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Production efficiency of Chinese agriculture: evidence from rural household survey data

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Abstract

A shadow-price profit frontier model is developed to examine production efficiency of Chinese rural households in farming operations. The model incorporates price distortions resulting from imperfect market conditions and socioeconomic and institutional constraints, but retains the advantages of stochastic frontier properties. The shadow prices are derived through a generalized profit function estimation. The shadow-price profit frontier is then estimated and an efficiency index based on the estimated profit frontier is computed and decomposed to household characteristics. Empirical results using data from China's Rural Household Survey for 1991 reject the neoclassical profit maximization hypothesis based on market prices in favor of the general model with price distortions. Farmers' resource endowment and education influence their response to the market restrictions, thus alter their performance in terms of efficiency. The estimated efficiency index ranges from 6% to 93% with a sample average of 62%. Households' educational level, family size and per capita net income are positively related to production efficiency. Households living in mountain areas or with family members employed by the government or state industries are relatively inefficient. Reducing market intervention, allowing right of use of farm land to be transferred among households, encouraging migration of excess farm labor, and promoting farmers' education will improve rural households' efficiency in agricultural production.

1. Introduction

The efficiency gains from improving resource allocation resulting from economic reforms in China's agriculture have been dramatic. Fan (1991) estimated that about 63% of the productivity change (at an average of 2.13% per year, 1965–1985) is attributable to improvement in efficiency. Lin (1992) found that the productivity change resulting from various reforms made up 42.23% of the output growth during 1978–1984, and no increasing trend in technological change was detected. Central to this transformation towards free markets in Chinese agriculture is the behavior of the individual rural household. With the Rural Household Responsibility System (RHRS) the basic production unit was shifted from collectivized farms to the rural households. Other reforms allowed for the sale of commodities to private parties and the free flow of surplus rural labor to local industries and urban areas. The agricultural sector responded to these reforms with increased production for most major commodities due to productivity gains. With the full implementation of RHRS nationwide in 1983–1984, the question of whether production efficiency is still a great potential for productivity growth remains unanswered. Although the economic reforms have greatly reduced direct control by government over production, various interferences in agricultural markets still distort

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farmers' production decisions. The relationships between efficiency and market indicators and household characteristics have not been well studied in this unfolding process of agricultural reform. A better understanding of these relationships should aid policymakers in creating improved efficiency-enhancing policies and in judging the efficacy of past reforms. These relationships are also of interest to policymakers in other nations where government plays a major role in traditional agriculture.

Production efficiency is usually analyzed by separately examining its two components: technical efficiency and allocative efficiency. Recent developments reported in the literature combine both measures into one system. This approach enables more efficient estimates to be obtained by simultaneously estimating the system (e.g. Kumbhakar, 1989; Kalirajan, 1990). However, previous research (post-1978) on Chinese agricultural productivity focused on total factor productivity, while technical efficiency and allocative efficiency were rarely examined [1].

Although stochastic production frontier functions are most commonly used in studying production efficiency, Yotopoulos and others argued that a production function approach may not be appropriate when estimating the production efficiency of individual farms because they may face different prices and have different factor endowments (Ali and Flinn, 1989). An attempt to incorporate firm level prices and input use led to profit function formulation. The early development of profit function models did not provide a numerical measure of firm specific efficiency (Aigner et al., 1977). Ali and Flinn (1989) directly estimated farm-specific efficiency from a random coefficient profit frontier function using market prices. In general, the use of standard dual representations of the production structure requires the corresponding maintained hypotheses of cost minimization or profit maximization, subject to parametric market prices. Thus, in the case of regulated industries or imperfect markets, as in China, these hypotheses may be invalid.

A generalized profit function (behavioral profit function) approach which incorporates market distortions resulting from imperfect market conditions has been developed in the literature. Kumbhakar and Bhattacharyya (1992) developed a behavioral profit function to test the appropriateness of a neoclassical profit function and the effect of education and farm size on allocative performance. Their model, however, does not provide a numerical measure of profit efficiency for each farm. A more recent study conducted by Ali et al. (1994) employed both stochastic frontier and behavioral profit functions separately in a study of Pakistan agriculture. The rejection of profit maximization based on observed market prices from the behavioral profit function, however, indicates that their stochastic frontier function, which was specified by using observed market prices, is subject to misspecification. Regarding post-1978 Chinese agricultural efficiency studies, very few employed the dual approach and none incorporated market distortions.

The objective of this study is to analyze production efficiency of farm households facing various market constraints in Chinese agriculture. An estimation process that incorporates market distortions but retains the advantages of stochastic frontier properties in efficiency analysis is developed in this study. China's Rural Household Survey data for 1991 are used for the empirical analysis. First, a behavioral profit function is used to derive farmers' shadow prices. Then a stochastic frontier profit function, using the shadow prices obtained from the behavioral profit function, is estimated and the efficiency index is derived and related to farm households' demographic variables to identify the factors that affect farm households' efficiency.

