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# Farm machinery use, off-farm employment and farm performance in China\*

Wanglin Ma , Alan Renwick  and Quentin Grafton <sup>†</sup>

We analyse the joint impacts of farm machinery use and off-farm employment on maize yields and agrochemical expenses from a household survey of 493 farmers in China. Our findings are obtained from an innovative two-stage econometric procedure that combines a bivariate ordered probit model with an endogeneity-corrected ordinary least square regression model. The results show that farmers are jointly making decisions to use farm machines and to work off the farm and that these two household activities affect maize yields and agrochemical expenses in different ways. We show that farm machinery use significantly increases both maize yields and agrochemical expenses, while off-farm employment significantly decreases agrochemical expenses. Our findings highlight the importance of additional machinery use in increasing farm production; the need to account for possible endogeneity in estimation; and the statistical significance of key household characteristics (gender, education, and household size) on overall farm production.

**Key words:** China, farm performance, machinery use, maize farmers, off-farm employment.

## 1. Introduction

The substitution of labour by farm machines has been fundamental to agricultural transformation and continues to play an important role in sustaining agricultural production in many developing countries (Kienzle *et al.* 2013; Benin 2015; Luo and Escalante 2015; Ahmed and Goodwin 2016; Wang *et al.* 2016; Zhang *et al.* 2017). Rural-to-urban migration has also led to the so-called feminisation of the agricultural labour force as men migrate at a higher rate than women and, increasingly, women are left responsible for the family farm. As a result, agricultural mechanisation, in particular, offers women in rural areas the potential, especially with continued migration, to maintain or increase their farm production.

Several studies have analysed the impacts of the use of farm machines (e.g. tractors, drills, harvesters) on agricultural production (Rahman *et al.* 2011;

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\* The authors gratefully acknowledge the financial support from the Faculty of Agribusiness and Commerce at Lincoln University (Seed Fund Project INT5056). Wanglin Ma is very grateful to Pei Zhang for his great help during household survey.

JEL Codes: D24; O47; R23;

<sup>†</sup> Wanglin Ma (email: wanglin.ma@lincoln.ac.nz) and Alan Renwick are with Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand. Quentin Grafton is at Crawford School of Public Policy, Australian National University, Canberra, Australian Capital Territory 2601, Australia.

Kienzle *et al.* 2013; Takeshima *et al.* 2013; Benin 2015; Luo and Escalante 2015; Sims *et al.* 2016; Wang *et al.* 2016). They find that farm machinery use boosts agricultural intensification and also conservation agriculture, supports labour- and energy-efficient technologies and promotes gender-friendly practices. Benin (2015), in particular, finds that the use of mechanisation services by farming households in Ghana significantly increases farm yields. Wang *et al.* (2016) find that machinery use in China significantly increases yields of crops including wheat, corn, Japonica rice, soybean, cotton and rapeseeds and that there is substitution between labour and machine use.

A potential benefit from the use of farm machines is that it frees up household's farm management time that can be reallocated to activities such as leisure and off-farm employment. Consequently, a number of theoretical and empirical studies have investigated the relationship between off-farm employment and agricultural production (Chikwama 2004; Phimister and Roberts 2006; Feng *et al.* 2010; Mathenge *et al.* 2015; Kousar and Abdulai 2016; Ma *et al.* 2017). There are two sets of findings arising from the literature. Kousar and Abdulai (2016), for example, find that participation in off-farm work tends to increase the investment in long-term soil-improving measures (e.g. organic manure and green manure) and farm productivity. By contrast, several authors find a so-called lost-labour effect due to off-farm employment (Phimister and Roberts 2006; Feng *et al.* 2010; Shi *et al.* 2011; Chang and Mishra 2012; Mathenge *et al.* 2015). This work highlights that off-farm employment reduces the labour available for farm production and, thus, lowers agricultural production. For instance, in their investigation of 2,419 farms in England and Wales, Phimister and Roberts (2006) show that the intensity of fertiliser use may decline as off-farm labour supply increases. Shi *et al.* (2011) also find that off-farm employment (and migration in particular) reduces the levels of chemical inputs and manure used in rice production in China.

Evidence from different countries shows that farmers' decisions to use farm machinery are jointly determined by their decisions to undertake off-farm employment (Ji *et al.* 2012; Kienzle *et al.* 2013; Luo and Escalante 2015; Ahmed and Goodwin 2016; Sims *et al.* 2016). In particular, Ji *et al.* (2012) show that farm labour use and small-sized machinery investments are gross complements in China when machinery services are available. Ahmed and Goodwin (2016) conclude that the use of tractors/power tillers significantly increases off-farm employment in Bangladesh. Thus, given the possible interdependence of farm machinery use and off-farm employment, their effects on farm performance should be modelled jointly.

Here, we analyse the joint impacts of farm machinery use and off-farm employment on farm performance in China. Our study utilises data from a survey conducted in 2017 that includes a sample of 493 maize-producing households in Western, Central and Eastern regions of China. Our contributions are threefold. First, we explicitly model the intensity of farm machinery use and the intensity of off-farm employment. In particular, we consider the number of machines used by households for a specific crop

production and the total time, which is measured in months, that is allocated to off-farm employment in the production year. While some studies have considered dichotomous decisions of farm machinery use and off-farm employment in their estimates (Ji *et al.* 2012; Ahmed and Goodwin 2016; Kousar and Abdulai 2016; Ma *et al.* 2017), only the partial effects have been captured related to these two decisions.

Our second contribution is to analyse the joint impacts of farm machinery use and off-farm employment on crop yields and agrochemical expenses. Agrochemical usages have known links to environmental quality, and lower levels of agrochemical usages may be associated with positive environmental performance (Chang and Mishra 2012; Jaraite and Kazukauskas 2012).

