as:

$$LnC_i = \beta_0 + \beta_1 M_{Si} + \delta LnF_{LDi} + \omega H_i + \sigma_i + \mu_i \quad (2)$$

where the dependent variable C_i is the cost of maize production (per kilogram) for the *i*th rural household *i*. The explanatory variables M_{Si} F_{LDi} and H_i are the same as in equation (1).

$\beta_0, \beta_1, \delta,$ and ω are parameters to be estimated. σ_i and μ_i are the same as in equation (1). Next, equation 3 represents the empirical model to estimate the income of smallholder households. In this study, we use per capita income (a measure of food security[5]) which can be expressed as:

$$LnPI_i = \gamma_0 + \gamma_1 M_{Si} + \gamma_3 FM_i + \delta LnF_{LDi} + \omega H_i + \lambda D_i + \sigma_i + \xi_i \quad (3)$$

where the dependent variable PI_i is the per capita income of the i^{th} rural household. The explanatory variables M_{Si} F_{LDi} and H_i are the same as in equation (1). In the above equation, we include information on fixed assets like farm machinery FM_i and D_i is the debt of rural households. Finally, $\gamma_0, \gamma_1, \gamma_2, \lambda, \delta$ and ω are parameters to be estimated and ξ_i is the random error term.

We acknowledge that a rural household's hiring of machinery services is potentially endogenous to maize productivity and household income. For example, unobserved characteristics such as a rural household's cognitive ability or farm management skills may affect its maize production and its decision to hire machinery services. Rural households with advantages in agricultural production are more likely to apply an efficient, organized approach in managing maize production and expanding farm size, thus increasing the likelihood of hiring machinery services and replacing household labor. Consequently, this enhances the scale effect of hiring machinery services. Endogeneity also may arise from reverse causation between hiring machinery services and maize productivity. On the one hand, rural households' hiring of machinery services improves the productivity of maize.[6] On the other hand, higher maize productivity may increase profits derived from maize production, helping farmers afford machinery services. As a result, we treat rural households' hiring of machinery services (M_{Si})

[5] Increased income implies increased consumption expenditures, thus increased food security.

[6] Rural households' hiring of machinery services improves the productivity efficiency of maize through more optimal allocation and application of inputs in maize production.

as an endogenous variable in Equations (1)-(3) and proceed to use an instrumental variable approach to correct for endogeneity. We predict this variable using:

$$M_{si} = \eta X_i + \pi Z_i + \mu_i \tag{4}$$

where $E(\mu_i \mid Z_i) = 0$ and $E(\mu_i, \varepsilon_i) \neq 0$. X_i refers to a vector of the explanatory variables of rural household *i*, and Z_i denotes an instrumental variable (IV) and η and π are parameters to be estimated.

Rural households reported whether their farmland was suitable for large-scale machine tillage (machine suitability). Thus, we use machine suitability as an instrumental variable in this study. The variable, machine suitability, takes a value of 1 if the farm is suitable for machine tillage and 0 otherwise (see Table 2). Generally, the application of large-scale machines requires the farmland to be relatively flat, large in area, and thick in the soil layer. To our knowledge, using agricultural machines on a farm requires farmland of a large enough scale. Thus, whether the farmland is suitable for large-scale mechanical tillage directly influences the probability of hiring machinery services for tillage. The basic requirements for an instrumental variable are easily satisfied. According to the first-stage F-statistics, a weak instrument test on single-equation instrumental variable estimation in a two-stage least squares (2SLS) method will test the instrumental variable's correlation. The instrumental variable method also controls for selection bias due to the absence of variables that capture an individual's decision ability and preference. Though the dependent variables in the first stage and the second stage should be continuous for 2SLS estimation, the 2SLS estimation can be used in our analysis since it is guaranteed that the first-stage residuals were uncorrelated with the fitted values and covariates in the first-stage estimation (Angrist and Pischke, 2008; Meyer, 2016).

In this case, the instrumental variable's main concern is that it might violate the exclusion restriction. The exclusion restriction here is that the instrument "machine suitability" should affect the outcome variables only through hiring machinery services. A possible violation of the exclusion restriction is that the farmland equipped with well machine suitability is likely to have a relatively good quality, which may be correlated with hiring agricultural machinery service. To address this problem, we consider farmland fertility in the regression model. Besides, farmland is distributed by village cadres within the village,[7] and they tend to allocate better-quality farmland (such as good quality land and land located to production infrastructure) to their families (Zhang et al., 2012). Thus, we also consider whether a rural household's family member is a village cadre in the regression model. As a result, the chosen instrument, machine suitability, is first used to predict the likelihood of hiring machinery services in this study. The second step examines how maize production or household income varies with the predicted values.

Finally, the study provides the mechanism through which the adoption of hired machinery services affects the employment of the family labor force (labor allocation). In this study, we investigate four different labor variables, namely the number of off-farm workers in the family, the average number of months in off-farm jobs, business entrepreneurship (whether the rural households started a business), and farm work (number of family members working on the farm). Descriptive statistics of the above dependent variables are presented in Appendix Table A1.

[7] Village cadres are appointed by member of the village committee. For details, see Graeme Smith (2013).

