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Determinants of technical efficiency and farmers' crop choice rationality: A case study of rural Gansu, China

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ABSTRACT

Land exchange based on market transactions in which lessors and lessees participate voluntarily not only makes them better off but also enhances the overall efficiency of land use and agricultural production. However, it is worthwhile to empirically explore the effect of land rental on overall technical efficiency in the context of Chinese agriculture because non-farm household producers have increasingly entered the farming business as cultivators. If such producers underperform farm households in terms of efficiency, land consolidation does not necessarily deliver the desired outcome. This study demonstrates that the development of land rental markets improves agricultural technical efficiency at the aggregate level. Another important issue addressed in this study is to examine farmers' crop choice rationality. China offers an interesting case in this respect. This is because, while the central government has long strived to maintain a high grain self-sufficiency rate, the relative prices of farm products have recently moved in favor of non-grain products. Our empirical result suggests that there is room for further increase in farm revenues of Gansu's producers by shifting resources away from cereal toward horticultural production.

1. Introduction

Well-functioning land markets could allow competent farmers to gain access to additional land, which not only raises the wealth of lessors and lessees of land, but also deliver the "desired market outcome" of an overall increase in agricultural production or productivity (Li & Ito, 2021). If, however, they cannot participate in the market on a voluntary basis or on an equal footing, the land transaction may not necessarily have the "desired market outcome". This perspective is particularly important in the Chinese context as non-farm household producers (NFHPs), such as agricultural cooperatives (ACs) and agribusiness firms (dragon head enterprises) have increasingly entered the farming business as cultivators (Cheng et al., 2019; Huang & Ding, 2016).[1] Unlike family farms, large-scale NFHPs incur additional costs due to the need to supervise hired labor working in widely dispersed agricultural environments where quality of work is hard to monitor; a lack of such monitoring would undoubtedly lead to poor performance in agriculture (Otsuka et al., 2016). As a result, NFHPs may underperform family-oriented smallholders in terms of production efficiency. Thus, we are convinced that exploring the causal effect of land rental on farm production efficiency at the market level constitutes an important

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[1] Luo and Andreas (2020) argue that farmland consolidation by NFHPs in China may be detrimental to agricultural production efficiency if local authorities resort to coercive measures to compel smallholders to part with their land-use rights.

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issue for empirical studies to investigate.

Since the early 2000 s, the central government of China has been promoting land usufruct accumulation in favor of large-scale farms and NFHPs (Li & Ito, 2021; Ye, 2015). The farmland consolidation program has accelerated under the rural revitalization strategy, the goals of which align with the government's strategy of solving the well-known "three rural problems," advocated officially since 2001 as essential for improving the economic status of rural populations.[2] It is considered, however, that the government's ultimate goals of promoting land exchange are to reinforce food production capacities to achieve the long-held policy objective of maintaining a high grain self-sufficiency rate.[3] Thus, this study carefully examines whether the development of land rental markets leads to overall improvement in agricultural technical efficiency.

Another important issue addressed in this study is to empirically examine farmers' crop choice rationality. Song et al. (2021) argue that policy-oriented forces to maintain food security played a leading role in Chinese agriculture for the long haul. Meanwhile, market-induced crop diversification resulting from a change in people's eating habit offers new opportunities for farmers to increase their farm revenues. Not only China but also other emerging Asian economies have followed a similar trajectory in this respect, with shifting away from the traditional grain towards fresh fruit and vegetable production (Ito, 2015). It can be said that the diversification and selective expansion of farm products are economic challenges that these countries are currently faced with. To the best of our knowledge, however, little is analyzed on this matter.

Methodologically, we estimate a stochastic frontier output distance function (SFODF) using panel data from 86 counties in Gansu Province. To correct the potential bias in the estimators stemming from the endogeneity problem, we employ an instrumental variable estimation method.[4] Gansu is a relatively underdeveloped area located in the northwest of China. The province's land–rental ratio (LRR), which is defined as the land rented area divided by the total contracted land area, was among the lowest in China (below 10 %) at the beginning of the 2010 s (Liu, Wang et al., 2019; Wang et al., 2018). However, it rose sharply thereafter, reaching 26 % in 2017 (Li & Ito, 2021). For this reason, Gansu Province appears to be a good place to examine the relationship between the development of land rental markets and technical efficiency.

Our first contribution to the literature is to provide empirical insights into the question of whether the development of land rental markets exerts a positive effect on technical efficiency at the aggregate level. Previous empirical studies, such as Feng (2008), Liu and Yan (2019), and Zhang et al. (2011), explore the relationship between land transactions or administrative reallocation and technical efficiency in Chinese agriculture, employing a standard stochastic frontier model. Their main objective is to explore whether farmer's land rental behavio improves technical efficiency at the individual level. However, they cannot identify the "market outcome" of land transaction because their empirical studies use household micro data. The transfer of farmland from less productive producers to more productive producers will inevitably improve the technical efficiency at the market level. However, this "desired market outcome" may not be delivered, due to the reasons mentioned above.

The second contribution of this study is to quantitatively examine the extent to which farmers make a rational decision on their product mix. It is reasonable to assume that farm managers intend not merely to maintain high technical efficiency but also to maximize their farm income by achieving high allocative efficiency. This may require them to diversify or selectively expand farm production in response to changes in product prices. China offers an interesting case in this respect, because the central government has long placed a high premium on national self-sufficiency in staple foods, but the relative price of farm products is moving in favor of non-grain products recently. Thus, the issue of crop choice rationality of farm producers is worth analyzing in economic terms. The SFODF with multiple inputs and outputs is most suitable for this purpose as it allows us to measure output-base allocative efficiency.

The remainder of this study is structured as follows. Section 2 reviews agricultural production and the burgeoning development of land rental markets and ACs in Gansu. Section 3 presents a theoretical model of the SFODF as well as the data processing required for the econometric analysis. Section 4 then presents the estimation results. Finally, Section 5 concludes the study with a summary of the findings and draws policy implications.

2. Outline of agriculture in Gansu

2.1. Farm production and land use

Gansu is predominantly an agricultural area, and the farm sector in the province plays an important role in developing the rural economy. The landforms in the province are complex and diverse, comprising mountainous regions, plateaus, and river valleys as well as plains and deserts. Mountainous and hilly areas account for the largest proportion, while the area of flatland is relatively small (only 22 % of the land area). Due to geographical constraints and atmospheric circulation effects, access to surface water resources is limited and unevenly distributed. Despite such multifarious topography and critical environmental conditions, the agricultural sector in Gansu

[2] Wu and Liu (2020), and Zhou and Li (2020) argue that land consolidation is an important platform and provides leverage for the promotion of rural revitalization.

[3] China's central government issued Number One Document in 2014 declaring the break away from full self-sufficiency to a new food security strategy – one that relies on domestic production with moderate imports (Zhang & Cheng, 2017).

[4] Chen and Huffman (2006) estimate a stochastic frontier production function using China's county-level data. However, they do not address the causal effect of land reallocation on technical efficiency. Lawin and Tamini (2019) analyze the land tenure security on the technical efficiency of smallholders in Benin. Michler and Shively (2015) also examine the relationship between land tenure and farm efficiency, using household panel data in the Philippines.

has maintained a stable growth rate over the years, with agricultural products being highly diversified. Fig. 1 illustrates the location of Gansu and the administrative boundaries of its 14 city-level governments. It also provides geographical information on the irrigation rate for those 14 cities in 2017, which forms an increasing gradient from the southwest to the northwest part of the province. Arguably, the availability of water resources for crop farming constitutes one of the key factors defining a production frontier.