The third contribution is that we employ an innovative two-stage econometric method that combines a bivariate ordered probit model and an endogeneity-corrected ordinary least square regression model to estimate the parameters. Our approach allows us to identify the factors that affect farmers' decisions to use machines on the farm and to work off the farm; to capture the interrelationship between these two decisions; and to estimate the unbiased and consistent effects of these two household activities on crop yields and agrochemical expenses.

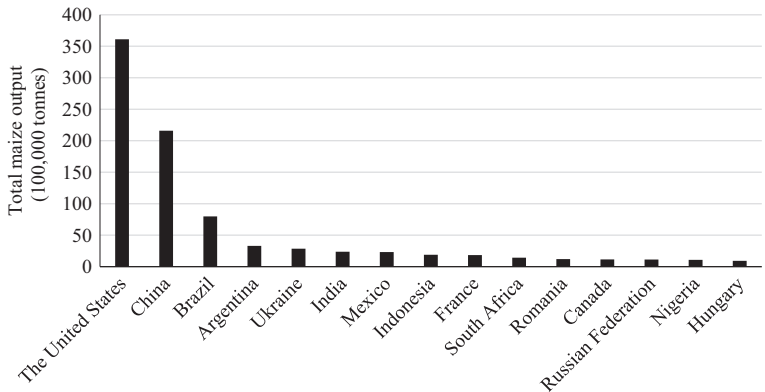
Our paper is structured as follows. Section 2 presents the background and data. Section 3 introduces the theoretical model and Section 4 presents the empirical specification used in the present study. The results are presented and discussed in Section 5. Section 6 concludes with a summary of the main findings, and policy implications.

## 2. Background and data

### 2.1 Background

China is the world's second largest producer of maize, after the United States (Figure 1), and accounted for approximately 21 per cent of global maize output in 2014 (FAOSTAT). In 2015, the output value of Chinese maize production was 4.32 billion Yuan, or over 4 per cent of the total Chinese agricultural output value. Moreover, maize is a major staple food in China with an annual per capita consumption of about 164 kg in 2015. The total land area used for maize production in China has increased from 23.06 million hectares in 2000 to 38.12 million hectares in 2015, with total maize output increasing from 106 million tonnes to just over 225 million tonnes over the same time period (CRSY 2016).

The significant role of farm machinery in boosting farm performance in developing countries is widely documented (Kienzle *et al.* 2013; Sims *et al.* 2016; Wang *et al.* 2016; Zhang *et al.* 2017). Indeed, China has been a leader among developing and emerging economies in the use of machines in agricultural production, and Wang (2013) has divided the mechanisation process into four stages: (i) preliminary stage (1950–1980); (ii) national

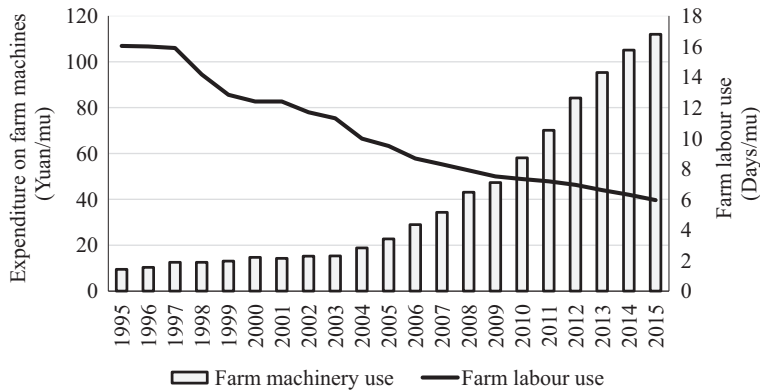


**Figure 1** Top 15 maize-producing countries by total output in 2014. Source: FAOSTAT.

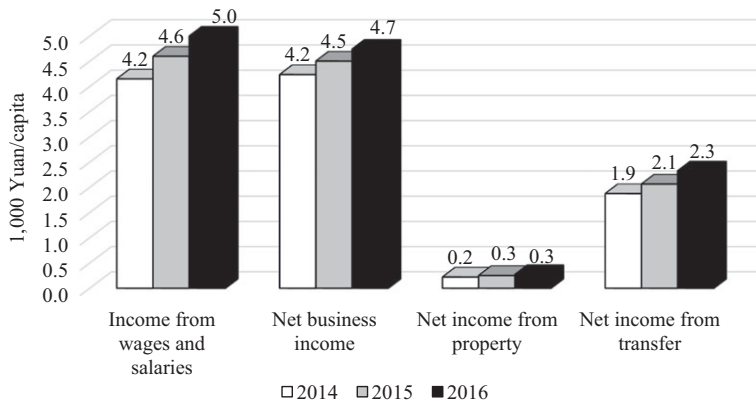
economic system reform stage (1980–2003); (iii) transformation of traditional farming into modern agriculture stage (2004–2009); and (iv) development of agricultural machinery manufacturing industries, investment opportunities and challenges stage (2010–present). The total power of agricultural machinery has significantly increased from 147 million kilowatts in 1980 to 972 million kilowatts in 2016 (CSY 2017).

Farm machines are used during maize production and postharvest management. Purchasing, renting and buying machinery services are the three main options to obtain farm machines. Ji *et al.* (2012) and Wang *et al.* (2016) show that purchasing machinery and buying machinery services are the two primary means by which smallholder farmers in China use farm machines in agricultural production. Figure 2 shows that expenditures on farm machines in maize production in China increased from 18.53 Yuan/mu in 1995 to 115.26 Yuan/mu in 2015, while labour use decreased from 16 to 6 days/mu over the same time period. This suggests that machinery and labour are substitutes, and as a result of the substitution between farm labour and machinery use, farm households may have reallocated their labour time to other activities, such as off-farm employment.