DATA

The analysis uses survey data from the 2015 China Household Finance Survey (CHFS),[8] conducted by the Survey and Research Center for China Household Finance of the Southwestern University of Finance and Economics. Based on an overall sampling and an on-site sampling scheme based on mapping, the survey draws a random sample of 37,289 households representing all Chinese families. The CHFS employs a random sample design stratified three-stage probability proportion to size (PPS). The primary sampling units (PSU) include 2,585 counties (including county-level cities and districts) from all provinces (including municipalities) in China except Tibet, Xinjiang, Inner Mongolia, Hong Kong, Macau, and Taiwan. The second sampling stage involves selecting residential committees/villages from the counties/cities selected in the earlier stage. Meanwhile, the last stage involves selecting households from the residential committees/villages chosen in the previous stage. Every sampling stage is performed with the PPS method and weighted by its population size (Gan et al., 2013). For this study, we focus on rural households specializing in maize production. Thus, the final sample comprised 3,248 rural Chinese households (see Appendix Table A2).

Agricultural production data were obtained from respondents' reports on their farmland. As shown in Table 2, maize yield per mu is computed as total maize production divided by the area of maize harvested. The cost of maize production is computed as the cost of total maize-related inputs divided by the area of maize. Previous studies on farm productivity generally controlled

[8] Source: Southwestern University of Finance and Economics, Survey and Research Center for China Household Finance, https://chfs.swufe.edu.cn/.

for farmer characteristics, regional factors, and time-specific factors. These factors include land quality, age and educational attainment, off-farm income, ownership, and management practices (whether a farm hires plant and machinery services). Farm inputs include land, machinery, and labor expenses, which comprise costs of hired labor and the estimated opportunity cost of family labor. Therefore, the cost of total inputs in maize production consists of variable and fixed input costs, except for farmland rent.[9]

Variable costs include the cost of seeds, fertilizer, pesticide, and labor (family and hired). Two methods compute family labor costs because of the limitations of the survey data. If the family members who planted maize were between 16 and 64 years old, we calculated the opportunity cost of farm work — the average monthly salary of other family members who participated in off-farm work multiplied by the number of months engaged in farming and the number of members. Otherwise, if the family members who planted maize were younger than 16 or older than 64, the family labor cost is derived from the 2015 Compilation of Cost and Benefit Information of China's National Agricultural Products.[10] Our method of computing family labor costs is similar to other studies (Guo et al., 2019; Zhong et al., 2016; Wang et al., 2015).

Fixed costs constitute fuel, maintenance, and depreciation costs for machinery based on the 2015 Compilation of Cost and Benefits Information of China's National Agricultural Products. Though the depreciation pattern for farm equipment varies (Cross and Perry, 1995), in this study, the depreciation of rural households' agricultural machinery is computed as the asset's current

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[9] Since land is given to farmers by the village collectives, farmers do not pay any rent on the farmland.
[10] Source: http://navi.cnki.net/KNavi/YearbookDetail?pcode=CYFD&pykm=YZQGN&bh=.

value depreciated at 5 percent of residual value divided by a 10-year useful life of the motor (see Du, 2013 for details). Since an inverse relationship between farm size and productivity exists in practice, we use land acreage in the regression model, including the cultivated area of maize and its squared term and self-reported land fertility. Because land fragmentation may impact maize yield and costs (Lu et al., 2018), we include the ratio of the largest plot area to total cultivated farmland.

Several studies have investigated the impacts of off-farm work participation and the household head's gender and age on agricultural performance (Zou et al., 2018, 2019). This study includes information on the farm family's labor allocation decisions. Specifically, we have the share of off-farm workers, the share of female workers, and the share of older workers in the family. Table 2 shows that about 1,532 sampled households hired machinery services. Indeed Table 2 shows that rural Chinese families that adopted machinery services had higher maize yields, slightly lower unit costs of maize production, and higher per capita income than their counterparts.

RESULTS AND DISCUSSION

Hiring machinery services, food security and household welfare

Table 3 presents the estimates of adoption of the hired machinery services on food security measures, namely maize productivity (output), cost of maize production, and per capita farm household income. The corresponding first stage results are reported in Appendix Table A3). Table 4 shows the marginal effects of the estimates obtained in Table 3. The estimated marginal effect of the adoption of hired machinery services is significantly positive in the models of maize productivity, cost of maize output, and per capita income of rural households. Findings suggest that the adoption of hired machinery services increases maize productivity by about 8 percent. Indeed, results indicate that hiring machinery services increases the food security of rural Chinese families. However, increased productivity comes with an increased cost of maize production. Table 4 column 3 suggests that the adoption of hired machinery services increases the cost of maize production by 7 percent. Finally, Column 4 of Table 4 reveals that the adoption of hired machinery services increases per capita rural Chinese households by about 10 percent. The results on unit costs of maize output are counterintuitive. A possible explanation is that, compared to the traditional form of labor-intensive production, which is based primarily on unpaid family labor, it is not surprising that maize production based on hiring machinery services seems to have a higher cost. However, it should be noted that the increase in the unit cost of maize production is less than the increase in maize yields resulting from the adoption of hired machinery services (Column 2, Table 4). Note that increased income also implies increased food security. Overall our findings suggest that the adoption of hired machinery services increases the food security of rural Chinese families. Our conclusion is consistent with (Zhou et al., 2020a), who found that farm machinery significantly increases maize yields.

Table 4 also shows that machinery ownership and other costs (like seed, fertilizer, pesticide, etc.) positively impact maize productivity (or food security). Estimates in Table 4 suggest that the additional value of owned machinery and other expenses increases maize yields by about 3.8 percent and 1.6 percent, respectively. Our result is consistent with the findings of Muyanga and Jayne (2019). Farm attributes have a direct impact on agricultural production. The estimated marginal effects of maize area (Column 3, Table 4) reveal that the maize acreage has a significantly negative effect on the unit cost of maize production. In contrast, the squared term of the cultivated maize acreage positively impacts the unit cost of maize output. An increase in maize acreage reduces the cost of maize production at first but then increases the cost of production. This finding affirms a quadratic relationship (or a *U*-shaped) between farm size and production costs. Further, the negative and significant relationship between *Largest_plot* and the unit cost of maize production suggests that an additional mu in the largest plot's share of total operating farmland reduces the cost of maize production by about 5.9 percent.