In this study, we divide farm products or production activities into three categories: Sector 1 is grain, including wheat, maize, and tubers; Sector 2 is cash crops, such as cotton and oil crops; and Sector 3 is vegetables and fruits. Table 1 presents farm production (10,000 tons) and the share of sown area by sector between 2000 and 2018. The production of all three sectors showed an increasing trend over the years, with the annual growth rate of Sector 3 being among the highest (5.6 %).[5] The right half of Table 1 shows the share of sown area, with the figures in parentheses representing the national average.[6] Sector 1 has accounted for the largest share of land use in Gansu consistently for the period concerned, but its share declined between 2000 and 2018, from 76.4 % to 69.9 %. Sector 2 has barely maintained a double-digit percentage, but its share has declined since 2005, accounting for 10.3 % in 2018. In contrast, the share of Sector 3 in Gansu increased significantly, from 10.8 % to 19.8 %. China's Statistical Yearbook overestimated the output and sown area of the horticulture and livestock industries in some provinces between 2007 and 2016. Therefore, using amended statistical data, we created Table 1; we discuss a way to re-estimate the data below in Section 3. Most noteworthy in Table 1 is that land-use patterns in Gansu agriculture show a similar trend with the national average.

Fig. 2 illustrates the Laspeyres price index of agricultural products (Sectors 1–3) and material in Gansu (the year 2005 =100). The index of Sector 1 showed an upward trend between 2005 and 2014, but the tendency was reversed thereafter. The index of Sector 2 followed basically the same trend, hitting a peak in the year 2015, and declining thereafter. Although the central government implemented a set of protectionist policy programs in the early 2000 s, including producer subsidy and price support for agricultural products, they launched a series of policy reforms in the mid-2010 s; they introduced a target price policy for soybean and cotton in 2014 for specified regions on a trial basis to decouple income support from the determination of farm product prices. The pilot project was followed by a reduction in the procurement prices for rice and wheat in 2015, and the implementation of the target price program for maize in 2016. Compared to Sectors 1 and 2, the terms of trade in Sector 3 improved significantly during the period concerned, with the index reaching 267 in 2018.

A close look at Table 1 and Fig. 2 reveals that the rapid growth of Sector 3 in terms of the production and share of sown area was probably caused by price movement in favor of horticultural products over the past few years. Another conceivable reason for the sharp growth of Sector 3 in Gansu lies in the central government's policy initiatives. Due to the recent worsening terms of trade in grain production, many, if not all, Chinese farmers are motivated to switch to more profitable crops. Although the government has restricted such crop diversification in the eastern and central provinces, which constitute the major production region for grain, they are encouraging farmers in western China (Gansu included) to grow fresh fruits and vegetables, with a view to narrowing the inter-regional rural income disparity.

2.2. Land rental markets and agricultural cooperatives

To use farmland efficiently, China's central government has shifted the land transaction mechanism among farm households (FHs) away from a dependence on the administrative reallocation toward the adoption of a decentralized and market-oriented means to transfer land-use rights. With a view to developing land rental markets, the government has implemented the comprehensive land rights realignment program, which lengthens contract times, prohibits administrative reallocation during rental periods, provides contract certificates, and guarantees the warranty of inherited contract rights. Among other things, the "three rights separation" policy initiated in 2014 had a significant effect on land rental markets in rural China. This program conceptually divides rural land rights into three components; non-tradable property rights; non-tradable contractual rights; and tradable land-use rights (Cheng et al., 2019; Wang, Li, Li et al., 2018; Ye, 2015; Zhou, Li, et al., 2020). Property rights are held by rural collectives, contract rights are rights of individual households to use collectively-owned lands, and land-use rights are their right to use land and obtain income from their contracted land. Under the three-rights-separation system, farmers planning to cease farming have become able to rent out their land use rights without worrying about the loss of their contracted land rights. Thus, the development of the land rental market in rural areas accelerated during the 2010 s

The LRR in China has increased significantly, from 14.7 % in 2010 to 37.0 % in 2017, with NFHPs' share of rented land areas rising from 20 % in 2010 to 33 % in 2017 (China Statistical Yearbook of Rural Operation and Management, the Ministry of Agriculture). This remarkable fact holds true for rural Gansu. Fig. 3 illustrates the LRR in Gansu Province between 2013 and 2017. The rental ratio rose sharply during the period examined in this study, from 15.6 % in 2013 to 26.0 % in 2017. In this process, NFHPs play an increasing role as lessees, with their market share of rented land area increasing from 33 % in 2013 to 42 % in 2017. Further, our field work over the past several years in rural Gansu reveals that ACs have made a sizable contribution toward the development of land rental markets, not

[5] In the early 2000 s, many maize seed companies launched their businesses in western Gansu, with the result that maize production grew more rapidly than Sector 3 production during this period, by 5.9 % per annum, although this is not shown in Table 1.

[6] The sown area of Sectors 1–3 covers around 90 % of the provincial total sown area. Production of traditional Chinese medication, which is grown in some specific areas, accounts for more than half of the remaining 10 %.

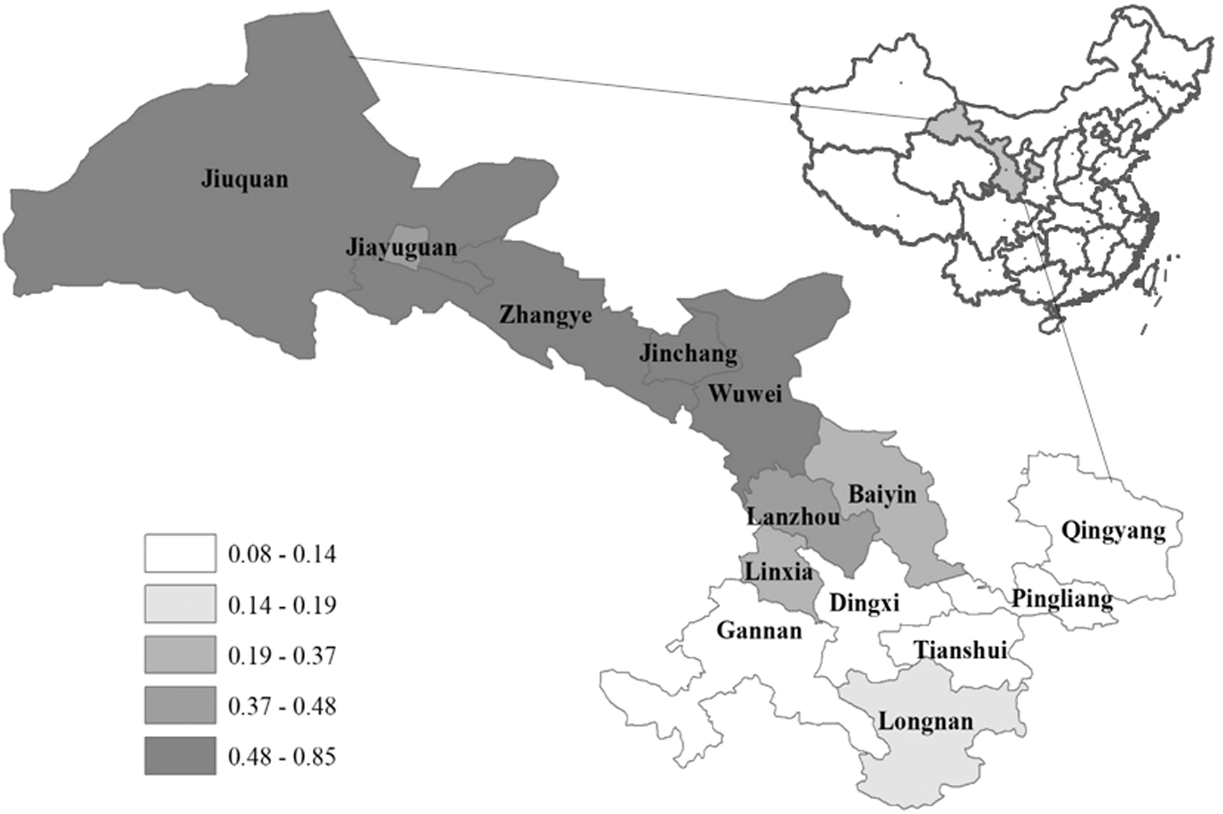

Fig. 1. Administrative boundaries and irrigation rate in Gansu.
Note: The agricultural patterns can be divided into the Longnan mountainous farming regions. (Longnan), Loess plateau dryland farming regions in the east (Lanzhou, Baiyin, Tianshui, Pingliang, Qingyang, Dingxi, and Linxia,), Gannan plateau farming regions (Gannan), and irrigation. agricultural regions of the Hexi Corridor (Jiayuguan, Jinchang, Wuwei, Zhangye, and Jiuquan).
Source: Google maps.