Extant studies on off-farm employment in China estimate that the flows of labour from rural villages to the cities range from 35 per cent to 65 per cent in 2008, and the number of off-farm work participants continues to increase (Cai and Wang 2010; Knight *et al.* 2011; Ma *et al.* 2017; Wang *et al.* 2017). Reallocation of surplus agricultural labour through off-farm activities appears to have contributed to labour productivity and the growth of Chinese economy as a whole (Cai 2018). In rural China, off-farm employment plays a key role in relaxing capital constraints of rural households. Nevertheless, as noted by Cai (2016) and summarised by Li (2017), China’s agricultural labour surplus may already be exhausted and the Lewis ‘turning point’ is imminent. Figure 3 presents the components of rural household income from 2014 to 2016, which are released by China



**Figure 2** Machine use and farm labour use in maize production between 1995 and 2015. Source: Yearbook of the Costs and Benefits of Agricultural Products (1996–2016).



**Figure 3** Per capita income of rural households. Source: CSY (2017).

Statistics Yearbook (2017). It shows that the income from wages and salaries (i.e. the income that is primarily from off-farm employment) and net business income (i.e. the income that is primarily from agricultural production) are the main income sources of rural households, and the former now exceeds the later.

The shift of labour from agriculture to other sectors appears to be irreversible for key reasons (Cai 2016). First, the agricultural transformation from labour-using to labour-saving technologies (e.g. the use of large sized tractors and medium-sized tractors and towing machinery) makes it impossible for migrant workers to return to rural jobs. Second, the younger generations of migrants have often grown up and been educated in cities and towns, and they do not intend to return to agricultural jobs. Thus, the rapid development of agricultural machinery in rural China may play an important role in improving farm productivity and the overall sustainability of agriculture.



Given the significant role of farm machinery use and off-farm employment in rural China, a study focusing on the joint effects of farm machinery use and off-farm employment on maize yields and agrochemical expenses is required. Such an approach is necessary to develop informed and effective policies in support of increased farm performance and rural development.

## 2.2 Data

Data used in this study were drawn from a household survey of maize farmers in China, conducted in January 2017. A multistage stratified random sampling technique was employed to select farm households from nine villages across three randomly selected provinces that include Gansu, Henan and Shandong from Western, Central and Eastern China. In 2015, the cultivated area of maize in Gansu, Henan and Shandong was 1.01, 3.34 and 3.17 million hectares, respectively, accounting for about 20 per cent of the country's total maize area (CRSY 2016). In each province, one county was randomly selected from which three villages were then randomly selected. In the final sampling stage, between 45 and 55 maize farmers were randomly selected from each village for the interview, resulting in a total sample of 493 farmers.

Face-to-face interviews were conducted by enumerators who spoke both Chinese and local dialects, using a detailed structured questionnaire. The survey gathered information on household and farm-level characteristics, agrochemical expenses and yields of maize production, the total time allocated to off-farm employment by the household heads, and machinery use status in maize production and postharvest management. The collected information refers to the year 2016.

Machinery use is measured as a count variable. Purchasing machinery and buying machinery services are the two main options for farmers to access farm machinery services (Ji *et al.* 2012). Here, we focus on whether or not a household uses a machine in a specific production and postharvest stage rather than how the household obtained the machine services. In the survey instrument for 2016 (see Table A1 in the Appendix S1), each household was asked to identify each of the stages of maize production and postharvest management when machinery was used. These stages were: (i) land ploughing; (ii) land filming; (iii) sowing; (iv) weeding; (v) fertiliser use; (vi) pesticide use; (vii) irrigation; (viii) harvesting; (ix) transport; (x) threshing; (xi) drying; and (xii) straw treatment. The accumulated values (1 = yes) were then used to represent the machinery use intensity of a farm household.

The variable representing off-farm employment is a count variable that represents the total time, measured in month(s), allocated to off-farm activities by a household head in 2016. Following Phimister and Roberts (2006) and Kousar and Abdulai (2016), we focus on household heads' decision in terms of off-farm employment rather than other household

members. We define maize yields per mu (1 mu = 1/15 hectare) and agrochemical expenses per mu as outcome variables.<sup>1</sup> The variable ‘agrochemical expenses’ refers to the total household expenses on agrochemicals including fertilisers and pesticides, which may indicate on-farm environmental quality (Chang and Mishra 2012; Jaraite and Kažukauskas 2012).

Table A2 in the Appendix S1 presents the sample distribution of the total number of machines used by farm households for maize production in 2016. It shows that only two surveyed households did not use any machines and that no farming households used machines in all 12 stages of maize production and postharvest management. The sample distribution of farm household time spent in off-farm employment is presented in Table A3 in the Appendix S1. We observe that 142 household heads did not participate in any off-farm activities and 21 of them were involved in off-farm employment for 12 months in 2016.<sup>2</sup>

Table A4 in the Appendix S1 presents the mean maize yields and agrochemical expenses by farm machinery use quintile and off-farm employment quintile, where quintile 5 represents households with the highest machinery use intensity and the highest off-farm employment intensity. The information presented in columns 3 and 4 of Table A4 shows that with the exception of quintile 4, mean maize yields and mean agrochemical expenses increase slightly from quintile 1 to quintile 5. With respect to off-farm employment, our descriptive analysis presented in the last two columns shows that for household heads who do not participate in any off-farm activities (quintile 1), the mean maize yields and mean agrochemical expenses are 477 kg/mu and 166 Yuan/mu, respectively.

The summary statistics of the variables used in the econometric analysis are presented in Table 1. To identify explanatory variables, we draw on the existing literature of both farm machinery use and off-farm employment (de Brauw and Rozelle 2008; Khanal and Mishra 2014; Benin 2015; Lai *et al.* 2015; Luo and Escalante 2015; Kousar and Abdulai 2016; Mottaleb *et al.* 2016; Wang *et al.* 2016; Ma *et al.* 2017). The table shows that the average time farm household heads allocated to off-farm employment was 5.37 months in 2016. On average, 5.70 machines were used during maize production and postharvest management.