2. Modeling market distortions and the stochastic profit frontier

Given the existence of binding constraints on decision-making, as revealed by a number of studies (e.g. Toda, 1976; Atkinson and Halvorsen, 1980; Kumbhakar and Bhattacharyya, 1992), the producers' decision is often made with respect to shadow prices—i.e. the prices that they actually paid and received, rather than observed market prices. The divergence between the shadow and observed market prices can be interpreted as the result of various

[1] Most post-1978 productivity studies focused on the effects of institutional changes on output and productivity growth (e.g. Lin, 1992; McMillan et al. (1989); Fleisher and Liu (1992). Only Ma et al. (1989) examined efficiency at farm level.

market constraints, as well as allocative inefficiency caused by errors in optimization. One commonly used measure of the divergence between the two prices, based on Lau and Yotopoulos (1971), is to define a relationship between the normalized shadow price, p^s (w^s for input), and the normalized market price, p (w), as $p_j^s = \theta_j p_j$ and $w_i^s = \theta_i w_i$, where θ_j and θ_i are (non-negative) price efficiency parameters. The subscripts j and i index outputs and inputs, respectively. If there are no bending market restrictions then θ equals unity. Thus, a farmer is allocatively efficient with respect to observed market prices only when the observed market prices reflect the farmer's opportunity cost of inputs and outputs [2].

Based on the above settings, a profit-maximizing farmer's behavior can be expressed by specifying a behavioral profit (shadow profit) function, $\pi^* = \pi(p^s, w^s, z)$ in the translog form, normalized by one input price, as:

$$\begin{aligned}
\ln\pi^* &= \alpha_o + \sum_j \alpha_j \ln(\theta_j p_j) + \sum_i^{n-1} \beta_i \ln(\theta_i w_i) \\
&\quad + \sum_q \gamma_q \ln z_q \\
&\quad + \frac{1}{2}\sum_j \sum_k \alpha_{jk} \ln(\theta_j p_j)\ln(\theta_k p_k) \\
&\quad + \frac{1}{2}\sum_i^{n-1} \sum_l^{n-1} \beta_{il} \ln(\theta_i w_i)\ln(\theta_l w_l) \\
&\quad + \frac{1}{2}\sum_q \sum_h \gamma_{qh} \ln z_q \ln z_h \\
&\quad + \sum_j \sum_i^{n-1} \delta_{ij} \ln(\theta_j p_j)\ln(\theta_i w_i) \\
&\quad + \sum_j \sum_q e_{jq} \ln(\theta_j p_j)\ln z_q + \sum_i^{n-1} \sum_q \mu_{iq} \ln(\theta_i w_i)\ln z_q
\end{aligned} \tag{1}$$

where $j,k = 1,2\ldots M$ are number of outputs, $i,l = 1,2\ldots N-1$ are number of inputs, $q,h = 1,2\ldots Q$ are number of fixed inputs, $(\theta_j p_j)$ and $(\theta_i w_i)$ are normalized shadow prices of outputs and inputs respectively, and z_q are quantities of fixed inputs.

Eq. (1) cannot be directly estimated to measure the profit efficiency [3] because the shadow prices are unobserved, and so is the shadow profit π^*. In an empirical sample, however, whether or not a good approximation of the shadow profit (π^*) exists depends on the specification of π^*, as well as on survey design and the data collection mechanism. Given the shadow profit π^* defined in Eq. (1), directly reported net returns that a farmer actually obtained from his operation under the market distortion can be a close approximation of π^* in the data set to be used in this study [4]. To make estimation of Eq. (1) possible, we need information on θ for the shadow prices. The following transformation serves the purpose.

The shadow profit π^*, normalized by $\theta_n w_n$, can be expressed as:

$$\pi^* = \sum_j (\theta_j p_j) y_j - \sum_i^{n-1} (\theta_i w_i) x_i - x_n \tag{2}$$

Similarly, a non-distorted profit, π^a (actual profit, as it is used in the literature [5]), computed by using

[2] Allocative efficiency is evaluated from the producer's point of view of profit maximization. It does not necessarily reflect social costs and therefore is not necessarily efficient in the sense of social cost–benefit assessment. It is also to be noted that the effects of errors in optimization on allocative efficiency cannot be separated from market distortions in this setting. Thus, the price efficiency parameter θ may contain a combined source of price inefficiency.

[3] This study combines the concepts of technical and allocative efficiency in the profit relationship. Within a profit function context, profit efficiency is defined as the capability of a farm to achieve the highest possible profit given the prices and level of fixed factors. Since there were very limited market alternatives for farmers in China to market their products in 1991, much of their returns was determined by production decisions rather than market decisions. Thus, the profit efficiency actually measures farmers' production efficiency.

[4] Further discussion will be given in the data section.