Table 1
Farm production and the share of sown area by sector.

	Farm production (10,000 ton)			The share of sown area (%) National average in parentheses					
	Sec. 1	Sec. 2	Sec. 3	Sec. 1		Sec. 2		Sec. 3	
2000	581.6	47.4	622.9	76.4	(68.6)	12.8	(14.1)	10.8	(17.3)
2005	703.2	61.4	640.9	71.2	(65.8)	14.0	(14.2)	14.8	(20.0)
2010	826.5	74.1	879.3	72.2	(69.1)	12.0	(12.5)	15.8	(18.5)
2011	902.0	74.2	944.2	71.9	(68.7)	12.0	(12.1)	16.1	(19.2)
2012	1022.1	79.0	1042.0	71.9	(68.9)	11.3	(11.7)	16.8	(19.4)
2013	1052.0	81.4	1127.6	71.8	(69.2)	11.0	(11.4)	17.2	(19.3)
2014	1074.0	84.2	1219.1	71.8	(69.2)	10.6	(11.2)	17.6	(19.6)
2015	1083.4	81.5	1306.7	72.1	(69.7)	10.0	(10.8)	18.0	(19.4)
2016	1049.8	84.4	1422.8	71.3	(70.1)	10.0	(10.5)	18.7	(19.4)
2017	1037.8	80.6	1609.5	70.2	(69.4)	10.8	(10.6)	19.0	(20.0)
2018	1072.8	73.9	1662.6	69.9	(68.7)	10.3	(10.5)	19.8	(20.8)

Source: Rural Operation and Management Statistics (Department of Agriculture and Rural Affairs, Gansu), China Statistical Yearbook.

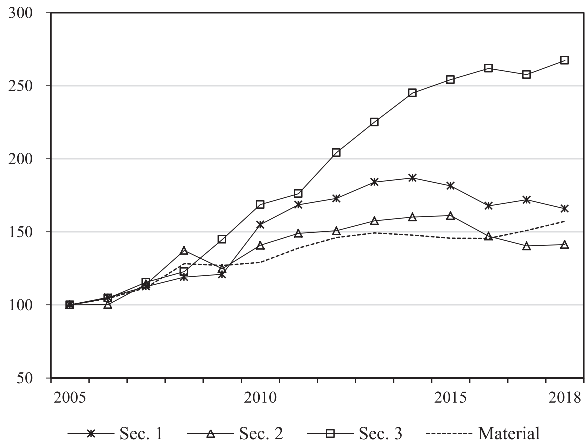

Fig. 2. Price indexes of agricultural products and material in Gansu.
Source: Gansu Development Yearbook (Gansu Statistical Bureau).

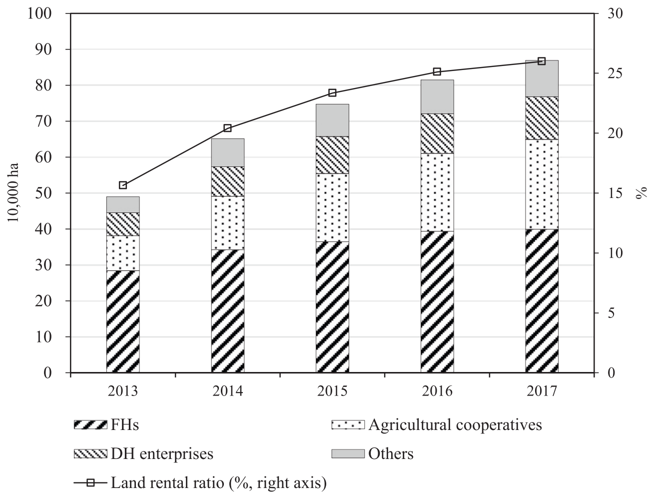

Fig. 3. The rented land area and land rental ratio.
Source: Rural Operation and Management Statistics (Department of Agriculture and Rural Affairs, Gansu).

only through renting land directly as lessees but also by serving as intermediate agents of land exchange among FHs.[7] However, it remains an empirical question whether this leads to an improvement in agricultural technical efficiency.

According to the Farmers' Professional Cooperatives Law (FPCL), ACs are characterized by NFHPs and mutual help economic organizations based on the principle of the Household Responsibility System. Following the embryonic development of rural producer organizations, which were established on a voluntary basis in the early 1990s, the central government tried to accelerate this movement by promulgating the FPCL in 2007 (Ito et al., 2012). Recent years have seen a surge in ACs in China, with the total number increasing 85-fold, from 26,000 in 2007–2.2 million in 2019. Likewise, the number of such cooperatives in Gansu increased rapidly, from 29,357 in 2013–83,908 in 2017. Apart from the intermediate role, we must consider the potential impact of ACs on agricultural productivity or technical efficiency. Previous studies, such as Gong et al. (2019), Ito et al. (2012), Jia et al. (2012), and Zhang et al. (2020), demonstrate that ACs have been fulfilling a major role in enhancing the overall economic efficiency and welfare of rural societies. Using the selectivity-corrected stochastic frontier production function, Dong et al. (2019) and Ma et al. (2018) show that average technical efficiency is consistently higher for AC participants relative to non-participants.

[7] Ito et al. (2016) show that rural shareholding cooperatives in Jiangsu, China have played an important role in reducing the transaction costs associated with the exchange of land use rights, thereby promoting land rental activities. However, the establishment of rural shareholding co-operatives in Gansu hovers at an experimental level.

3. Methodology

3.1. Stochastic frontier output distance function (SFODF)

This study specifies a frontier production function as an output distance function with multiple inputs and multiple outputs, partly because agricultural production has recently become diversified across regions in rural Gansu, and partly because the distance function approach allows us to simultaneously measure technical efficiency and output-base allocative efficiency.

Based on Brümmer et al. (2006), Coelli and Perelman (2000), and O'Donnell and Coelli (2005), we assume the following equation:

$$\ln Y_1 = -\ln D_O(\boldsymbol{X},\ 1,\ \boldsymbol{Y}/Y_1) + \ln D_O = -\ln D(\boldsymbol{X},\ \boldsymbol{Y}^*) + \ln D_O, \tag{1}$$

where the vectors $\boldsymbol{X}$ and $\boldsymbol{Y}$ denote vector inputs and outputs, respectively, whereas D_O denotes the output distance function (ODF). Since we have $0 < D_O \leq 1,\ -u = \ln D_O$ is negative with the maximum value equal to zero. The term of $-u$ represents the inefficiency element with a one-sided disturbance; the closer the value of D_O is to unity, the more technically efficient are the farmers' choices. Thus, Eq. (1) is rewritten as:

$$\ln Y_1 = -\ln D(\boldsymbol{X},\ \boldsymbol{Y}^*) - u. \tag{2}$$

By specifying $\ln D(\boldsymbol{X},\ \boldsymbol{Y}^*)$ in Eq. (2) as the trans-log form, we express the SFODF as:

$$\begin{aligned} -\ln Y_{1it} = {} & \alpha_0 + \sum_k \alpha_k \ln X_{kit} + \sum_m \beta_m \ln Y^*_{mit} + \gamma_t \ln t + \frac{1}{2}\sum_k \sum_l \alpha_{kl} \ln X_{kit} \ln X_{lit} \\ & + \sum_k \sum_m \chi_{km} \ln X_{kit} \ln Y^*_{mit} + \sum_l \alpha_{lt} \ln X_{lit} \ln t + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln Y^*_{mit} \ln Y^*_{nit} \\ & + \sum_n \beta_{nt} \ln Y^*_{nit} \ln t + \gamma_{tt}(\ln t)^2 + \chi \cdot \text{Irrigation rate}_{it} + u_{it} + v_{it} \end{aligned} \tag{3}$$

where i and t denote county and time, respectively. To take account of the difference in production technologies or heterogeneity in the SFODF among counties, the variable of irrigation rate is included in Eq. (3). Albeit very simple, this is an effective method to reduce the estimation biases arising from the assumption of homogeneous frontier function.