Household characteristics also influence maize production. The sign and magnitude of household characteristics variables are consistent with previous literature (Zhang et al., 2017). For instance, the age and educational attainment of the head of household have a significant and positive impact on maize productivity. For instance, an additional year increases maize productivity by about 28.2 percent. Thus, older farm families are likely to be more experienced in farming and, as a result, more food secure than young farm families. Compared to rural household heads with primary school education, rural Chinese household heads with junior high school and high school education have higher maize productivity, about 1.5 percent and 0.7 percent, respectively. Again, educated farmers are likely to make sound farming decisions and have higher food security than their counterparts. The marginal effect of *Agri_income* is positive and significant, suggesting that a higher share of agricultural income increases maize productivity by about 5.2 percent. A plausible explanation is that farm families with higher agricultural income depend more on income from farming to support the family's consumption.

These households specialize in farming, where operators and family members know better farming practices, new technology, and risk management strategies.

Similarly, the variable *Off_farm_labor* has a positive impact on maize productivity. Results in Table 4 reveal that an increase in the share of off-farm labor increases food security—maize yield by 1.4 percent. Thus, participation in off-farm work increases the food security of rural Chinese households. A plausible explanation is that off-farm work by family members relaxes the liquidity constraint of farming enterprises. With the increased income (from off-arm), farmers can invest more productivity-enhancing inputs (Ma, Abdulai and Ma, 2017)[11], quality farm inputs (Zhang *et al*., 2020)[12], and rent-in farmland (Gebregziabher et al., 2012; Tiwari et al., 2008; Evan and Ngau, 1991). Correspondingly, the variable *Off_farm_labor* in Table 4 has a negative and significant impact on the cost of maize production, suggesting that an increase in the share of off-farm labor reduces the cost of maize production by 2.8 percent. The variable *Aging_labor* has a negative and significant impact on the cost of maize, suggesting that an increase in the share of aging workers reduces the cost of maize production by 2 percent. A possible explanation is that older farmers are more experienced and likely to improve input efficiency than young farmers.

The fourth column of Table 4 shows the estimated marginal effects of the factors affecting rural households' per capita income. Results reveal that the adoption of hired machinery services

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[11] Ma, Abdulai, and Ma (2017) found that off-farm work stimulates agricultural production by increasing the investments in productivity-enhancing inputs.
[12] Zhang *et al*. (2020) found that off-farm employment increased the rate of chemical fertilizer intensity in plains areas of China.

increases rural households' per capita income by 9.5 percent. Table 4 shows that an additional year in the household head's age increases per capita income by 24.5 percent. The probable reason may be that households with aging household heads may have accumulated more wealth than families with young household heads. Results show that compared to a household head with primary school education or below, household heads with high school education or above are likely to increase per capita income by 1.2 percent and 0.5 percent, respectively. Our finding is consistent with the notion that increased schooling allows farmers to process and adopt new technologies and production systems and enhance technical and allocative efficiencies. Our result is consistent with Huffman (1977), Huffman (1985), and Khaldi (1975).

The share of total family income, off-farm workers' share of total family workers, female workers' share in total family workers, and value of machinery positively affect per capita household income. The above finding suggests that a 1 percent increase in the share of agricultural income, the share of off-farm workers, the share of female workers, and the value of farm machinery increases per capita household income by 7.2 percent, 9.6 percent, 2.2 percent, and 3.5 percent, respectively. In contrast, loans acquired by rural households for business ventures has a negative and significant effect on per capita household income, suggesting that an additional debt for business ventures decreases per capita household income by about 0.1 percent.

A test for instrument validity

A valid instrumental variable needs to satisfy both correlation and exogeneity conditions. Generally, if rural households' farmland is suitable for large-scale mechanical tillage, they are more likely to adopt hired machinery services. The basic requirements for the correlation of instrumental variables are easily satisfied. Moreover, the corresponding result of the first stage is reported in Appendix Table A3, which shows a significant and positive relationship between the variables *Machine_suitability* (instrumental variable) and hired machinery services (endogenous variable). We also test whether the *Machine_suitability* variable is weak using the first-stage *F*-statistic. The results of the *F*-statistic in Table A3 suggest that *Machine_suitability* is not a weak instrumental variable.

Next, we tried to rule out other ways that *Machine_suitability* may affect maize productivity and household welfare. First, the farmland suitable for large-scale mechanical tillage is perhaps of better quality, leading to higher maize productivity. Second, rural households owning the farmland suitable for large-scale mechanical tillage are likely to rent in farmland to achieve economies of scale. Third, rural households owning the farmland suitable for large-scale mechanical tillage may take advantage by adjusting the structure of farming operations or by engaging in farm specialization. Therefore, we explore the relevance of the *Machine_suitability* variable like farmland fertility, choice of renting in farmland, number of agricultural enterprises, and number of crops planted.[13] The results in Table A5 suggest that *Machine_suitability* only significantly influences farmland fertility, affecting maize productivity. Recall that we controlled for farmland fertility in our main regression. In sum, the instrumental variable satisfies the requirement of exclusiveness.

[13] The definitions and summary statistics of the above variables are shown in Table A4.