### 3. Theoretical model

The focus of the study is to analyse the joint effects of farm machinery use and off-farm employment on farm performance indicators such as maize yields and agrochemical expenses. To link farm machinery use and off-farm

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<sup>1</sup> Although income obtained from maize production and marketing is a useful indicator, we did not consider using this variable in our study because some farmers had not yet sold their maize at the time of the survey.

<sup>2</sup> For household heads participating in off-farm work, they usually determine farm production practices by communicating with their spouses through the use of mobile phones.



**Table 1** Definition and descriptive statistics

Variables	Definition	Mean (SD)
<b>Dependent variables</b>		
Machinery use	Total number of machines used in maize production and postharvest management in 2016 (0–12)	5.70 (3.13)
Off-farm employment	Total time used for off-farm employment by household head in 2016 (0–12 months)	5.37 (4.19)
Maize yields	Maize yields (100 kg/mu)	4.83 (1.30)
Agrochemical expenses	Expenses on fertiliser and chemical (100 Yuan/mu) <sup>†</sup>	1.78 (0.75)
<b>Independent variables</b>		
Age	Age of household head (year)	46.79 (10.32)
Gender	1 if household head is male, 0 otherwise	0.84 (0.37)
Education	Schooling of household head (years)	6.78 (2.76)
Household size	Number of people residing in household	4.55 (1.45)
Farm size	Total farm size for maize production in 2016 (mu)	3.51 (2.96)
Irrigated farm size	Total farm size that can be irrigated (mu)	2.37 (2.69)
Computer	1 if household uses computer, 0 otherwise	0.40 (0.49)
Information service	1 if household subscribes agricultural information service, 0 otherwise	0.02 (0.13)
Soil fertility	1 if it is fertile soil, 0 otherwise	0.28 (0.45)
Extension contact	1 if farmer receives extension service, 0 otherwise	0.20 (0.40)
Distance to market	Distance to input market (km)	7.16 (7.52)
Gansu	1 if household resides in Gansu, 0 otherwise	0.33 (0.47)
Shandong	1 if household resides in Shandong, 0 otherwise	0.33 (0.47)
Henan	1 if household resides in Henan, 0 otherwise	0.34 (0.48)
Perception	1 if household head perceives it is easy to get a local off-farm job (i.e. work in the local region and live in his/her village), 0 otherwise	0.36 (0.48)
Subsidy	1 if household receives subsidy for farm machine purchasing, 0 otherwise	0.14 (0.35)

Note: <sup>†</sup>1 mu = 1/15 hectare and 1 USD = 6.80 Yuan in 2017.

employment with the potential farm outcomes of interest, we assume that a risk neutral farmer maximises the expected profits or net returns ( $\pi$ ) from maize production, subject to a competitive input and output market and other confounding factors such as farm machinery use, off-farm employment and household and farm-level characteristics. This relationship may be expressed as:

$$\text{Max } \pi = PQ(W, M, E, X) - WI \quad (1)$$

where  $P$  is maize price and  $Q$  is the total maize output;  $W$  is a vector of input prices and  $I$  is a vector of input variables such as agrochemicals;  $M$  refers to farm machinery use, while  $E$  refers to off-farm employment; and  $X$  is a vector of household and farm-level characteristics. Thus, net returns can be expressed as the following:

$$\pi = \pi(P, W; M, E, X) \quad (2)$$

Application of Hotelling's lemma to Equation (2) with respect to input price and output price yields the reduced form equations for negative input demand and output supply, respectively:

$$\frac{d\pi}{dW} = -I = I(P, W; M, E, X) \quad (3a)$$

$$\frac{d\pi}{dP} = Q = Q(P, W; M, E, X) \quad (3b)$$

The specifications in Equations (3a) and (3b) show that the demand for inputs (e.g. agrochemicals) and the level of output (i.e. maize yields) are affected by inputs and output prices, farm machinery use, off-farm employment and farm and household-level characteristics. In the following, we apply a reduced form approach to relate farm machinery use and off-farm employment to maize production for estimation purposes.

#### 4. Empirical specification

To analyse the joint impacts of farm machinery use and off-farm employment on farm outcomes such as maize yields and agrochemical expenses, we assume that farm outcomes are a linear function of a vector of explanatory variables ( $X_i$ ) and two variables ( $M_i$ ,  $E_i$ ), respectively, representing farm machinery use and off-farm employment specified as follows:

$$H_i = \xi_i M_i + \varpi_i E_i + v_i X_i + \varepsilon_i \quad (4)$$

where  $H_i$  refers to farm outcome variables such as maize yields or agrochemical expenses;  $M_i$  is an indicator variable of farm machinery use;  $E_i$  is an off-farm employment variable; and  $X_i$  is a vector of household and farm-level characteristics (e.g. age, education and farm size) that might affect farm outcomes. The terms  $\xi_i$ ,  $\varpi_i$  and  $v_i$  are parameters to be estimated, while  $\varepsilon_i$  is an error term. We note that the effects of farm machinery use and off-farm employment on farm outcomes are captured by the estimates of the parameters  $\xi_i$  and  $\varpi_i$ , respectively.

We could employ an ordinary least square (OLS) regression model to estimate Equation (4) if  $M_i$  and  $E_i$  are exogenous. However, as identified in previous studies on farm machinery use (Ji *et al.* 2012; Ahmed and Goodwin 2016) and off-farm employment (Kousar and Abdulai 2016; Ma *et al.* 2017), the decision to use machines on the farm and the decision to work off the farm are likely to be influenced by unobserved factors (e.g. farmers' innate

abilities, motivations and attitudes on income diversification strategies, and managerial capability) that may also affect farm outcomes. Thus, machinery use and off-farm employment variables are potentially endogenous in Equation (4), and a failure to account for endogeneity would result in biased estimates.