In Eq. (3), v_{it} is i.i.d. $N(0,\ \sigma_v^2)$, that is, independent and identically distributed with zero mean and variance σ_v^2, and u_{it} is i.i.d. $N^+(\mu_{it},\ \sigma_u^2)$ with one-sided distribution. The two components u and v are also assumed to be distributed independently of one another: $\sigma_{uv} = 0$. Technical efficiency can be calculated as $TE_{it} = \exp(-u_{it})$. The parameters in Eq. (3) have properties of $\alpha_{kl} = \alpha_{lk}$, $\beta_{mn} = \beta_{nm}$ from the symmetric conditions. A trans-log function is a second-order Taylor-series approximation centered at zero. Therefore, prior to the estimation, all of the respective output and input variables are normalized such that $\ln \bar{X} = \ln \bar{Y} = \ln \bar{t} = 0$.

Given the estimators, the elasticity of scale is given by:

$$\eta = \sum_k \frac{\partial \ln D(\boldsymbol{X},\ \boldsymbol{Y}^*)}{\partial \ln X_k} = -\sum_k \frac{\partial \ln Y_1}{\partial \ln X_k}.$$

The production technology exhibits constant returns to scale when $\eta = 1$. If $\eta > (<)\ 1$, the technology exhibits increasing (decreasing) returns to scale. The monotonicity condition of the SFODF requires both $\partial \ln Y_1/\partial \ln Y^*_m > 0$ and $\partial \ln Y_1/\partial \ln X_l < 0$, which are reduced to $\beta_m > 0$ and $\alpha_l < 0$ at the mean values of the variables, respectively.

Meanwhile, convexity in outputs will be ensured if and only if all the principal minors of the following Hessian matrix are non-negative:

$$H = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1M} \\ h_{21} & h_{22} & \cdots & h_{2M} \\ \vdots & \vdots & \cdots & \vdots \\ h_{M1} & h_{M2} & \cdots & h_{MM} \end{bmatrix}$$

where $h_{ij} = \partial^2 D(\boldsymbol{X},\ \boldsymbol{Y}^*)/\partial Y^*_i \partial Y^*_j$. From Eqs. (1) to (3), we have:

$$\frac{\partial \ln D(\boldsymbol{X},\ \boldsymbol{Y}^*)}{\partial \ln Y_k} = -\frac{\partial \ln Y_1}{\partial \ln Y^*_k} \equiv \beta_k^{TL} \quad (k = 2,\ 3).$$

Thus, the second derivatives of $D(\boldsymbol{X},\ \boldsymbol{Y}^*)$ are given by:

$$\frac{\partial^2 D(\boldsymbol{X},\ \boldsymbol{Y}^*)}{\partial Y^{*2}_m} = -\frac{D(\boldsymbol{X},\ \boldsymbol{Y}^*)}{Y^{*2}_m}\left[\beta_{mm} - \beta_m^{TL}(\beta_m^{TL} + 1)\right],$$

$$\frac{\partial^2 D(\boldsymbol{X},\ \boldsymbol{Y}^*)}{\partial Y^*_m \partial Y^*_n} = -\frac{D(\boldsymbol{X},\ \boldsymbol{Y}^*)}{Y^*_m Y^*_n}\left[\beta_{mn} - \beta_m^{TL}\beta_n^{TL}\right].$$

We did not impose the convexity constraints when estimating the SFODF (Henningsen & Henning, 2009).

3.2. Technical and allocative efficiency

The inefficiency term can be linearly expressed as:

$$-\mathrm{TE}_{it} = \delta_0 + \boldsymbol{Z}_{it}{}'\boldsymbol{\delta} + \varepsilon_{it}, \tag{4}$$

where $\boldsymbol{Z}_i$ denotes a vector of explanatory variables expected to influence technical efficiency. These variables include the LRR, the AC participation ratio (ACR), and other control variables. The ACR is defined as the number of employees working for crop-farming cooperatives divided by the total labor force engaged in the primary sector. To obtain the consistent and unbiased estimators, we have to estimate Eqs. (3) and (4) simultaneously (Battese & Coelli, 1995).

We can argue the maximization of farm revenues only when a SFODF satisfies the convexity condition in outputs. The first-order condition of revenue maximization for technically efficient producers ($D_0 = 1$ in Eq. (1)) is given by:

$$\mathrm{MRTS}_{mn} = \frac{p_m}{p_n},$$

where MRTS_{mn} represents the marginal rate of technical substitution, given by:

$$\mathrm{MRTS}_{mn} = \frac{\partial D(\boldsymbol{X},\ \boldsymbol{Y}^*)/\partial Y_m}{\partial D(\boldsymbol{X},\ \boldsymbol{Y}^*)/\partial Y_n},$$

and p_k denotes output price of sector k. Thus, the allocative efficiency score is defined as:

$$\mathrm{AE}_{mn} = \frac{\mathrm{MRTS}_{mn}}{p_m/p_n} \tag{5}$$

When AE_{mn} is larger (smaller) than unity, sector m is over (under)-produced relative to sector n. To put it another way, when AE_{mn} is unequal to unity, the product mix between sectors m and n is allocatively inefficient.

3.3. Estimation strategy

While estimating Eqs. (3) and (4), we must control for potential bias stemming from time-invariant unobservables and the endogeneity problem in the equations. Since panel data are available in this study, we can remove bias arising from time-invariant unobservables by employing a fixed effects model. To overcome the remaining bias associated with endogeneity, we can employ the instrumental variable (IV) estimation method. The Stata command of "xtsfkk" developed by Karakaplan (2017) is very powerful for the present study. The advantage of this command is that it can control for the endogeneity problem in the frontier and/or inefficiency equations in longitudinal settings.[8] In this study, we eliminate the potential estimation bias stemming from endogeneity with respect to the two key variables of LRR and ACR. The instruments must be correlated with LRR and ACR but must not directly affect the technical efficiency.

We use LRR and ACR at the city level, except county i itself, as excluded instruments of LRR and ACR, following Kung (2002), Li and Ito (2021), Liu et al. (2017), Rao et al. (2020), and others.[9] It is reasonable to consider that LRR at the city level is correlated with that of the county level as the promotion of land exchange has gained momentum nationally since the 2000 s. However, it must be unrelated to technical efficiency at the county level. The city-level ACR is also considered to be a valid instrument. After embryonic development in the early 1990 s, ACs have evolved nationally since the 2000s. The Chinese central government tried to accelerate this movement by promulgating the FPCL, suggesting that the establishment of ACs was motivated by policy initiatives in a top-down fashion. Considering the extent to which rural people in neighboring counties interact and consult with each other on this policy issue, the participation in ACs at the county level is likely to be associated with ACR at the city level (Li & Ito, 2021). More importantly, AC activities at the city level do not directly affect technical efficiency at the county level.