Mechanism of hiring machinery services on households' welfare

Findings suggest that rural Chinese households hiring machinery services increase the number of family workers working off the farm. Table 5 shows that hiring machinery services has significant and positive impacts on family workers' labor allocation decisions. Column 2 of Table 5 reveals that hiring machinery services increases the number of family members working off-farm jobs by 41 percent. Besides, Column 3 of Table 5 shows that hiring machinery services increases the intensity of off-farm work (months per person) by 71 percent. Our finding is consistent with Charlton and Taylor (2016), who found that Mexican farmers were transitioning out of farm work due to Mexican agriculture globalization. Simiarly, Oshiro (1985) found that rice farming mechanization in Japan increased the number of persons working off the farm. Additionally, due to the risk associated with farm income, farm families diversify their labor allocation to more stable and higher-income activities by supplying labor to non-farming sectors (Jovanovic and Gilbert, 1993; McNamara and Weiss, 2001; Mishra and Goodwin, 1997).

Finally, the last column of Table 5 reveals that hiring machinery services decreases the number of family members working on the farm by about 13 percent. Our finding is consistent with Oshiro (1985), who found that mechanization on Japanese rice farms decreased farm labor demand. Finally, Pingali et al. (1987) concluded that farms adopting tractors used less farm labor per hectare of crop production than farms using draft animals. The above findings underscore the importance of machinery services in modernizing Chinese agriculture. Like those in Japan and Western economies, farm mechanization releases surplus farm labor and moves them into more rewarding off-farm jobs. The above findings' policy implications underscore the importance of the non-farm sector in increasing rural households' welfare. This is a win-win situation for improving food security for rural Chinese farmers and smallholders throughout South and Southeast Asia.

Turning to farm characteristics, Table 5 shows that the area of maize has a negative and significant effect on the number of off-farm workers, suggesting that a 1 percent increase in maize area decreases the number of off-farm family workers by about 34.3 percent. However, the coefficient of maize area squared is positive and significant at the 10% level of significance. Results show that increasing farm size at first decreases the number of off-farm workers, but as farm size increases further, it increases the number of off-farm workers in the farming family. A plausible explanation is that farm families first use family workers on the farm. After achieving sufficient farm size, additional family workers, especially those who are educated, explore off-farm employment opportunities. Finally, Column 5 of Table 5 shows that a large maize farm (maize area squared term) coefficient is positive and statistically significant at the 10% level of significance.

The gender and age of the household head is negative and significantly correlated with the intensity of off-farm work by family workers. Results show that an additional year decreases the intensity of off-farm work by family members by about 16 percent. A plausible explanation is that as heads of households age, they are less likely to seek off-farm employment (due to travel time, wealth effect, and hard work required to perform the job), and/or they reduce the number of months worked off the farm. The intensity of off-farm work also may be reduced due to government regulations. Similarly, Column 5 of Table 5 shows that an additional year in the household head's age reduces farm workers by about 30 percent. Farm work demands effort level, managerial activities, training, and learning of new technologies. Thus, older household heads are less likely to work on the farm. The above results are consistent with findings in the United States (McNamara and Weiss, 2001; Mishra and Goodwin, 1997).

Table 5 shows a positive and significant relationship between the household head's education and the number of off-farm laborers, the intensity of off-farm work, and starting a business. Results show that, compared to household heads with primary school education, household heads with high school or higher educational attainment are more likely to engage in off-farm work, more likely to have increased months of off-farm employment, and more likely to start a business. Our finding is consistent with theory and evidence from the literature (see Huffman (1985); Khaldi (1975); Mishra and Goodwin (1997); Mishra and Sandretto (2002)). The above findings underscore the importance of education in the welfare of rural farming households. A higher level of schooling empowers family members to engage in non-farm employment, which provides higher incomes and, as a result, increased food security. Results also show that agricultural income's share in total household income negatively impacts off-farm employment but positively influences entrepreneurial and farming activities. Our finding is consistent with Donovan and Poole (2014), who argue that household members engage in livelihood activities associated with the endowment of livelihood assets.

Finally, the results in Table 5 show that an increase in a farming family's share of female workers increases the number of off-farm workers and the intensity of off-farm work per household worker. A plausible explanation is that education is more accessible to girls in China, and a larger share of girls is getting educated than males. Thus, females are more likely to have an off-farm job (Wu and Zhang, 2010; Xie et al., 2019).[14] It is not surprising that the share of aged persons in the household (> 50 years) has a significant negative impact on off-farm work. Older Chinese are less likely than younger Chinese to work in off-farm jobs. Off-farm jobs demand effort and time. However, we find (Column 5, Table 5) that the share of older individuals in the household increases the number of workers on the farm. In these cases, the older individuals are more likely to perform low-stress jobs, managing the farm's daily operations.

The coefficient of the value of machinery is positive and significant in influencing the number of off-farm workers and the intensity of off-farm work per worker (Table 5). This result is consistent with previous studies, which found the endogenous linkages and substitution effects between farmers' machinery investment and off-farm work participation (Ji et al., 2012; Ma et al., 2018a). Findings suggest that owning farm machinery helps free family labor from farming activities and shift them to off-farm jobs. The above actions diversify income risk and maximize household income via the appropriate allocation of household labor. In sum, reallocation of labor increased the income of rural Chinese households and thus food security. Indeed, the findings emphasize mechanization's importance to the welfare of rural Chinese families. The finding corroborates the above results that the pathway to modernizing Chinese agriculture passes through farm mechanization. This study's results are relevant for China and other smallholder

[14] According to the National Bureau of Statistics of China of 2011 and 2019, the share of females (aged 15 and above) increased from 45.09% in 2010 to 49.42% in 2018. Moreover, the share of females with undergraduate education increased from 44.73% in 2010 to 48.24% in 2018 to the total population with undergraduate education. Data source: http://www.stats.gov.cn/tjsj/ndsj/.)

farming countries, such as India.