[5] The terminology of 'actual profit' used for $\pi^a = \Sigma p_j y_j - \Sigma w_i x_i$ in the literature is misleading. π^a states what a farmer's profit would be if there were no market distortions or what the profit would be if the market prices were used for profit calculation based on the farmer's choices of y_j and x_i made under market distortions. Since the market prices are not necessarily equal to the prices that the farmer actually paid and received, π^a is not the actual profit that the farmer truly obtained from his practice in the distorted market.

the market prices and normalized by the price w_n, can be written as:

$$\pi^a = \sum_j p_j y_j - \sum_i w_i x_i - x_n \tag{3}$$

Substituting x_n from Eq. (3) into Eq. (2) and applying Hotelling's lemma to the non-distorted profit function π^a to obtain profit shares (s_j^a, s_i^a), yields the following relationship between π^* and π^a:

$$\pi^* = \pi^a \left[1 + \sum_j (\theta_j - 1) s_j^a + \sum_i (\theta_i - 1) s_i^a \right] \tag{4}$$

where

$$y_j = \frac{\partial \pi^a}{\partial p_j}, \; x_i = -\frac{\partial \pi^a}{\partial w_i}, \; \frac{\partial \ln \pi^a}{\partial \ln p_j} = \frac{p_j y_j}{\pi^a} = s_j^a, \; \frac{\partial \ln \pi^a}{\partial \ln w_i} = -\frac{w_i x_i}{\pi^a} = s_i^a \tag{5}$$

Further, by specifying a translog function for the non-distorted profit function (π^a), and taking logarithm on π^*, we obtain the shadow profit expressed as the non-distorted profit function in translog form plus a distortion-adjusted component as:

$$\begin{aligned}
\ln \pi^* = {} & \alpha_0 + \sum_j \alpha_j \ln p_j + \sum_i \beta_i \ln w_i + \sum_q \gamma_q \ln z_q \\
& + \frac{1}{2} \sum_j \sum_k \alpha_{jk} \ln p_j \ln p_k + \frac{1}{2} \sum_i^{n-1} \sum_l^{n-1} \beta_{il} \ln w_i \ln w_l \\
& + \frac{1}{2} \sum_q \sum_h \gamma_{qh} \ln z_q \ln z_h \\
& + \sum_j \sum_i^{n-1} \delta_{ij} \ln p_j \ln w_i + \sum_j \sum_q e_{jq} \ln p_j \ln z_q \\
& + \sum_i^{n-1} \sum_q \mu_{iq} \ln w_i \ln z_q \\
& + \ln \left[1 + \sum_j (\theta_j - 1) s_j^a + \sum_i^{n-1} (\theta_i - 1) s_i^a \right]
\end{aligned} \tag{6}$$

It is worth noting that we specify π^* as a function of π^a and price efficiency parameters, θ, rather than π^a as a function of π^* and θ in the literature. This specification is designed for the case where farmers' actually paid (received) prices are different from observed market prices and the farmers directly reported their actual profit or total revenue and total costs based on the prices they actually paid (received). In such a case, π^*, the profit that farmers actually obtained in a distorted market, contains more information than π^a does [6].

Although the shadow prices are eliminated, Eq. (6) still contains the unobserved price efficiency parameters, θ_j and θ_i, which are latent variables. They are assumed to be farm-specific in order to reflect an individual farmer's response to market distortions. Since one of our objectives is to examine whether education and relative resource endowment have any influence on price response to market distortions, we model θ as follows for each input and output price:

$$\theta_b = \exp(a_{b0} + a_{bt} R + a_{be} \mathrm{ED}) \tag{7}$$

where $b = 1,2 \ldots M, M+1, \ldots M+N-1$, R is household labor/land ratio and ED is the summation of a household labor's educational level measured by the number of school years [7].

The parameter α_0 in Eq. (6) is assumed to embody fixed effects resulting from regional differences in average quality or initial average prices of outputs and inputs, so that it is specified as a function of county dummy variables D_c:

$$\alpha_0 = \omega_0 + \Sigma \omega_c D_c \tag{8}$$

Further, a profit shifter can be formed to capture technical efficiency across households. Following Kumbhakar and Bhattacharyya (1992), technical efficiency is modeled as a function of farm size, FS, and the household labor's highest educational level achieved, EL:

$$\tau = \tau_0 + \tau_1 \mathrm{FS} + \tau_2 \mathrm{EL} \tag{9}$$

With the specifications of θ in Eq. (7), α_0 in Eq. (8) and τ in Eq. (9), Eq. (6) can be empirically

[6] In cases where π^* is unknown, a more generalized alternative which uses fitted $\bar{\pi}^*$ has been developed by Wang, Wailes and Cramer.

[7] A preliminary statistical analysis shows that the labor/land ratio is correlated with several farm characteristic variables, such as farm size, off-farm employment, machinery use, because these variables are mainly affected by the scarcity of land and abundance of labor in China's agriculture.

estimated to obtain the estimated price efficiency parameter θ and the effects of FS and EL on technical efficiency.

The second step is to construct a stochastic shadow-profit frontier function. The estimated θ values from the first step are used to derive the shadow prices. The shadow prices are used directly as arguments in the translog profit function (Eq. (1)) with an error term, ξ_i, which is assumed to behave in a manner consistent with the stochastic frontier concept:

$$\xi_i = v_i + u_i \tag{10}$$

It is assumed that v_i, reflecting random disturbance, is normally distributed, while u_i is a one-sided disturbance term used to represent the inefficiency measures. We assume u_i has a half-normal non-negative distribution, $|N(0,\sigma_u^2)|$. The population average efficiency is given as:

$$\mathrm{E}(\mathrm{e}^{-u}) = 2\mathrm{e}^{\sigma_u^2/2}[1 - F(\sigma_u)] \tag{11}$$

where F is the standard normal distribution function. Following Jondrow et al. (1982), the farm-specific estimates of inefficiency, u_i, for each observation are derived from the conditional distribution of u_i, given $\xi_i = v_i + u_i$:

$$E(u_i|\xi_i) = \frac{\sigma_u\sigma_v}{\sigma}\left[\frac{f(\xi_i\lambda/\sigma)}{1 - F(\xi_i\lambda/\sigma)} - \frac{\xi_i\lambda}{\sigma}\right] = u_i^* \tag{12}$$

where σ_v^2 and σ_u^2 are the variance of v_i and u_i, $\lambda = \sigma_u/\sigma_v$, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, and f and F are the standard normal density and cumulative distribution functions, respectively, estimated at $\xi_i\lambda/\sigma$.