3.4. Data

We primarily draw on three sources of data for this study. The first is Rural Operation and Management Statistics, sourced by the authors from the Department of Agriculture and Rural Affairs, Gansu. This source contains a wealth of statistics regarding land use and its transaction, farmers' participation in agricultural cooperatives, the economic activities of rural households and collectives, and other socioeconomic and sociodemographic information by county. The second data source is the Gansu Rural Yearbook published by the Gansu Statistics Bureau, which provides a broad range of information on the quantity of farm inputs and outputs. The third data source is the Gansu Development Yearbook (Gansu Statistical Bureau), from which data on the quantity and price of farm outputs are

[8] Unlike the standard control function approach, we can estimate parameters with a one-step procedure (Karakaplan & Kutlu, 2017).

[9] Liu et al. (2017) and Rao et al. (2020) and others adopted this method for their analysis using household-level analysis. We consider that this method can be applied to analyses using macro-level data as long as instrumental variables chosen are valid.

Table 2
Variable descriptions and summary statistics.

Variables	Descriptions		Mean	SD
Sec. 1 (weight)	Sector 1′s production by weight (1000 tons)	overall	130.4	114.8
		between		114.2
		within		16.1
Sec. 2 (weight)	Sector 2′s production by weight (1000 tons)	overall	8.77	10.7
		between		10.4
		within		2.95
Sec. 3 (weight)	Sector 3′s production by weight (1000 tons)	overall	166.8	191.0
		between		187.2
		within		41.9
Sec. 1 (value)	Sector 1′s output value at constant prices (million yuan)	overall	347.1	311.6
		between		309.3
		within		48.1
Sec. 2 (value)	Sector 2′s output value at constant prices (million yuan)	overall	68.5	126.7
		between		116.2
		within		51.8
Sec. 3 (value)	Sector 3′s output value at constant prices (million yuan)	overall	415.6	474.7
		between		462.0
		within		118.2
fer	Chemical fertilizer consumption (1000 tons)	overall	10.6	10.4
		between		10.0
		within		3.00
lab	Total number of workers engaged in primary production (1000 persons)	overall	53.6	40.4
		between		40.1
		within		5.22
cap	Farm machinery measured by power (1000 kilowatt hours)	overall	262.3	237.1
		between		229.6
		within		63.1
lad	Contracted land area (1000 ha)	overall	39.0	31.0
		between		30.9
		within		3.61
time	Year minus 2010	overall	5.00	1.42
		between		0.00
		within		1.42
irri	Irrigated area divided by total contracted land area	overall	0.50	0.60
		between		0.56
		within		0.25

Note: Farm output data are measured by the weight or value at constant prices alternatively.

available. To perform the econometric analysis, we compile a panel dataset for 86 counties from 2013 to 2017.

Table 2 presents descriptive statistics of variables used for the estimation of the SFODF. Farm production for the three sectors (*Sec. 1*, *Sec. 2*, and *Sec. 3*), as defined in the Section 2, is measured by two alternative methods: the weight in tons, and the output value of agriculture at constant prices. As was pointed out in Section 2, China's Statistical Yearbook overestimated the production of vegetables, fruits, and livestock products in some provinces between 2007 and 2016. The Statistical Bureau reported statistically corrected data in 2017 based on the third Agricultural Census in 2016. It was discovered that the degree to which the production of vegetables and fruits was overestimated for this period in Gansu was around 1.7 and 1.4, respectively. Using these coefficients, we re-estimated the county-level data on horticultural output. Further, we removed three counties from the sample whose gross agriculture output value accounted for less than 10 % of the primary industry's gross output value.[10] Additionally, three counties and 10 observations are excluded from the analysis due to the lack of sector 2 output and labor input data, respectively.

Factor inputs include fertilizer (*fer*), farm labor (*lab*), farm machinery (*cap*), and contracted farmland (*lad*). Fertilizer is measured by the total chemical fertilizer consumption that is converted to net ingredients (1000 tons). Farm labor is measured by the total number of workers engaged in crop farming (1000 persons), which is not obtained directly from the Gansu Development Yearbook. Thus, we first compute the ratio of gross output value of agriculture to that of the primary industry at the county level, and then estimate farm labor by multiplying the ratio by the total labor force in the primary industry. Farm machinery is measured by the total power of agricultural machines (1000 kilowatt hours) used for agricultural production, which includes the power of the machinery services that are provided by cooperatives or machinery service providers.

Farmland is measured by the total area of contracted land (1000 ha). When considering multiple cropping in Sector 3, we ideally would have used the sown area instead of contracted land area. However, because the sown area of horticultural land in Gansu was overestimated between 2007 and 2016, we have used contracted land area instead.[11] Time trend (year minus 2010) is included as a

[10] The gross output value of agriculture in Gansu, as a whole, accounted approximately for 70 % of the recent total, which is followed by animal husbandry with 20 %.

[11] The total contracted land and sown area in 2017 was 3.34 and 3.68 million ha, respectively (Jiayuguan city excluded).

proxy for technological progress. Finally, the variable of irrigation rate (*irri*) measures the irrigated area divided by the total contracted land area. Table 2 shows that just half of the contracted land area was irrigated in Gansu, although there is a huge inter-regional variance in *irri*, as shown in Fig. 1.

4. Estimation results and discussion

4.1. Estimation result for the SFODF

Tables 3 and 4 show the estimation results of the model. In addition to trans-log, this study specifies the SFODF as the CD form, in which all quadratic and interaction terms in the right-hand side of Eq. (3) drop. Since all of the output and input variables are normalized, $\partial \ln Y_1/\partial \ln Y_m^*$ and $\partial \ln Y_1/\partial \ln X_l$ evaluated at the sample mean values of the variables for the trans-log are given by β_m and α_l, respectively, which are comparable to the CD estimators. A joint test of parameters regarding the trans-log terms rejects the null hypothesis of a nested CD production technology ($p > \chi^2 = 0.000$), suggesting that the trans-log form is more appropriate for the SFODF specification. However, considering the advantage of a small number of parameters (parsimonious model), we show the results when the SFODF is specified as the CD form in Tables 4–1 and 4–2. Further, to check robustness of the estimators, we show the results when the two alternative types of farm production data (weight and real output value) are used for the estimation of Eq. (3).[12]

The estimated trans-log function satisfies the monotonicity and convexity conditions for more than half of data domains. The CD function also satisfies the monotonicity conditions, as is evident from Tables 4-1 and 4-2. Moreover, we cannot reject the null hypothesis that the estimated SFODF exhibits constant returns to scale. As is expected, the coefficient of irrigation rate is negative and highly significant, suggesting that an increase in the irrigation rate helps expand the SFODF frontier outward.

4.2. Estimation results of the technical inefficiency equation

The test statistic does not reject the null hypothesis regarding the joint exogeneity of LRR and ACR, with the exception that the SFODF is specified as the trans-log form, with farm production being measured by real output value. In the case of rejection, we interpret the estimation results based on endogenous model.[13] The lower parts of Tables 3 and 4 show the estimation results of Eq. (4). As described by Tian and Wan (2000), there exists no formal procedure to be followed when deciding which variables should be included in the inefficiency equation. In addition to LRR and ACR, we use the following two variables, the migration ratio (MR) and the land-labor ratio (LLR), as regressors of the technical inefficiency equation. Migratory movement of rural people from farm to non-farm sectors may play a role in determining the level of agricultural technical efficiency (Zhang et al., 2016), although previous studies do not provide unambiguous direction on the impact (Feng, 2008). The MR variable measures the number of migrants working outside their home village continuously for more than six months of the year divided by the total number of FHs. The LLR is a proxy for the average farm size at the county level and may have some impact on technical efficiency. Appendix Table 1 presents descriptive statistics of variables used for the estimation of the inefficiency equation.