In the present study, we follow the two-stage estimation procedure used in the conventional instrumental variable approach to correct for endogeneity issues (Wooldridge 2010; Chang and Mishra 2012). In the first stage, a bivariate ordered probit model is used to investigate the factors that influence farmers' decisions to use farm machines and their decisions to work off the farm. This stage captures the potential interrelationship between these two decisions. The second stage investigates the impact of farm machinery use and off-farm employment on maize yields and agrochemical expenses. The predicted values of farm machinery use and off-farm employment from the first-stage estimation (which account for endogeneity issues) are used to replace the original values of these two variables.

#### 4.1 First-stage estimation

A bivariate ordered probit model is estimated that includes a separate univariate ordinal probit model for the farm machinery use equation and off-farm employment equation. Following Sajaia (2008) and Chang and Mishra (2012), the bivariate ordered probit model is specified as:

$$\begin{aligned} Y_{1i}^* &= \beta_{1i}X_{1i} + \eta_{1i}Z_{1i} + \varepsilon_{1i} \\ Y_{2i}^* &= \beta_{2i}X_{2i} + \eta_{2i}Z_{2i} + \varepsilon_{2i} \end{aligned} \quad (5)$$

$$Y_{1i} = \begin{cases} 1 & \text{if } Y_{1i}^* \leq U_{11} \\ 2 & \text{if } U_{11} < Y_{1i}^* \leq U_{12} \\ \dots & \dots \\ J & \text{if } U_{J-1} < Y_{1i}^* \end{cases} \quad \text{and} \quad Y_{2i} = \begin{cases} 1 & \text{if } Y_{2i}^* \leq U_{21} \\ 2 & \text{if } U_{21} < Y_{2i}^* \leq U_{22} \\ \dots & \dots \\ K & \text{if } U_{K-1} < Y_{2i}^* \end{cases}$$

where  $Y_{1i}^*$  and  $Y_{2i}^*$  are the unobserved latent variable of farm machinery use and off-farm employment decisions, respectively, for farm household  $i$ .  $X_{1i}$  and  $X_{2i}$  represent the same exogenous factors that determine both of the two decisions, and  $\beta_{1i}$  and  $\beta_{2i}$  are the corresponding parameters;  $Z_{1i}$  and  $Z_{2i}$  are the instrumental variables which directly affect these two decisions and indirectly affect maize yields and agrochemical expenses.  $U_{si}$  are unknown parameters of threshold points to be estimated. The random errors ( $\varepsilon_{1i}$ ,  $\varepsilon_{2i}$ ) are assumed to follow a standard normal distribution across individuals with a zero mean and unit variance as follows:

$$\begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} \sim N \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{\varepsilon 12} \\ \rho_{\varepsilon 12} & 1 \end{pmatrix} \right] \quad (6)$$

where  $\rho_{\varepsilon 12}$  is cross-equation correlation coefficient of the error terms  $\varepsilon_{1i}$  and  $\varepsilon_{2i}$ . The consistent estimators  $(\beta_{1i}, \eta_{1i}, \beta_{2i}, \eta_{2i}, \rho_{\varepsilon 12})$  are obtained by implementing the maximum-likelihood estimation (MLE) method with the following log-likelihood function (Sajaia 2008):

$$\text{Ln}L = \sum_{i=1}^N \sum_{j=1}^J \sum_{k=1}^K I(Y_{1i}=j, Y_{2i}=k) * \text{LnPr}(Y_{1i}=j, Y_{2i}=k) \quad (7)$$

where  $I(\cdot)$  is a binary indicator that specifies one of the  $J*K$  categories into which each individual is categorised. To test whether these two decisions are independent, we conduct the Wald test under the null hypothesis that  $\rho_{\varepsilon 12}$  is equal to zero.

#### 4.2 Second-stage estimation

In the second stage, an OLS regression model is used to estimate the outcome equations for maize yields and agrochemical expenses. Specifically, the predicted values of farm machinery use and off-farm employment are used as explanatory variables. The endogeneity-corrected outcome equation is rewritten as:

$$H_i = d_{1i}\hat{Y}_{1i} + d_{2i}\hat{Y}_{2i} + \gamma_i X_i + \mu_i \quad (8)$$

where  $H_i$  represents maize yields or agrochemical expenses.  $X_i$  represents the exogenous variables as defined in Equation (5), and  $\gamma_i$  is the vector of corresponding parameters.  $\hat{Y}_{1i}$  and  $\hat{Y}_{2i}$  are predicted values for farm machinery use and off-farm employment from Equation (5), respectively. Wooldridge (2010) and Chang and Mishra (2012) stress that by using the instrumental variables in the first stage, the predicted values of farm machinery use and off-farm employment included in Equation (8) correct for potential endogeneity. Thus, the parameters  $(d_{1i}, d_{2i})$  capture the unbiased and consistent effects of these two decisions on maize yields and agrochemical expenses.

In relation to Equation (8), within-group dependence in estimating the standard errors of regression parameter estimates must be taken into account. Given that the data used in the present study were collected from nine villages across three provinces in China, the true OLS standard errors can be greatly underestimated due to intravillage autocorrelation (Cameron *et al.* 2008).<sup>3</sup>

<sup>3</sup> We are grateful to the journal editor John Gibson for bringing our attention to this issue during the review process.

To correct for such clustering issues, we used a bootstrap procedure with 400 bootstrap iterations – as proposed by Cameron and Miller (2015) for cases where there are relatively few (between five and thirty) clusters, to obtain more accurate cluster-robust inference (i.e. bootstrap-based cluster-robust standard errors).