Finally, the farm-specific efficiency index ($\exp[-u_i^*]$) can be constructed using the results from Eq. (12). Since the inefficiency term u_i is truncated at zero by the assumption of the frontier function, a truncated regression of a semi-log efficiency index against household demographic variables provides an appropriate decomposition of the efficiency index.

3. Data and empirical estimation

The data used for this empirical application are a subsample of China's National Rural Household Survey for 1991. This survey, started in 1955 by the General Organization of Rural Socio-Economic Survey of the State Statistical Bureau (SSB), evolved from the Chinese Rural Household Expenditure Survey initiated in the late 1970s. Since 1984, a multi-stage sampling procedure combined with interval sampling at the lowest level has been used in the survey design to ensure the random nature of the sample and to minimize sampling errors (State Statistical Bureau of China, 1993). The survey records all major production and consumption activities of 70000 participating households during the survey year.

Farmers' production activities were influenced by various market distortions which mainly came from government intervention. By 1991, for example, the state contract purchase for a specified quantity of output at a price fixed below the market price and the procurement of amounts that exceeded the contract quantities under the so-called 'negotiated prices', which in most cases were also lower than market prices, were major government influences in agricultural output markets. In the agricultural input markets, government-owned businesses delivered farm inputs, such as chemical fertilizers and diesel fuel, at low fixed prices to producers for many years. To facilitate procurement, the government has often used input subsidies to induce cooperation from farmers [8].

Other sociopolitical and institutional constraints faced by Chinese farmers also cause market distortions. For instance, there are always shortages in major material input supplies such as fertilizer. Some farmers may be able to obtain an adequate supply of fertilizer at the state distribution prices because of their personal relationship with state agencies, while others may have to pay a 'shortage premium'. Village leaders and/or families with non-farm-workers may have special privileges, such as access to credit or receive cash payment for their sales to the state

[8] Since 1993, China has brought reforms to its input supply system. Currently, a wide variety of businesses owned collectively and by the government are delivering inputs to rural area (US Department of Agriculture, 1993). However, the state planning system still imposes quantitative restrictions on farmers' access to subsidized inputs (Ye and Rozelle, 1994).

purchasing organizations, while others are forced to accept the state's use of promissory notes (IOU) instead of cash for their products [9]. In many cases, special fees have been levied by local governments on farmers that are related to procurement and input supply. In these situations, the actual prices received and paid by farmers are different from what has been observed in the market because of the existence of these non-price restrictions.

The subsample used in this study is randomly selected from the national sample [10]. For the analysis in this study, 1786 observations were used. The survey contains no price variables. All farm-specific price variables in the analysis are unit values, imputed by using quantity and expenditure or revenue variables [11]. When imputed values are not possible (i.e. the household did not produce or purchase a specific output or input), the missing prices are set according to the average of the province where the household is located. Price indices for outputs and variable inputs are constructed using the Divisia index:

$$\ln p_j^h = \frac{1}{2} \sum_i \left(r_{ij}^h + \bar{r}_{ij} \right) \left(\ln p_{ij}^h - \ln \bar{p}_{ij} \right) \tag{13}$$

where $\ln p_j^h$ is the price index for the jth aggregate for the hth household, r_{ij}^h is the share of the ith item in the jth aggregate for the hth household, $\ln p_{ij}^h$ is the price of the ith item in the jth aggregate for the hth household, $\bar{r}_{ij}$ and $\ln \bar{p}_{ij}$ are the averages of the shares and prices for all households in the sample, respectively. The base for these indices is the average of the sample. Two output prices of crops and livestock, two variable input prices of chemical fertilizer and other purchased materials (including fuel, seeds, plastic sheets, pesticides, etc.), and three fixed inputs of labor (no hired labor was recorded), land and capital are aggregated from various of outputs and inputs recorded in the data set. Through the above aggregation, all households in the sample produced the two outputs and used the two variable inputs.

For the non-land capital inputs, it is assumed that the service flow from the stock of capital is proportional to the stock. Consequently, a certain percentage of the stock value can be used as a proxy for the service flow. Land is taken as the total area of cultivated land including both contracted areas and private plots. The labor variable is defined as the total number of male-equivalents engaged in agricultural production. These fixed inputs are expressed in index form with the average of the sample used as a base. For the variables FS and EL in Eq. (9), four dummy variables—SF (small farm), LF (large farm), LE (low education) and HE (high education)—are constructed to distinguish relative farm size and the highest education level household labor achieved. The selected household demographic variables are family size, per capita net income, whether the household has any family member operating as a village leader or employed by government or state industries, and the household's geographic location [12].