Tables 3-1 and 3-2 show the estimation results when the SFODF is specified as the trans-log form. When farm production is measured by weight (Table 3-1), the null hypothesis of the joint exogeneity cannot be rejected. Thus, we examine the estimation result based on the exogenous model. The estimator of LRR and ACR are negative and significant at the 1 % and 10 % level, respectively. Thus, our estimation result lends support to the assertion that the development of land rental markets and ACs helps improve the technical efficiency of farm production at the county level. Meanwhile, the other variables, such as MR and LLR have no explanatory power for technical efficiency.

Table 3-2 shows the estimation results when the SFODF is specified as the trans-log form, with farm production being measured by real output value. As the null hypothesis of the joint exogeneity is rejected, we examine the estimation result based on the endogenous model. Although the coefficient of LRR is negative and significant at the 1 % level, that of ACR is positive but not significant. Thus, we cannot say for certain that ACs serve as a facilitator of raising technical efficiency. The coefficient of LLR is positive and significant at the 10 % level, suggesting that an increase in farm size at the county level has a detrimental effect on technical efficiency. This is consistent with Gautam and Ahmed (2019) who estimate a standard stochastic frontier production function using FH data in Bangladesh. Their result indicates that large farms are more technically inefficient than small farms.

When the SFODF is specified as the CD form, the null hypothesis of the joint exogeneity cannot be rejected. However, the estimation results are robust in the sense that the coefficients of LRR and ACR are negative and highly significant, irrespective of whether the exogenous or endogenous model is used and how farm production is measured. Unlike the estimation results based on the trans-log form, LLR has nothing to do with technical efficiency.

Tables 3 and 4 show that migration has no explanatory power for technical efficiency in all cases. Due to the massive migration of rural young people to cities, Chinese agriculture is currently undertaken by women and elderly people left behind in the countryside, resulting in the "feminization" and "graying" of agriculture (Ye, 2015). This may impede improvement of technical efficiency. Meanwhile, it is likely that the migratory movement of rural people mitigates the production inefficiency associated with agricultural

[12] Lawin and Tamini (2019) measure the farm production by the quantity in kg for the estimation of the SFODF of Beninese agriculture.

[13] There is no weak instrument problem with the city level LRR and ACR because they are strongly correlated with the LRR and ACR at the county level.

Table 3-1
Estimation result of the trans-log SFODF (output: weight).

	Exogenous		Endogenous	
	Estimates	SE	Estimates	SE
Eq. (3)				
ln (*fer*)	-0.243***	0.043	-0.246***	0.043
ln (*lab*)	-0.215***	0.046	-0.217***	0.047
ln (*cap*)	0.014	0.034	0.018	0.035
ln (*lad*)	-0.462***	0.065	-0.469***	0.065
ln (*Sec.* 2)	0.072***	0.015	0.077***	0.016
ln (*Sec.* 3)	0.251***	0.019	0.247***	0.019
ln (*time*)	0.011	0.030	0.016	0.032
ln (*fer*)*ln (*lab*)	0.048	0.047	0.037	0.048
ln (*fer*)*ln (*cap*)	0.167***	0.057	0.187***	0.059
ln (*fer*)*ln (*lad*)	0.107	0.079	0.130*	0.079
ln (*lab*)*ln (*cap*)	-0.030	0.055	-0.016	0.056
ln (*lab*)*ln (*lad*)	0.194	0.148	0.192	0.146
ln (*cap*)*ln(*lad*)	-0.193***	0.074	-0.200***	0.075
0.5*ln (*fer*)*ln (*fer*)	-0.184***	0.044	-0.205***	0.045
0.5*ln (*lab*)*ln (*lab*)	-0.209	0.151	-0.213	0.149
0.5*ln (*cap*)*ln (*cap*)	-0.068	0.071	-0.108	0.075
0.5*ln (*lad*)*ln (*lad*)	-0.136	0.160	-0.146	0.160
ln (*fer*)*ln (*Sec.* 2)	0.045**	0.019	0.055***	0.020
ln (*lab*)*ln (*Sec.* 2)	-0.085***	0.033	-0.084**	0.033
ln (*cap*)*ln (*Sec.* 2)	0.025	0.021	0.018	0.022
ln (*lad*)*ln (*Sec.* 2)	-0.062	0.041	-0.070*	0.040
ln (*fer*)*ln (*Sec.* 3)	0.046**	0021	0.043**	0021
ln (*lab*)*ln (*Sec.* 3)	-0.056**	0.028	-0.047*	0.028
ln (*cap*)*ln (*Sec.* 3)	-0.035	0.023	-0.037	0.023
ln (*lad*)*ln (*Sec.* 3)	-0.005	0.032	-0.014	0.032
ln (*fer*)*ln (*time*)	0.048	0.047	0.036	0.048
ln (*lab*)*ln (*time*)	0.003	0.046	-0.009	0.046
ln (*cap*)*ln (*time*)	-0.209***	0.047	-0.199***	0.048
ln (*lad*)*ln (*time*)	0.070	0.062	0.086	0.064
ln (*Sec.* 2)*ln (*Sec.* 3)	-0.051***	0.011	-0.052***	0.010
0.5*ln (*Sec.* 2)*ln (*Sec.* 2)	0.084***	0.016	0.079***	0.016
0.5*ln (*Sec.* 3)*ln (*Sec.* 3)	0.103***	0.016	0.102***	0.016
ln (*Sec.* 2)*ln (*time*)	-0.019	0.021	-0.022	0.021
ln (*Sec.* 3)*ln (*time*)	-0.025	0.021	-0.020	0.021
0.5*ln (*time*)*ln (*time*)	0.589***	0.192	0.573***	0.195
Irri	-0.548***	0.062	-0.536***	0.063
Eq. (4)				
Land—rental ratio	-1.512***	0.413	-2.044***	0.543
AC participation ratio	-1.168*	0.631	-0.464	0.873
Migration ratio	0.230	0.260	0.196	0.264
Land—labor ratio	0.086	0.069	0.068	0.067
Joint endogeneity test	-	-	$\chi^2 = 2.67$	$p = 0.263$
Number of observations	390		390	
Log likelihood	173.8		1080.0	
Mean technical efficiency	0.697		0.696	

Note: *, ** and *** indicate statistical significance at the 1 %, 5 % and 1 % levels, respectively.

surplus labor (Chen et al., 2009). Our estimation result suggests that the two effects on technical efficiency cancel each other out.[14] Besides MR and LLR, we examine other control variables for the inefficiency regression, such as the ratio of part-time FHs and of contract certificate holders, and the share of small-scale FHs. We conclude, however, that these variables are neither statistically significant nor influential to the final result.

Fig. 4 illustrates the kernel density of the estimated technical efficiency scores by year. To create this figure, we used the estimation results when the SFODF is specified as the trans-log form, with farm production being measured by real output value. The distributions are characterized by negative skew with the tail on the left. Table 5 shows the provincial average of technical efficiency, its standard deviation, and the minimum and maximum scores by year. Overall, the average efficiencies are within 0.6–0.7, meaning that farm production in Gansu could be increased by 30–40 % by performing farm management more efficiently. A close look at Table 5 reveals that the average technical efficiency scores show an increasing trend between 2013 and 2017. This supports our empirical finding in this study that land rental markets have developed in Gansu over the years, and have played a central role in improving technical efficiency.

[14] Yang et al. (2016) relying on a stochastic frontier model claim that neither migration nor local off-farm employment has a negative effect on the technical efficiency of China's grain production.

Table 3-2
Estimation result of the trans-log SFODF (output: real output value).