With respect to the usage of instruments in Equation (5), our identification strategy relies on the use of variables affecting farm machinery use and off-farm employment, respectively, but not directly influencing maize yields and agrochemical expenses. For the farm machinery use equation, a variable representing whether or not a farm household receives a machinery purchasing subsidy is used as an instrument. For the off-farm employment equation, a variable representing whether or not a farm household head perceives it is ‘easy’ to access local off-farm work (i.e. work in the local region and remain in his/her village) is employed as an instrument. We expect that farmers with easy access to local off-farm work are more likely to participate in off-farm work, because they can live at home and still help undertake tasks in their own households. This argument is supported by Ma *et al.* (2017) who find that farmers who perceive that local off-farm work is readily accessible are more likely to participate in off-farm work.

To test the validity of the employed instruments, we estimated two ordered probit models (one for farm machinery use and another for off-farm employment) and two OLS regression models (one for maize yields and another for agrochemical expenses) with inclusion of the employed instrumental variables, respectively. Results, which are not presented here, but are available on request, show that the estimated coefficient for the machine subsidy variable has a positive and statistically significant impact on farm machinery use, while it has no statistically significant impact on maize yields and agrochemical expenses. Similarly, the estimated coefficient for the perception variable about the ease of finding local off-farm work has a statistically significant impact on off-farm employment, but it does not affect maize yields and agrochemical expenses significantly. The findings justify the validity of the employed instruments in Equation (5).

## 5. Results and discussion

### 5.1 Determinants of farm machinery use and off-farm employment

The results of the bivariate ordered probit model for farm machinery use and off-farm employment are presented in Table 2. We begin with a justification of the model specification. The estimated correlation coefficient ( $\rho_{\varepsilon 12}$ ) is 0.185 and statistically significant at the 1 per cent significance level. This result indicates that the decision that a farmer chooses to use farm machines is related to the decision to supply off-farm labour through unobserved effects captured in the model’s error terms. That is, unobserved effects, such as farmers’ innate abilities and motivations to save labour or diversify

**Table 2** Joint estimation of farm machinery use and off-farm employment

Variables	Farm machinery use		Off-farm employment	
	Coefficients	z-value	Coefficients	z-value
Age	0.005 (0.010)	0.52	−0.014 (0.007)*	−1.93
Gender	−0.402 (0.166)**	−2.43	0.317 (0.202)	1.56
Education	0.009 (0.036)	0.24	0.073 (0.031)**	2.37
Household size	−0.106 (0.054)*	−1.96	0.002 (0.030)	0.08
Farm size	0.083 (0.035)**	2.40	0.012 (0.038)	0.32
Irrigated farm size	0.026 (0.061)	0.42	−0.127 (0.049)***	−2.59
Computer	0.330 (0.318)	1.04	0.082 (0.201)	0.41
Information service	0.772 (0.499)	1.55	−0.215 (0.383)	−0.56
Soil fertility	0.614 (0.193)***	3.19	0.306 (0.218)	1.40
Extension contact	0.312 (0.294)	1.06	0.135 (0.188)	0.72
Distance to market	0.010 (0.020)	0.48	−0.017 (0.018)	−0.93
Gansu	−0.603 (0.493)	−1.22	−0.043 (0.233)	−0.19
Shandong	4.428 (0.771)***	5.75	1.088 (0.442)**	2.46
Subsidy	0.560 (0.153)***	6.65		
Perception			0.295 (0.168)*	1.75
Cut points				
cut_1_1	−2.729 (1.050)***	−2.60		
cut_1_2	−1.119 (0.867)	−1.29		
cut_1_3	−0.613 (0.845)	−0.73		
cut_1_4	0.066 (0.807)	0.08		
cut_1_5	0.513 (0.833)	0.62		
cut_1_6	1.185 (0.943)	1.26		
cut_1_7	1.788 (1.023)*	1.75		
cut_1_8	2.275 (0.940)**	2.42		
cut_1_9	2.659 (0.879)***	3.02		
cut_1_10	4.560 (1.101)***	4.14		
cut_1_11	7.185 (1.202)***	5.98		
cut_2_1	−0.288 (0.496)	−0.58		
cut_2_2	−0.247 (0.493)	−0.50		
cut_2_3	−0.147 (0.492)	−0.30		
cut_2_4	0.006 (0.493)	0.01		
cut_2_5	0.129 (0.477)	0.27		
cut_2_6	0.285 (0.474)	0.60		
cut_2_7	0.470 (0.468)	1.00		
cut_2_8	0.592 (0.472)	1.26		
cut_2_9	0.986 (0.511)*	1.93		
cut_2_10	1.097 (0.542)**	2.02		
cut_2_11	1.996 (0.583)***	3.42		
cut_2_12	2.245 (0.609)***	3.68		
atanhrho	0.187 (0.096)*	1.95		
Log pseudolikelihood	−1,755.136			
$\rho_{e12}$	0.185 (0.093)***			
Wald $\chi^2$ (9)†	5,239,532.02			
Prob > $\chi^2$	0.000			
Observations	493			

Note: \*\*\* $P < 0.01$ , \*\* $P < 0.05$  and \* $P < 0.1$ . †Standard errors are adjusted for nine clusters because we collected data from nine villages in three provinces; robust standard errors are in parentheses. The reference province is Henan.



household income, are not captured by the data, but may have an indirect influence on farmers' decisions to use farm machines and to work off the farm. We note that the estimated sign for  $\rho_{\varepsilon 12}$  is positive, which suggests that farm machinery use and off-farm employment are complementary decisions.

The determinants of farm machinery use are presented in the second column of Table 2. The gender variable has a negative and statistically significant coefficient. This suggests that relative to male household heads, female household heads are more likely to use farm machines. The feminisation of farm machinery use can be explained by the fact that men in rural areas have migrated in search of higher incomes while women are left in charge of the family farm. Agricultural mechanisation provides rural women with new opportunities to adapt themselves to traditional agricultural work norms. Our finding in terms of gender is contrary to that of Mottaleb *et al.* (2016) for Bangladesh who find that male-headed households are more likely than female-headed households to use farm machines such as irrigation pumps, threshers and power tillers.