Profit is defined as total revenue (including self-consumption and storage) minus total variable costs. The data contain households' total revenue and total variable costs which are directly reported by the survey households for their operations of crops and livestock. The data also record the households' pro-

[9] Well into the 1991 harvest season, some provinces had reportedly not completely paid off IOUs on the 1990 harvest (US Department of Agriculture, 1991).

[10] Several changes were made on the experimental design of the survey samples between 1950 and 1990. This may raise the question of consistency in a time series study, but it should not affect our use of a cross-section sample. Since the subsample we used in the analysis is randomly selected from the survey, the inadequate randomness and lack of sampling weight should not limit our statistical reference drawn from the random sample.

[11] The survey requires participating households to record only immediate revenue and cost without any associated benefits or expenditures for each sale or purchase. For example, if a farmer made a trip to buy some fertilizer, his travel and fertilizer transportation expenses would not be recorded under 'fertilizer expenditure' but under 'other expenditure'.

[12] The sample mean for FS is 12.8 mu (1 mu equals 1/15 ha). The small (large) farms are the households that operate less (great) than 1.3 (100) mu of land. Lower education level is assigned if EL is primary school or less. Higher education level is assigned if EL is high school or college graduate. For the dummy variables used in the efficiency decomposition regression, small (large) families are the households having less (more) than three (six) people. High (low) income households are assigned if the household's per capita net income is greater (less) than 1000 (500) yuan. They are arbitrarily determined.

Table 1
Parameter estimates of behavioral profit function

Variable	Parameter	Coefficient	t-ratio
Constant	α_0	8.3452	23.24
$\ln p_1$ (crops)	α_1	0.4676	1.21
$\ln p_2$ (livestock)	α_2	0.5531	2.91
$\ln p_1 \ln p_1$	α_{11}	3.5677	3.61
$\ln p_2 \ln p_2$	α_{22}	0.2999	1.40
$\ln p_1 \ln p_2$	α_{12}	−0.7983	−1.83
$\ln w_c$ (chemicals)	β_1	−0.0420	−0.60
$\ln w_c \ln w_c$	β_{11}	−0.0467	−1.03
$\ln z_1$ (land)	γ_1	0.3645	2.44
$\ln z_2$ (labor)	γ_2	0.0599	0.33
$\ln z_3$ (capital)	γ_3	−0.0181	−0.24
$\ln z_1 \ln z_2$	γ_{12}	0.2541	2.16
$\ln z_1 \ln z_3$	γ_{13}	−0.1017	−1.88
$\ln z_2 \ln z_3$	γ_{23}	0.2505	3.96
$\ln z_1 \ln z_1$	γ_{11}	−0.5001	−5.15
$\ln z_2 \ln z_2$	γ_{22}	−0.3429	−1.82
$\ln z_3 \ln z_3$	γ_{33}	0.0213	0.52
$\ln p_1 \ln z_1$	e_{11}	0.0287	0.14
$\ln p_1 \ln z_2$	e_{12}	−0.7273	−2.10
$\ln p_1 \ln z_3$	e_{13}	0.0033	0.02
$\ln p_2 \ln z_1$	e_{21}	0.0146	0.13
$\ln p_2 \ln z_2$	e_{22}	0.0591	0.32
$\ln p_2 \ln z_3$	e_{23}	−0.1148	−1.51
$\ln p_1 \ln w_c$	δ_{11}	−0.5846	−2.22
$\ln p_2 \ln w_c$	δ_{21}	0.0587	0.78
$\ln w_c \ln z_1$	μ_{11}	−0.1018	−1.88
$\ln w_c \ln z_2$	μ_{12}	0.2505	3.96
$\ln w_c \ln z_3$	μ_{13}	0.1088	2.85
Constant (θ_1)	a_1	−0.1459	−1.09
R(θ_1)	a_{1r}	−0.1364	−1.45
ED(θ_1)	a_{1e}	0.0959	1.74
Constant (θ_2)	a_2	−0.8903	−1.34
R(θ_2)	a_{2r}	0.4103	4.28
ED(θ_2)	a_{2e}	−0.1588	−1.20
Constant (θ_c)	a_c	1.3249	2.25
R(θ_c)	a_{cr}	−1.4945	−2.38
ED (θ_c)	a_{ce}	−0.1528	−0.86
Small farm (SF)	τ_{1s}	−0.5696	−2.71
Large farm (LF)	τ_{1l}	0.8273	3.24
Low education (LE)	τ_{2l}	−0.0489	−0.61
High education (HE)	τ_{2h}	0.0217	0.08

duction and sales of each commodity and input factors used for the operations. A means test shows that the means of the farmers' directly reported revenues and costs are significantly different from those computed using market prices. The differences may be caused by the existence of market restrictions and the prices used in valuing products of inventory and direct household consumption [13]. To be consistent with the argument that π^* contains more information than π^a does, the revenues and costs directly reported by the farmer are used to generate the shadow profit for π^*.