CONCLUSION AND POLICY IMPLICATIONS

The study discussed the possibility of a third path to modernizing agriculture for smallholders in China. That is hiring of agricultural machinery services in farm production. We explored the impact of hiring machinery services on farm performance and rural Chinese households' welfare by using the China Household Finance Survey (CHFS) of 2015. Results showed that hiring machinery services positively and significantly affected maize yield and rural Chinese households' per capita income. Developing a robust private farm machinery market with private entrepreneurs can support the demand for farm machinery services. Modernizing Chinese agriculture at a smaller scale could be achieved by hiring machinery services. Hiring machinery services would release surplus family labor for off-farm employment opportunities and increase farming efficiency. Therefore, hiring machinery services serves as a strategy to diversify income risk and maximize total household income—thus increasing food security.

This study highlighted the crucial role of hiring machinery services in transforming traditional smallholder agriculture, especially at China's current agricultural technology and economic development stage. This is also critical because it ensures food and income security for rural Chinese families tied to the land and a land tenure system where land cannot be bought and sold.

The policy implications of these findings underscore the non-farm sector's importance in increasing rural households' welfare. As a result, government policies that influence general economic conditions profoundly impact smallholder Chinese households. Policies aimed at increasing off-farm job opportunities should be enacted carefully. One such policy tool could be tax incentives for economic development by private-sector investment in places with low income, higher poverty, and higher unemployment rates. Off-farm employment opportunities require higher human capital. A higher level of schooling by family members equips them to use their labor for higher returns on education. Policymakers can provide educational subsidies that promote the public secondary education curriculum. Facilitating access to education and job opportunities is paramount in determining off-farm employment and smallholder agriculture transformation.

Since most farms worldwide are small and family-operated, particularly in developing countries, understanding the significance of hiring machinery services in rural China has important policy implications for agricultural development. The small size of farms caused by limited land resources and the rise in agricultural labor's opportunity cost is the root cause of rural households' demand for agricultural machinery services. Development of the farm machinery services market can realize the effective compatibility of small farmers' decentralized operation and high-horsepower machinery, promoting the modernization of traditional agriculture. Adopting agricultural machinery services promotes green and efficient agrarian development and increases food security and the welfare of rural households. Hence, the government and policymakers should encourage the development of agrarian services like farm mechanization through firms offering involved in machinery services and farm specialization. In sum, government policies that influence general economic conditions have a much more profound influence on the food security of rural Chinese families and, by extension, smallholder farm families across South and Southeast Asia.

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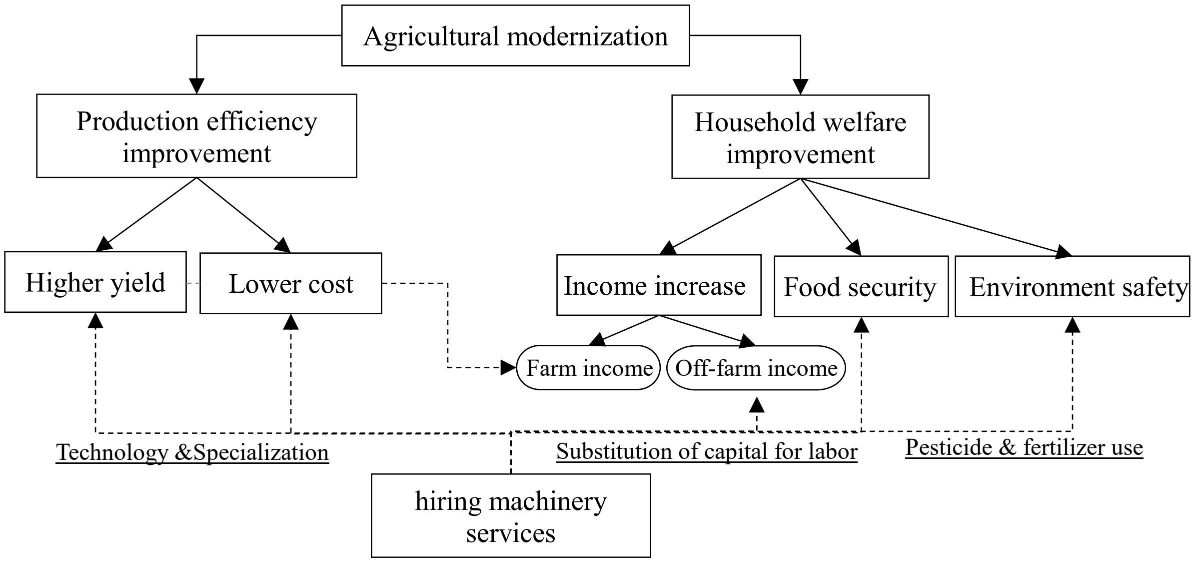

Figure 1: Conceptual framework of agricultural modernization- machinery service outsourcing nexus

Table 1. The Distribution of Farm size operated by Chinese rural households, 2015.