Household size appears to have a negative and statistically significant impact on machinery use. This may be explained by the fact that larger households potentially have a greater supply of family farm labour, which leads to less need for labour-saving technologies such as machinery. The estimated coefficient of the farm size variable is positive and statistically significant from zero, suggesting that households operating larger farms are more likely to use farm machines. This result is consistent with Lai *et al.* (2015) who find that machinery use of wheat and corn farmers in Hebei and Shandong of China is significantly and positively determined by total operating area. By contrast, Luo and Escalante (2015) estimate a negative relationship between farm size and machinery use among Chinese vegetable farmers.

The positive and statistically significant coefficient of soil fertility variable suggests that farmers cultivating fertile soil are more likely to use machines on their farms. Our results highlight the importance of farm machinery as a means of promoting the efficient application of agricultural technologies, which help maintain or enhance soil fertility, thereby increasing production. Compared with farmers in Henan (the reference province), farmers in Shandong are more likely to use farm machinery. These findings suggest the presence of location fixed effects (e.g. geographical conditions and institutional arrangements) that may affect farmers' decisions to use farm machines.

With respect to the determinants of off-farm employment, our results indicate that time allocated to off-farm work is inversely related to the age of the household head. This finding is consistent with Khanal and Mishra (2014) who found that older farmers typically have poorer health levels and are lacking skills that are transferable to off-farm employment and, thus, have fewer motivations or opportunities to participate in off-farm activities. The estimated coefficient of the education variable is positive and statistically significant in the off-farm employment equation. This finding is consistent with other off-farm employment studies (de Brauw and Rozelle 2008; Kousar

and Abdulai 2016). For instance, in their investigation of 1,199 households in 60 villages in rural China, de Brauw and Rozelle (2008) find that an additional year of education is associated with being between 1.1 and 1.3 more likely in finding off-farm employment.

The coefficient of the irrigated area variable is negative and statistically significant, suggesting that farmers with more irrigated land are less likely to have a higher intensity of off-farm employment. A possible explanation for this finding is that farmers with access to irrigation facilities are located in areas with favourable conditions for agricultural production, and are able to generate sufficient income from their farming activities. We also note that relative to farmers in Henan (the reference province), farmers in Shandong are more likely to work off the farm.

## 5.2 Joint impacts of machinery use and off-farm employment on farm performance

Table 3 presents the results of the joint impacts of farm machinery use and off-farm employment on maize yields and agrochemical expenses, as estimated by Equation (8). As noted earlier, the predicted values of farm machinery use and off-farm employment from the bivariate ordered probit model are included in the regression. These predicted values account for

**Table 3** Impact of machinery use and off-farm employment on maize yields and agrochemical expenses: estimations correcting for endogeneity issues

Variables	Maize yields		Agrochemical expenses	
	Coefficients	<i>t</i> -value	Coefficients	<i>t</i> -value
Machinery use (predicted)	0.743 (0.377)**	1.97	0.994 (0.367)***	2.71
Off-farm employment (predicted)	0.365 (0.472)	0.77	-0.468 (0.247)*	-1.89
Age	0.017 (0.009)*	1.84	-0.004 (0.007)	-0.65
Gender	0.310 (0.285)	1.09	0.520 (0.195)***	2.66
Education	0.010 (0.025)	0.39	0.054 (0.015)***	3.64
Household size	0.107 (0.064)*	1.67	0.064 (0.057)	1.13
Farm size	-0.015 (0.045)	-0.34	-0.113 (0.041)***	-2.75
Irrigated farm size	0.024 (0.077)	0.31	-0.068 (0.043)	-1.57
Computer	-0.162 (0.240)	-0.67	-0.074 (0.235)	-0.31
Information service	0.333 (1.312)	0.25	-0.982 (0.371)***	-2.64
Soil fertility	0.194 (0.469)	0.41	-0.198 (0.336)	-0.59
Extension contact	-0.298 (0.251)	-1.19	-0.334 (0.170)**	-1.97
Distance to market	0.002 (0.026)	0.07	-0.012 (0.014)	-0.85
Gansu	1.912 (0.803)**	2.38	0.733 (0.266)***	2.75
Shandong	-2.274 (2.061)	-1.10	-3.429 (1.669)**	-2.05
Constant	2.041 (0.571)***	3.57	1.137 (0.295)***	3.86
<i>R</i> -squared	0.309		0.202	
Observation	493		493	

Note: \*\*\* $P < 0.01$ , \*\* $P < 0.05$  and \* $P < 0.1$ ; Maize yields are measured in 100 kg/mu, and the agrochemical expenses are measured in 100 Yuan/mu; bootstrap-based cluster-robust standard errors are in parentheses; the reference province is Henan.

endogeneity issues associated with machinery use and off-farm employment and, thus, help to ensure consistent estimation. As already noted, bootstrap-based cluster-robust standard errors that permit heteroscedasticity and within-cluster error correlation were estimated (Cameron *et al.* 2008; Cameron and Miller 2015).

Our results show that farm machinery use has a positive and statistically significant impact on maize yields and agrochemical expenses. In particular, an additional use of a farm machine tends to increase maize yields by about 74 kg/mu and agrochemical expenses by 99 Yuan/mu. These values translate into an increase of 15 per cent in maize yields and 56 per cent in agrochemical expenses, using the sample mean values presented in Table 1 as the reference. The finding of a positive impact of machinery use on maize yields is broadly consistent with the literature (Rahman *et al.* 2011; Benin 2015; Lai *et al.* 2015). For example, Lai *et al.* (2015) find that a 10 per cent increase in machinery use increases wheat yields by 1 per cent and corn yields by 0.8 per cent in China. Cai (2016) highlights the importance of productivity growth as a key contributor to China's economic growth. Our findings, within agriculture, provide supporting evidence in that increased farm machinery use supports higher output. Further, our results with respect to the impact of machinery use on agrochemical expenses, are consistent with Takeshima *et al.* (2013) who note that the use of tractors in Ghana is associated with more intensive use of inputs, such as fertiliser and chemicals.