	Exogenous		Endogenous	
	Estimates	SE	Estimates	SE
Eq. (3)				
ln (*fer*)	-0.230***	0.045	-0.222***	0.046
ln (*lab*)	-0.264***	0.049	-0.246***	0.050
ln (*cap*)	-0.025	0.038	-0.030	0.040
ln (*lad*)	-0.452***	0.074	-0.495***	0.076
ln (*Sec.* 2)	0.079***	0.016	0.083***	0.016
ln (*Sec.* 3)	0.287***	0.020	0.276***	0.021
ln (*time*)	0.011	0.033	0.025	0.036
ln (*fer*)*ln (*lab*)	0.058	0.055	0.005	0.052
ln (*fer*)*ln (*cap*)	0.163***	0.061	0.214***	0.064
ln (*fer*)*ln (*lad*)	0.129	0.090	0.208**	0.087
ln (*lab*)*ln (*cap*)	-0.041	0.059	-0.001	0.060
ln (*lab*)*ln (*lad*)	0.227*	0.128	0.248*	0.128
ln (*cap*)*ln (*lad*)	-0.108	0.079	-0.149*	0.077
0.5*ln (*fer*)*ln (*fer*)	-0.179***	0.047	-0.231***	0.047
0.5*ln (*lab*)*ln (*lab*)	-0.312**	0.132	-0.308**	0.127
0.5*ln (*cap*)*ln (*cap*)	-0.094	0.078	-0.175**	0.083
0.5*ln (*lad*)*ln (*lad*)	-0.268*	0.152	-0.336**	0.160
ln (*fer*)*ln (*Sec.* 2)	0.022	0.020	0.049**	0.020
ln (*lab*)*ln (*Sec.* 2)	-0.058*	0.030	-0.059*	0.031
ln (*cap*)*ln (*Sec.* 2)	0.002	0.021	-0.010	0.022
ln (*lad*)*ln (*Sec.* 2)	-0.021	0.039	-0.043	0.037
ln (*fer*)*ln (*Sec.* 3)	0.060***	0023	0.060***	0023
ln (*lab*)*ln (*Sec.* 3)	-0.050*	0.030	-0.028	0.029
ln (*cap*)*ln (*Sec.* 3)	-0.009	0.024	-0.013	0.025
ln (*lad*)*ln (*Sec.* 3)	-0.025	0.035	-0.046	0.037
ln (*fer*)*ln (*time*)	0.097*	0.051	0.079	0.053
ln (*lab*)*ln (*time*)	0.007	0.050	-0.015	0.052
ln (*cap*)*ln (*time*)	-0.133**	0.053	-0.108*	0.056
ln (*lad*)*ln (*time*)	-0.042	0.063	-0.024	0.067
ln (*Sec.* 2)*ln (*Sec.* 3)	-0.047***	0.011	-0.049***	0.011
0.5*ln (*Sec.* 2)*ln (*Sec.* 2)	0.064***	0.014	0.055***	0.014
0.5*ln (*Sec.* 3)*ln (*Sec.* 3)	0.099***	0.014	0.101***	0.013
ln (*Sec.* 2)*ln (*time*)	0.012	0.021	0.011	0.022
ln (*SSec.* 3)*ln (*time*)	-0.054**	0.021	-0.045**	0.022
0.5*ln (*time*)*ln (*time*)	0.454**	0.216	0.418*	0.226
Irri	-0.423***	0.069	-0.434***	0.072
Eq. (4)				
Land—rental ratio	-1.291**	0.516	-2.478***	0.662
AC participation ratio	-0.718	0.890	1.285	0.952
Migration ratio	0.411	0.308	0.266	0.320
Land—labor ratio	0.144***	0.054	0.098*	0.051
Joint endogeneity test	-	-	$\chi^2 = 11.24$	$p = 0.004$
Number of observations	390		390	
Log likelihood	140.8		1067.3	
Mean technical efficiency	0.639		0.701	

Note: *, ** and *** indicate statistical significance at the 1 %, 5 % and 1 % levels, respectively.

4.3. Allocative efficiency

As the estimated SFODF satisfies the convexity condition for the most data domains, we argue the crop-choice rationality based on the estimated allocative efficiency. Fig. 5 shows the provincial average of allocative efficiency between 2013 and 2017.[15] The scores of $\mathrm{AE}_{mn}(V)$ and $\mathrm{AE}_{mn}(W)$ represent the allocative efficiency when farm production is measured by real output value and weight in tons, respectively.[16] There is no serious contraction between the estimated $\mathrm{AE}_{mn}(V)$ and $\mathrm{AE}_{mn}(W)$. As evidenced by Eq. (5), we have $\mathrm{AE}_{13} = \mathrm{AE}_{12} \times \mathrm{AE}_{23}$, meaning that the pairwise allocative efficiency scores are not independent. Fig. 5 illustrates that AE_{12} was larger than unity but moved close to unity in 2016, suggesting that the extent of over-production of Sector 1 relative to Sector 2 improved somewhat during the period examined. However, such a trend was reversed in 2017. Meanwhile, AE_{23} was also larger than unity and increased between 2013 and 2016, suggesting that the extent of over-production of Sector 2 relative to Sector 3 worsened during the period, and thereafter improved slightly.

15 Using the provincial average values of outputs and inputs, we estimate the allocative efficiency based on Eq. (5).

16 As noted in Section 3, the CD form does not satisfy the convexity condition by nature. Thus, we use the trans-log function for the computation of allocative efficiency.

Table 4-1
Estimation result of the Cobb-Douglas SFODF (output: weight).

	Exogenous		Endogenous	
	Estimates	SE	Estimates	SE
Eq. (3)				
ln (*fer*)	-0.037*	0.019	-0.034*	0.020
ln (*lab*)	-0.219***	0.061	-0.229***	0.062
ln (*cap*)	-0.084***	0.031	-0.082**	0.032
ln (*lad*)	-0.579***	0.070	-0.573***	0.070
ln (*Sec. 2*)	0.079***	0.018	0.077**	0.018
ln (*Sec. 3*)	0.161***	0.023	0.162**	0.023
ln (*time*)	0.087***	0.031	0.086***	0.034
Irri	-0.558***	0.057	-0.566***	0.058
Eq. (4)				
Land—rental ratio	-1.676***	0.388	-1.515***	0.517
AC participation ratio	-2.778***	0.416	-3.071***	0.607
Migration ratio	-0.152	0.219	-0.148	0.220
Land—labor ratio	-0.004	0.039	-0.003	0.039
Joint endogeneity test	-	-	$\chi^2 = 0.62$	$p = 0.733$
Number of observations	390		390	
Log likelihood	81.4		886.7	
Mean technical efficiency	0.621		0.622	

Note: *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 4-2
Estimation result of the Cobb-Douglas SFODF (output: real output value).

	Exogenous		Endogenous	
	Estimates	SE	Estimates	SE
Eq. (3)				
ln (*fer*)	-0.029	0.020	-0.031	0.021
ln (*lab*)	-0.247***	0.042	-0.246***	0.042
ln (*cap*)	-0.061*	0.033	-0.065*	0.034
ln (*lad*)	-0.600***	0.067	-0.598***	0.066
ln (*Sec.* 2)	0.097***	0.017	0.096***	0.017
ln (*Sec.* 3)	0.175***	0.020	0.172***	0.021
ln (*time*)	0.103***	0.032	0.098***	0.034
irri	-0.498***	0.059	-0.493***	0.059
Eq. (4)				
Land—rental ratio	-1.595***	0.453	-1.536**	0.598
AC participation ratio	-3.372***	0.547	-3.153***	0.684
Migration ratio	0.030	0.273	0.016	0.278
Land—labor ratio	0.029	0.039	0.027	0.040
Joint endogeneity test	-	-	$\chi^2 = 0.46$	$p = 0.796$
Number of observations	390		390	
Log likelihood	62.2		868.5	
Mean technical efficiency	0.657		0.660	

Note: *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Most noteworthy in Fig. 5 is that the score of AE_{13} was far larger than unity and increased consistently during the period concerned, suggesting a substantial degree of overproduction of Sector 1 relative to Sector 3.[17] As shown in Appendix Table 2, the value of $MRTS_{13}$ demonstrated an increasing trend between 2013 and 2017. On the other hand, the relative price of p_1/p_3 decreased during the period, the reason for which was discussed at length in Section 2. An increase in AE_{13} above unity is caused by producers' failure in adjusting product mix consistent with the farm revenue maximization. As noted in Section 2, the central government took the initiative to encourage farmers in western China to grow fresh fruits and vegetables. Nevertheless, they did not respond immediately to either the market signal of relative price change or the government's directive toward crop diversification. It is considered that some technical and institutional factors must be involved, but at this stage we cannot ascertain specific factors that prevent farmers from behaving rationally.