In the first-step estimation, Eq. (6) is estimated using s_j^a and s_i^a derived from the non-distorted translog profit function ($\ln\pi^a$) to obtain estimates for the price efficiency parameters (θ). It is necessary to substitute the price efficiency parameters θ in Eq. (7) with the regional intercept in Eq. (8) and to add Eq. (9) to measure the technical efficiency. The model is estimated using a non-linear iterative seemingly unrelated regression (ITSUR) technique with symmetry and homogeneity conditions imposed. Kmenta and Gilbert (1968) have shown that the parameters estimated from the ITSUR procedure converge to maximum likelihood estimates. The estimates are reported in Table 1. In the second-step estimation, the behavioral (shadow-price) profit function (Eq. (1)) with all price variables adjusted by the estimated θ, along with the error term $\xi_i = v_i + u_i$, is estimated by the stochastic frontier technique (LIMDEP, Green, 1992) to obtain the shadow-profit frontier. The estimated coefficients are given in Table 2 [14].

4. Empirical results

With the estimation of Eq. (6), the hypothesis of profit maximization based on market prices is tested by imposing the parameter restrictions of $\theta_b = 1$ for all b. The value of the test statistic is 19. Compared

[13] The enumerators in each county construct the local prices used to evaluate products of inventory and own-consumption according to an average market price for each commodity at its peak season. Since the proportions of inventory and own-consumption varies across households (national average of own-consumption for grain products was 49.4% in 1990), the effect of these constructed prices on profit will not be reflected by the county dummy variables.

[14] To save space, the estimates of the county dummy variables are not reported in the tables. Based on the t-statistics, 56% of the estimates are significantly different from zero at the 0.05 level of significance for the behavioral estimation and 58% for the frontier estimation.

with the critical value 16.92 of χ^2 with 9 degrees of freedom at the 0.05 level of significance, the restricted market price model is rejected in favor of the model with market distortion and allocative inefficiency. The test result indicates that profit maximization based on market prices may be inappropriate. Thus, the shadow profit model that incorporates market distortions is more suitable for this data sample [15].

The estimated farm-specific price efficiency parameters for crops (θ_1), livestock (θ_2), and chemical fertilizer (θ_c) are computed for all observations. On average, θ_1 takes the value of 0.84 with 99% of the individual values less than one. The mean for θ_2 is found to be 0.86 and 96% of the individual values were less than one, indicating that the 'prices' actually received by farmers for their products of crops and livestock are less than the observed market price because of the existence of market distortions. On the input side, the mean of the farmers' shadow price of using chemical fertilizer is greater than the observed market price based on a mean for the estimated θ_c of 1.16 with 53% of the individual values greater than one.

The estimated values of θ_1, θ_2 and θ_c show that a farm household's educational level and labor/land ratio, as two primary variables of resource endowment, influence its allocative performance. The estimated values of θ_1, and θ_c approach unity as the level of education increases, holding the labor/land ratio at the mean level (the estimated coefficient on education for θ_2 is not significant). This result indicates that the level of education improves allocative efficiency. The estimates of households' labor/land ratio exhibit a mixed effect on allocation performance. For example, a higher ratio raises the distortion effect on crops (in bringing θ_1 below unity); on the other hand, it reduces the distortion effect on livestock production and fertilizer use (in bringing the θ_2 and θ_c close to unity) when holding education at the mean level. These results may reflect the fact that small-sized crop farms bear much output price distortion while some livestock producers may take advantage of specialization in livestock production.

Table 2
Maximum-likelihood estimates of profit frontier function

Variable	Parameter	Coefficient	t-ratio
Constant	α_0	8.7189	71.356
$\ln p_1$ (crops)	α_1	−0.4396	−1.41
$\ln p_2$ (livestock)	α_2	0.4847	2.41
$\ln p_1 \ln p_2$	α_{12}	−1.0591	−2.76
$\ln p_1 \ln p_1$	α_{11}	1.3671	2.78
$\ln p_2 \ln p_2$	α_{22}	0.0887	0.84
$\ln w_c$ (chemical)	β_1	0.0003	0.00
$\ln w_c \ln w_c$	β_{11}	−0.0173	−0.71
$\ln z_1$ (land)	γ_1	0.3235	2.86
$\ln z_2$ (labor)	γ_2	0.0742	0.55
$\ln z_3$ (capital)	γ_3	0.1682	3.30
$\ln z_1 \ln z_2$	γ_{12}	−0.0546	−0.56
$\ln z_1 \ln z_1$	γ_{11}	−0.0972	−2.83
$\ln z_2 \ln z_2$	γ_{22}	0.0119	0.16
$\ln z_1 \ln z_3$	γ_{13}	0.0767	1.80
$\ln z_2 \ln z_3$	γ_{23}	0.0726	1.46
$\ln z_3 \ln z_3$	γ_{33}	−0.0021	−0.13
$\ln p_1 \ln z_1$	e_{11}	−0.7767	−2.49
$\ln p_1 \ln z_2$	e_{12}	0.4521	1.20
$\ln p_1 \ln z_3$	e_{13}	−0.1788	−1.23
$\ln p_2 \ln z_1$	e_{21}	0.1304	1.13
$\ln p_2 \ln z_2$	e_{22}	−0.1677	−1.17
$\ln p_2 \ln z_3$	e_{23}	0.0341	0.66
$\ln p_1 \ln w_c$	δ_{11}	−0.0143	−0.06
$\ln p_2 \ln w_c$	δ_{21}	−0.0140	−0.19
$\ln w_c \ln z_1$	μ_{11}	0.0011	0.02
$\ln w_c \ln z_2$	μ_{12}	−0.0067	−0.09
$\ln w_c \ln z_3$	μ_{13}	0.0238	0.95
Lambda (σ_u / σ_v)		2.1448	11.99
Sigma ($\sqrt{\sigma_u^2 + \sigma_v^2}$)		0.76 38	40.76
	σ_u^2	0.47 92	
	σ_v^2	0.1042	
log likelihood = −1351.0			

The estimated coefficients of technical efficiency variables show that the larger farms tend to be relatively technically efficient ($\tau_{1L} = 0.83$) and the small farms are technically inefficient ($\tau_{1S} = -0.57$).