Farm size	1996 (%)	2011 (%)	2015 (%)	2018 (%)
Below 10 mu	76.00	86.00	85.74	85.20
10-30 mu	20.20	10.70	10.32	10.50
30-50 mu	2.30	2.30	2.60	2.70
Above 50 mu	1.50	1.00	1.33	1.60

Notes: Data for 1996 is based on the household data from a National Fixed-Point Survey, implemented by China's Ministry of Agriculture. Data for 2011 and 2015 are from the National Rural Management and Administration (2011, 2015, 2018) compiled by the Ministry of Agriculture Economics and Management Department.

Table 2. Definition and summary statistics of variables

Variable	Description	Total sample	Hiring service	No hiring service
Sample size		3,248	1,532	1,716
Dependent variables				
Yield per mu	Maize yield per mu	543.460	569.419	520.284
Cost per unit	Maize production costs per kilogram	18.595	18.335	18.828
Per capita income	Per capita income of rural household (Yuan, RMB)	27,118.720	28,280.810	26,081.240
Input variables				
Mechanization service	=1 if rural household hired mechanization service; 0 otherwise	0.472	1.000	0.000
Family labor	Cost of family labor per mu of maize (Yuan, RMB)	416.298	414.055	418.301
Hiring labor	Cost of hiring labor per mu of maize (Yuan, RMB)	92.055	62.360	118.565
Machinery	Cost of fuel, maintenance and depreciation of agricultural machinery owned by rural household per mu of maize (Yuan, RMB)	42.252	27.405	55.507
Other costs	Cost of seed, fertilizer, pesticide, and other expenses per mu of maize (Yuan, RMB)	62.631	62.187	63.027
Farm characteristics				
Area_maize	Sown area of maize (mu)	19.797	17.925	21.467
Largest_plot	Share of the area of the largest plot to total farmland operated	0.540	0.537	0.543
Fertility_01	=1 if fertility of farmland is very good; 0 otherwise (base group)	0.042	0.034	0.050
Fertility_02	=1 if fertility of farmland is good; 0 otherwise	0.121	0.104	0.137
Fertility_03	=1 if fertility of farmland is mediocre; 0 otherwise	0.501	0.497	0.504
Fertility_04	=1 if fertility of farmland is poor; 0 otherwise	0.216	0.237	0.196
Fertility_05	=1 if fertility of farmland is very poor; 0 otherwise	0.120	0.128	0.112
Household characteristics				
Gender	=1 if household head (HH) is male; 0 otherwise	0.634	0.638	0.629
Age	Age of household head (years)	52.681	52.424	52.910
Education_01	=1 if education of HH is primary school, 0 else (base group)	0.127	0.117	0.137

Education_02	=1 if education of HH is junior high school; 0 otherwise	0.392	0.333	0.445
Education_03	=1 if education of HH is high school; 0 otherwise	0.366	0.411	0.327
Education_04	=1 if education of HH is above high school; 0 otherwise	0.114	0.140	0.091
Agri_income	Share of agricultural income to total family income	0.486	0.520	0.455
Off_farm_labor	Share of off-farm laborers to total family laborers	0.246	0.271	0.224
Female_labor	Share of female laborers to total family laborers	0.458	0.462	0.456
Aging_labor	Share of labores aged from 51 to 64 in total family laborers	0.328	0.326	0.329
Village_cadre	=1 if one of rural household's family members is a village cadre;0 otherwise	0.062	0.061	0.062
Machinery value	Total value of agricultural machinery owned by rural household (Yuan, RMB)	4911.604	3872.750	5839.066
Debt_agriculture	=1 if rural household had loans for agriculture; 0 otherwise	0.063	0.060	0.066
Debt_business	=1 if rural household had loans for business; 0 otherwise	0.09	0.007	0.011
Instrumental variable				
Machine_suitability	=1 if farmland is suitable for large-scale mechanical tillage; 0 otherwise	0.573	0.749	0.416

Source: 2015 China Household Finance Survey (CHFS).

Table 3. Impacts of mechanization service, Instrumental-variables regression (2SLS), China

Variable	Yield per mu (log)	Cost of maize production per kilo (log)	Per capita income (Yuan) (log)
Mechanization service	1.027***	0.347*	1.983***
	(0.303)	(0.190)	(0.424)
Family labor (log)	-0.018		
	(0.047)		
Hiring labor (log)	-0.002		
	(0.019)		
Machinery (log)	0.094***		
	(0.028)		
Other cost (log)	0.033*		
	(0.020)		
Area_maize (log)	0.593	-4.563***	0.650
	(1.175)	(0.767)	(1.061)
Area_maize squared (log)	-0.466	2.281***	-0.177
	(0.525)	(0.342)	(0.486)
Largest_plot	-0.099	-0.222***	0.006
	(0.096)	(0.061)	(0.135)
Fertility_02	0.136	-0.085	0.253
	(0.142)	(0.103)	(0.255)
Fertility_03	0.111	-0.107	0.299
	(0.129)	(0.093)	(0.234)
Fertility_04	0.0350	-0.136	0.247
	(0.140)	(0.098)	(0.243)
Fertility_05	0.114	-0.176*	0.248
	(0.148)	(0.103)	(0.259)
Gender	0.0921	0.060	-0.120
	(0.0632)	(0.039)	(0.0878)
Age (log)	0.391**	0.072	0.536***
	(0.159)	(0.094)	(0.184)
Education_02	0.206**	-0.030	0.147
	(0.0949)	(0.059)	(0.139)
Education_03	0.139	0.005	0.298**
	(0.104)	(0.064)	(0.146)
Education_04	0.331***	0.036	0.450**
	(0.117)	(0.077)	(0.187)
Agri_income	0.610***	0.013	1.334***
	(0.0908)	(0.057)	(0.165)
Off_farm_labor	0.299**	-0.229***	3.782***