5. Conclusion and policy implications

Agricultural economists take it for granted that a decentralized and market-oriented means to transfer land-use rights could not

[17] This is consistent with Ito (2015), which computes the allocative efficiency using China provincial data between 1991 and 2009.

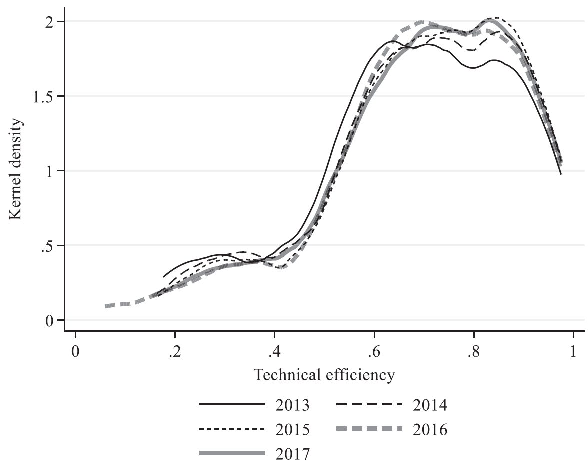

Fig. 4. Estimated technical efficiency distributions over time.

Table 5
Average technical efficiency.

Farm production	Function form		Mean	SD	Min	Max
		2013	0.680	0.208	0.200	0.977
		2014	0.692	0.205	0.210	0.977
Weight	Trans-log	2015	0.703	0.200	0.217	0.976
		2016	0.702	0.200	0.095	0.978
		2017	0.709	0.195	0.216	0.977
		2013	0.685	0.198	0.176	0.975
		2014	0.701	0.195	0.164	0.976
Real output value	Trans-log	2015	0.710	0.190	0.166	0.975
		2016	0.700	0.197	0.060	0.976
		2017	0.707	0.191	0.154	0.976
		2013	0.589	0.233	0.099	0.965
		2014	0.608	0.230	0.120	0.969
Weight	CD	2015	0.624	0.223	0.117	0.970
		2016	0.638	0.216	0.127	0.970
		2017	0.642	0.214	0.126	0.96
		2013	0.625	0.228	0.132	0.948
		2014	0.645	0.223	0.149	0.949
Real output value	CD	2015	0.659	0.217	0.151	0.948
		2016	0.676	0.212	0.167	0.952
		2017	0.678	0.210	0.156	0.951

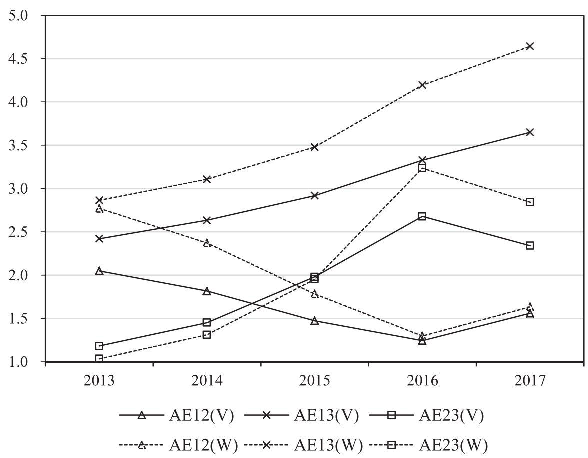

Fig. 5. Changes in allocative efficiencies.

only raise the wealth of lessors and lessees but also enhance the overall efficiency of land use and agricultural productivity. However, a caveat is needed before applying this theoretical prediction to the Chinese context because NFHPs, such as ACs and private enterprises, have recently entered the farming business as cultivators. To the extent that such organizations underperform FHs in terms of production efficiency, land consolidation by NFHPs does not necessarily deliver the desired outcome. For this reason, we empirically examine in this study the causal effect of land rental on farm production efficiency based on a SFODF. Previous studies that explore the relationship between farmland exchange or administrative reallocation and technical efficiency cannot identify the "market outcome" of land transaction because they use household micro-level data.

Our estimation result illustrates that the development of land rental markets has a significant effect on raising technical efficiency scores at the aggregate level. This offers unambiguous evidence that land usufruct has accumulated in the hands of cultivators whose agricultural productivity is relatively high. Meanwhile, our analysis weakly supports the assertion that ACs are an important avenue for farm producers to increase production efficiency. Therefore, there is no serious inconsistency with previous studies that show that average technical efficiency is consistently higher for participants in ACs relative to non-participants.

This study shows that cereals are excessively over-produced relative to vegetables and fruits from the perspective of farm revenue maximization. The Chinese government issued a policy directive promoting crop diversification and selective expansion of farm products in western China, which aimed to narrow the inter-regional income gap. Nevertheless, our quantitative analysis suggests that there is room for further increase in farm revenues of Gansu's producers by shifting resources away from cereal toward horticultural production.

We acknowledge that our empirical results cannot be generalized at the national level as the sample is limited to just one province in northwest China, which is not necessarily representative of the entire country. However, the examined issues are likely to be of relevance to other parts of rural China characterized by similar underdeveloped rural societies. Ensuring the efficient use of scarce resources poses serious challenges to pro-poor agricultural growth in China and other developing countries. In this context, further research efforts should be devoted to the analysis of the economic impact of land rental markets and agricultural cooperatives. Needless to say, agricultural growth is integral to Gansu's future development; raising farm income is not only important from the perspective of farmers but is most certainly in the public interest.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix Table 1. Variable descriptions and summary statistics

Variables	Descriptions		Mean	SD
Land—rental ratio	Land rental area divided by contracted land area	overall	0.24	0.13
		between		0.12
		within		0.06
Agricultural cooperative ratio	Number of employees working for agricultural cooperatives divided by labor force engaged in the primary sector	overall	0.11	0.11
		between		0.11
		within		0.05
Migration ratio	Number of migrants working outside their home village continuously for more than six months out of the year divided by the total number of FHs	overall	0.75	0.27
		between		0.26
		within		0.09
Land—labor ratio	Contracted land area divided by farm labor force	overall	0.94	1.50
		between		2.16
		within		0.41

Source: Rural Operation and Management Statistics (Department of Agriculture and Rural Affairs, Gansu).

Appendix Table 2. MRTSs and relative prices

	$MRTS_{12}$	$MRTS_{13}$	$MRTS_{23}$	p_1/p_2	p_1/p_3	p_2/p_3
2013	2.05	2.42	1.18	1.00	1.00	1.00
2014	1.88	2.39	1.27	1.03	0.91	0.88
2015	1.42	2.49	1.75	0.96	0.85	0.88
2016	1.17	2.86	2.43	0.94	0.86	0.91
2017	1.54	3.11	2.02	0.99	0.85	0.86

Note: We compute MRS_{mn} based on the SFODF, with farm production being measured by real output value.

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