Based on the estimated price efficiency parameters (θ) from the first step, a maximum-likelihood estimate of the shadow profit frontier (Eq. (1) with Eq. (10)) is obtained and a profit efficiency index is derived. The mean of the profit efficiency measure, $E(e^{-u})$, is 0.62. This result implies that an average of 38% of profit is lost due to inefficiency. The frequency distribution of the individual household's

[15] Lopez (1985) shows that empirically the most flexible functional forms do not satisfy the properties of monotonicity and convexity globally. We did not test these properties for our profit function.

efficiency index (Table 3) shows that there is a wide variation in the level of efficiency among households. The efficiency estimates range from 0.06 to 0.93. About 11.8% of households are in an efficiency range below 0.50. The standard errors of the inefficiency factor (σ_u) contribute 91% to that of the total error term (σ), which indicates that the inefficiency term dominates the total error term. These results imply that a considerable amount of profit can be obtained by improving technical and allocative efficiency in Chinese agriculture.

The derived farm-specific efficiency index facilitates decomposition of the efficiency performance at the farm level. Such analyses allow us to identify the factors that influence farmers' efficiencies. Table 4 contains the estimates of the truncated regression of the efficiency decomposition that explains relationship between a household's profit efficiency and its demographic characteristics. The results show that a household's educational level, family size and per capita net income are positively related to its efficiency. Households in mountain areas and households with family members employed by the government or state industries are relatively inefficient [16]. The estimated coefficients also show relatively large magnitude of net per capita income (0.40 for high net income and −0.17 for low net income) and household size (0.14 for a large family and −0.25 for a small family) to efficiency performance. These results demonstrate the existence of economies of size in China's household farming system. The positive coefficients for a more highly educated household and village leader, although of relatively small magnitude, may reflect these households' privileges on accessing technology and market information.

To verify how close a farmer's shadow profit can be approximated by his directly reported profit in the survey, and to evaluate the effect of this approximation on the farmer's efficiency analysis, we performed a sensitivity analysis by using predicted shadow profit from a predicted shadow-profit model suggested in Wang et al. (1996). The distribution of the estimated efficiency index and its decomposition from the predicted profit model are very close to that derived from the model developed in this study. Both models yield the same mean of the profit efficiency, 0.62. The predicted profit model estimates a slightly larger proportion of households (12.5% compared to 11.8%) with an efficiency level below 0.50. The results of the efficiency decomposition (Table 4) show that the estimates from two different models are comparable. The sign of the estimates between the two models is the same for each variable. The magnitude of the estimates, as well as level of statistic significance, are similar between the two groups of estimates. This result indicates that farmer directly reported profit can be used as a proxy of shadow profit in shadow-profit analysis to simplify the estimation procedures. It also indicates the robustness of estimates obtained from the model specified in this study.

The estimated parameters of the county dummy variables show that there are significant differences

Table 3
Frequency distribution of farm-specific profit efficiencies

	Efficiency index	Frequency	Percentage	Cumulative frequency	Cumulative percentage
	0.1–0.2	33	1.9	38	2.3
	0.2–0.3	66	3.7	99	5.5
	0.3–0.4	121	6.8	220	12.3
	0.4–0.5	211	11.8	431	24.1
	0.5–0.6	313	17.5	744	41.7
	0.6–0.7	428	24.0	1172	65.6
	0.7–0.8	416	23.3	1588	88.9
	0.8–0.9	192	10.8	1780	99.7
	0.9–1.0	6	0.3	1786	100
Mean	0.6212				
STD	0.1658				
Minimum	0.0598				
Maximum	0.9299				

[16] Most off-farm employees, especially those employed by the government and state industries, are married males. Their wives and children have remained in rural households. Farm-land was distributed basically according to the number of people in each household; therefore, relative lack of labor and experience causes lower efficiency. In general, this kind of household has less incentive to improve its performance because its well-being depends on off-farm income.

Table 4
Parameter estimates of efficiency index decomposition

Variable	Actual profit model		Predicted profit model	
	Coefficient	*t*-ratio	Coefficient	*t*-ratio
Constant	−0.7460	−14.23	−0.7721	−14.11
High education	0.0503	1.44	0.0926	2.48
Off-farm employment	−0.1737	−3.19	−0.1514	−2.62
Large family	0.1414	2.89	0.1726	3.33
Small family	−0.2548	−3.01	−0.2507	−2.83
Mountain area	−0.1343	−5.03	−0.1425	−5.10
High net income	0.4030	7.68	0.4153	7.58
Low net income	−0.1738	−1.84	−0.1995	−2.03
Village leader	0.0426	0.82	0.0785	1.41
Sigma	0.4247	34.10	0.4415	33.78
Log-likelihood	−401.15		−453.41	

in average profit across the regions. The county dummy variables explain 20.45% of total sample variations in this model and 25.56% in the predicted profit model. This result indicates that regional differences in socioeconomic conditions have a substantial influence on profit patterns among rural households in China. Further discussion of the regional effects, however, is beyond the scope of this study.