	(0.132)	(0.080)	(0.225)
Female_labor	0.0631	0.130	0.420**
	(0.135)	(0.086)	(0.191)
Aging_labor	0.053	-0.131**	0.0702
	(0.084)	(0.054)	(0.126)
Village_cadre	0.142	0.053	-0.090
	(0.106)	(0.072)	(0.164)
Machinery value (log)			0.093***
			(0.0131)
Debt_agriculture			0.161
			(0.155)
Debt_business			-1.272**
			(0.643)
Constant	3.428***	2.638***	4.080***
	(0.880)	(0.549)	(0.986)
Province dummy	Yes	Yes	Yes
N	3248	3248	3248
R^2	0.090	0.201	0.194

Note: ***=1% significance; **=5% significance; *=10% significance. Robust standard errors are reported in the parentheses. The logarithm of a variable is that it does not allow retaining zero-valued observations because ln(0) is undefined. Thus, the logarithm of a variable is estimated as log(x+1).

Table 4. Marginal effects for impacts of mechanization service (IV regression, 2SLS, second step)

Variable	Yield per mu (log)	Cost of production per kilo of maize (log)	Per capita Income (log)
Mechanization service	0.080***	0.070**	0.095***
	(0.022)	(0.036)	(0.019)
Family labor (log)	-0.020		
	(0.051)		
Hiring labor (log)	0.000		
	(0.002)		
Machinery (log)	0.038***		
	(0.011)		
Other cost (log)	0.016*		
	(0.009)		
Area_maize (log)	0.196	-3.496***	0.131
	(0.389)	(0.592)	(0.214)
Area_maize squared (log)	-0.277	3.040***	-0.064
	(0.312)	(0.458)	(0.174)
Largest_plot	-0.010	-0.059***	0.000
	(0.010)	(0.017)	(0.009)
Fertility_02	0.003	-0.005	0.004
	(0.003)	(0.006)	(0.004)
Fertility_03	0.010	-0.025	0.017
	(0.012)	(0.022)	(0.013)
Fertility_04	0.001	-0.014	0.006
	(0.006)	(0.010)	(0.006)
Fertility_05	0.002	-0.010*	0.003
	(0.003)	(0.006)	(0.003)
Gender	0.011	0.018	-0.009
	(0.007)	(0.012)	(0.006)
Age (log)	0.282***	0.136	0.245***
	(0.115)	(0.177)	(0.084)
Education_02	0.015**	-0.006	0.007
	(0.007)	(0.011)	(0.006)
Education_03	0.009	0.001	0.012**
	(0.007)	(0.011)	(0.006)
Education_04	0.007***	0.002	0.005***
	(0.002)	(0.004)	(0.002)
Agri_income	0.052***	0.003	0.072***
	(0.008)	(0.012)	(0.009)
Off_farm_labor	0.014**	-0.028***	0.096***
	(0.006)	(0.010)	(0.006)

Female_labor	0.005	0.028	0.022**
	(0.011)	(0.018)	(0.010)
Aging_labor	0.003	-0.020**	0.003
	(0.005)	(0.009)	(0.005)
Village_cadre	0.002	0.001	-0.001
	(0.001)	(0.002)	(0.001)
Machinery value (log)			0.035***
			(0.005)
Debt_agriculture			0.001
			(0.001)
Debt_business			-0.001*
			(0.001)

Note: Average marginal effects by ey/ex. ***=1% significance; **=5% significance; *=10% significance. Delta-method robust standard errors are reported in the parentheses.

Table 5. Instrumental-variables regression results for the mechanism of the impact of mechanized services on rural households' labor allocation and business entrepreneurship, China

Variable	2SLS Off-farm participation (log)	2SLS Off-farm time (log)	IV probit Business	2SLS Farm labor (log)
Mechanization service	0.410***	0.714***	0.256	-0.128**
	(0.078)	(0.160)	(0.338)	(0.060)
Area_maize (log)	-0.343*	-0.396	0.938	-0.268
	(0.200)	(0.414)	(1.043)	(0.170)
Area_maize Squared (log)	0.167*	0.203	-0.458	0.128*
	(0.091)	(0.188)	(0.470)	(0.076)
Largest_plot	0.014	-0.050	0.131	-0.119***
	(0.025)	(0.053)	(0.108)	(0.020)
Fertility_02	0.036	0.046	-0.034	0.023
	(0.041)	(0.089)	(0.209)	(0.032)
Fertility_03	0.074**	0.096	0.095	-0.007
	(0.036)	(0.081)	(0.186)	(0.029)
Fertility_04	0.036	0.038	0.150	-0.027
	(0.039)	(0.086)	(0.196)	(0.031)
Fertility_05	0.052	-0.019	0.458**	-0.006
	(0.041)	(0.091)	(0.200)	(0.033)
Gender	-0.022	-0.079**	0.024	0.032**
	(0.016)	(0.034)	(0.073)	(0.013)
Age (log)	-0.045	-0.167**	-0.135	-0.303***
	(0.038)	(0.077)	(0.137)	(0.032)
Education_02	0.024	0.077	0.137	0.02
	(0.026)	(0.053)	(0.126)	(0.019)
Education_03	0.060**	0.111*	0.406***	0.044**
	(0.028)	(0.057)	(0.130)	(0.021)
Education_04	0.117***	0.228***	0.474***	-0.018
	(0.035)	(0.072)	(0.157)	(0.027)
Agri_income	-0.627***	-1.448***	0.237***	0.0902***
	(0.021)	(0.042)	(0.088)	(0.016)
Female_labor	0.225***	0.348***	0.173	0.270***
	(0.039)	(0.082)	(0.147)	(0.030)
Aging_labor	-0.187***	-0.302***	-0.459***	0.220***
	(0.022)	(0.048)	(0.108)	(0.018)
Village_cadre	0.106***	0.214***	0.187	0.014
	(0.032)	(0.069)	(0.125)	(0.024)
Machinery value (log)	0.011***	0.025***	0.003	0.002