We find that off-farm employment has a negative and statistically significant impact on agrochemical expenses. Specifically, an additional month of off-farm employment reduces, on average, agrochemical expenses by 47 Yuan/mu. Importantly, this result supports previous studies that off-farm employment reduces input use as a result of the so-called lost-labour effect, but it may improve environmental quality. For example, Feng *et al.* (2010) and Shi *et al.* (2011) show that off-farm employment reduces the application of chemical inputs and manure among rice farmers in China. In turn, this may have a beneficial effect on farm environmental quality. Chang and Mishra (2012) also find, in the case of farmers in the United States, that agrochemical expenses decrease as the off-farm labour supply increased.

Among other factors that influence maize yields and agrochemical expenses, we find that the age of the household head contributes significantly to higher maize yields. Age can be seen as a proxy of a farmer's experience and farm management ability. Thus, more experienced farmers are more likely to enjoy greater agricultural production. This finding is consistent with Kabunga *et al.* (2012) who find that age has a positive and significant impact on banana yields in their analysis based on data from Kenya. Relative to female household heads, male household heads spend more on agrochemical inputs. The estimated coefficient of the education variable is positive and statistically significant in the fourth column of Table 3. This suggests that farmers with more education spend more on agrochemicals. Mishra *et al.* (2005) also find that better educated farmers spend more on fertilisers and

pesticides, and this is attributed to them being more adept at identifying, acquiring and processing information from different channels.

The coefficient of the household size variable in the second column is positive and statistically significantly different from zero. This suggests that larger households with more labour endowments tend to achieve higher maize yields. The estimated coefficient of the farm size variable in column 4 of Table 3 is negative and statistically significant, suggesting that households with larger farms spend less on agrochemical inputs, per unit of land area. Subscription to an information service and contact with an extension agent help farmers to reduce agrochemical expenses, highlighting the importance of extension and information in achieving sustainable practices. The province dummies are significantly different from zero, which suggests that agro-climatic variation and possibly other differences are important in explaining regional variations. Our results show that overall, relative to farmers in Henan (the reference province), farmers in Gansu spend more on agrochemical inputs and obtain higher maize yields, while their counterparts in Shandong spend less on agrochemicals.

For the purpose of comparison, we present in Table A5 in the Appendix S1 the results of the impact of farm machinery use and off-farm employment on maize yields and agrochemical expenses, which are estimated based on Equation (4), that is without correcting for endogeneity issues. By comparison with Table 3, the results given in Table A5 show important differences. For instance, the results in Table A5 show that an additional use of a farm machine tends to increase maize yields by 9 kg/mu and agrochemical expenses by 14 Yuan/mu, which are significantly smaller than the values we observed in Table 3.

Table A5 also shows that off-farm employment has a negative and statistically significant impact on maize yields, but an insignificant impact on agrochemical expenses. By contrast, as shown in Table 3, after we control for endogeneity, the estimated impact of off-farm employment on maize yields is positive, although it is not statistically significant from zero. The results presented in Table A5 further show that the estimated coefficients for the education and farm size variables have a positive and significant impact on maize yields, but these results are not observed in Table 3 after accounting for endogeneity. These differences between the estimated coefficients in Table 3 and Table A5 underscore the importance of using an instrumented bivariate ordered probit model to respond to endogeneity issues and, thus, estimate consistent and unbiased effects of machinery use and off-farm employment on maize yields and agrochemical expenses.

## 6. Conclusions and policy implications

There is a growing body of literature that shows farmers are jointly making decisions to use machines on their farm and to work off the farm, but relatively little is known about the joint impacts of these two household decisions on farm performance. To respond to this gap in understanding, we

use farm-level data collected from Gansu, Henan and Shandong provinces in China and analyse the joint impacts of farm machinery use and off-farm employment on maize yields and agrochemical expenses. We employ an innovative two-stage econometric procedure that combines a bivariate ordered probit model and an endogeneity-corrected ordinary least square regression model to account for the possibility for a joint decision to use farm machines and to work off the farm.

We find evidence that farmers' decisions to use farm machines are positively and significantly correlated with their decisions to work off the farm through unobserved effects captured in the model's error terms. Importantly, our results show that these two household activities affect maize yields and agrochemical expenses in different ways. In particular, an additional use of a farm machine appears to significantly increase maize yields by 74 kg/mu and agrochemical expenses by 99 Yuan/mu. By contrast, off-farm employment has a negative and statistically significant impact on agrochemical expenses. Further, our results show that overall, an additional month of off-farm employment reduces agrochemical expenses by 47 Yuan/mu. Among other factors, the age of the head of the household and household size are positively associated with maize yields, while agrochemical expenses are positively affected by gender differences (males use more agrochemicals) and education. We also provide evidence that failing to account for endogeneity issues associated with farm machinery use and off-farm employment may result in biased estimators.

A critical finding is that women are more likely to use farm machines. With the increasing feminisation of agriculture due to the increased propensity of men to migrate to urban areas, there is a need to take into account gender-specific interventions in developing farm mechanisation programs. Further, the result that off-farm employment has a negative and statistically significant impact on agrochemical expenses suggests that improving the access of rural households to off-farm employment opportunities may have beneficial on-farm environmental effects, because the lower levels of agrochemical usages may be associated with positive environmental performance.

In summary, while our results only apply to three provinces in China, they do show the absolute importance of farm machinery use and the joint decision of machinery use and the off-farm employment. At least in terms of maize production, our findings provide important policy insights as to how to support increased farm production and account for important gender differences in the use of farm machinery.

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### Supporting Information

Additional Supporting Information may be found in the online version of this article:

**Appendix S1.** Additional data descriptive statistics and empirical results for comparison.