5. Summary and policy implications

This study uses a profit function approach which combines technical and allocative efficiency in the profit relationship to analyze farm households' production efficiency in China. To address the existence of various market distortions in Chinese agriculture, we adopt a concept of shadow-price profit frontier in this study. Measurement and decomposition of the households' production efficiency are obtained by estimating the shadow profit frontier function, which incorporates price distortions resulting from imperfect markets, socioeconomic and institutional constraints. Empirical results using 1991 China's Rural Household Survey data indicate that a profit-maximizing farm's decision on outputs and inputs is based on their shadow prices rather than observed market prices. It is also found that there is a significant variation in production efficiency among farm households in China. Estimated production efficiency, measured by the profit efficiency index, range from 6% to 93%, with 11.8% percent of the farm households' efficiency levels being lower than 50%. The mean of the profit efficiency is 62%, which is close to the 69% for the coastal region and the 48% for the central region found in Wu (1995) using 1985–1991 provincial data. These results suggest a great scope for improvement in production efficiency.

The profit efficiency is significantly explained by the production-related characteristics and farm management practices. In particular, farmers' education, farm size and per capita net income are important variables to raise profit efficiency. The factors affecting profit efficiencies negatively are small family size (less than three people) and low per capita net income. Households living in mountain areas and households with family members employed in the government or state industries are profit inefficient.

Given the existing regime of input and output prices in China's agriculture, one conclusion that can be drawn from this study is that effects of price distortions must be considered in farm behavior studies. This model has implicitly internalized these distortions through the shadow prices. Rejection of the market price model indicates that opportunity costs of resources are not reflected by the observed market prices when there are binding external constraints and allocative inefficiency. Thus, empirical studies that use profit (cost) function with observed market prices as the opportunity costs of resources may give inappropriate results.

The second conclusion drawn from the study is that a great potential of efficiency gain can be obtained by reducing market distortions in China's agriculture. The Rural Household Responsibility System, as the first phase of the rural economic reforms that focused on the production operating mechanism, has substantially improved farm households' efficiency. Although rural input and output market reforms have been implemented since 1985, various market constraints still remain effective in preventing farm households' optimum resource allocation. The significant differences between the market prices and farmer's opportunity costs, found in this study, implies that farm households' allocative efficiency is influenced by the market distortions.

The study also finds evidence that economies of scale exist in China's household farming system. Both technical efficiency and allocative efficiency are positively related to operational size, which is also partly determined by family size and per capita net income.

The above findings have important policy implications. All previous studies reveal that a substantial improvement in China's agricultural production efficiency has occurred from the institutional changes made from 1978 to 1984. With the full implementation of the household responsibility system nationwide in 1983–1984, slow growth in crop production and productivity has shifted the focus of agricultural development towards technical change. This study indicates that substantial productivity gains can be obtained by continuously improving farm households' production efficiency. Both technical and allocative efficiencies can be improved by eliminating market distortions that mess up the function of price signal and cause allocative inefficiency. In particular, removing the government's monopsonistic power and administrative forces on major agricultural product procurement and purchase of quota obligations in the output market should allow market prices to reflect the opportunity costs of the products. In the input market, promoting the supply of inadequate material inputs, such as chemical fertilizer and fuel, rather than rationing and price subsidies, could eliminate the 'shortage premium' paid by some farmers and over-use of the inputs by others. A more liberalized market enables production (profit) to return to its frontier from the interior and shifts the frontier upward. The reason for this shift is that the potential of the economic reforms and modern technologies appears to be underestimated because the best practice farms, which are basis for estimating the potential, would probably also be constrained by socioeconomic and institutional factors.

The study also suggests that potential efficiency gain can be achieved by increasing a household's operating scale. In particular, allowing a relatively scarce resource, land, to be transferred to households with a high labor/land ratio should increase the production efficiency of these crop farms. Consequently, improved resource use requires development of a land rental market or a well-conducted land use right transfer mechanism as a complement to the land contract system [17]. The market can pick winners and losers and allocate land to those who can utilize it efficiently.

Clearly, a farm household's production efficiency is affected by its management practices and the farm's production-related characteristics, which in turn are influenced by socioeconomic conditions. For instance, a farmer's management capability is influenced by school availability and cost of schooling. It is thus important for China's agricultural development to have an institutional environment that facilitates the farmers' accessibility to education, and provides a socioeconomic environment that encourages market exchange in land and labor.

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[17] Under the original land contract system, land is equally distributed to households on a per capita basis. Currently, there is not a well-defined land market in China. Sales of farmland are very rare. However, the right of land use can be transferred in accordance with the law that was approved on 12 April 1988, and farmers have found a way to transfer land use rights through village committees and township government that manage the land contract system (Zhang and Makeham, 1992; US Department of Agriculture, 1993).

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