	(0.003)	(0.005)	(0.011)	(0.002)
Constant	0.699***	1.989***	-2.410***	1.403***
	(0.210)	(0.433)	(0.852)	(0.173)
Province dummy	Yes	Yes	Yes	Yes
N	3248	3248	3248	3248
R^2	0.249	0.303		0.183

Note: ***=1% significance; **=5% significance; *=10% significance.

Robust standard errors are reported in the parentheses.

Appendix

Appendix Table A1: Descriptive statistics of dependent variables

Variable	Description	Total sample	Hiring service	No hiring service
Farm labor	number of workers working on the farm in a household (person)	0.966	0.942	0.987
		(0.703)	(0.673)	(0.728)
Off-farm participation	number of workers with off-farm jobs in a household (person)	0.815	0.887	0.751
		(0.971)	(0.961)	(0.975)
Off-farm time	total months per year of off-farm work by members/number of laborers with an off-farm job (months/ person)	3.487	3.836	3.175
		(3.932)	(4.017)	(3.828)
Business	=1 if the rural households started a business; 0 otherwise	0.087	0.101	0.074
		(0.281)	(0.301)	(0.262)
Obs.		3,248	1,532	1,716

Note: The value in the table is the mean of the variable. Standard errors are reported in the parentheses.

Appendix Table A1: Sample distribution

Province	Freq.	Percent	Province	Freq.	Percent
Beijing	18	0.55	Hubei	109	3.36
Tianjin	35	1.08	Hunan	89	2.74
Hebei	277	8.53	Guangdong	13	0.40
Shanxi	274	8.44	Guangxi	66	2.03
Neimenggu (Inner Mongolia)	76	2.34	Hainan	4	0.12
Liaoning	192	5.91	Chongqing	134	4.13
Jilin	264	8.13	Sichuan	187	5.76
Heilongjiang	158	4.86	Guizhou	167	5.14
Jiangsu	35	1.08	Yunnan	197	6.07
Zhejiang	35	1.08	Shaanxi	114	3.51
Anhui	153	4.71	Gansu	201	6.19
Fujian	3	0.09	Qinghai	2	0.06
Jiangxi	3	0.09	Ningxia	32	0.99
Shandong	192	5.91	Total	3,248	100.00
Henan	218	6.71			

Appendix Table A3: Impact of mechanization service, First-Stage of IV regression (2SLS), China

Variable	Dependent variable: Mechanization service		
	Yield per mu	Cost of maize production per kilo	Per capita income (Yuan)
Machine_suitability	0.209***	0.211***	0.212***
	(0.019)	(0.019)	(0.019)
Family labor (log)	-0.014		
	(0.014)		
Hiring labor (log)	0.013**		
	(0.005)		
Machinery (log)	-0.054***		
	(0.006)		
Other cost (log)	0.022***		
	(0.005)		
Area_maize (log)	-0.240	-0.089	-0.154
	(0.234)	(0.224)	(0.228)
Area_maize squared (log)	0.109	0.040	0.074
	(0.105)	(0.101)	(0.103)
Largest_plot	-0.043*	-0.030	-0.068***
	(0.026)	(0.026)	(0.026)
Fertility_02	-0.049	-0.048	-0.052
	(0.044)	(0.045)	(0.044)
Fertility_03	-0.009	-0.009	-0.008
	(0.040)	(0.041)	(0.040)
Fertility_04	0.005	-0.003	0.004
	(0.042)	(0.043)	(0.043)
Fertility_05	0.007	-0.005	0.007
	(0.045)	(0.046)	(0.045)
Gender	0.022	0.012	0.025
	(0.017)	(0.018)	(0.017)
Age (log)	-0.006	0.012	-0.009
	(0.038)	(0.039)	(0.038)
Education_02	0.018	0.020	0.024
	(0.025)	(0.025)	(0.025)
Education_03	0.070***	0.072***	0.078***
	(0.026)	(0.027)	(0.026)
Education_04	0.111***	0.112***	0.121***
	(0.034)	(0.034)	(0.034)
Agri_income	0.055**	0.055**	0.071***
	(0.023)	(0.023)	(0.023)

Off_farm_labor	0.117***	0.125***	0.125***
	(0.032)	(0.032)	(0.032)
Female_labor	0.010	0.019	0.020
	(0.039)	(0.039)	(0.039)
Aging_labor	-0.022	-0.014	-0.021
	(0.025)	(0.025)	(0.025)
Village_cadre	-0.021	-0.035	-0.023
	(0.033)	(0.034)	(0.033)
Machinery value (log)			-0.019***
			(0.002)
Debt_agriculture			0.033
			(0.035)
Debt_business			-0.003
			(0.082)
Constant	0.628***	0.353*	0.484**
	(0.228)	(0.216)	(0.212)
Province dummy	Yes	Yes	Yes
N	3248	3248	3248
Adj R^2	0.241	0.216	0.235
F-stats	126.432***	126.672***	129.916***

Note: Robust standard errors in parentheses.

*, ** and *** denote significance at .10, .05 and .01 levels. These results correspond to the models in Table 3.