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Agricultural reforms and production in China: Changes in provincial production function and productivity in 1978–2015

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ABSTRACT

A series of fundamental and market-oriented reforms since 1978 have dramatically reshaped China's agricultural sector, which had been sluggish during the socialist period. Besides productivity growth and efficiency changes, the shape of the production function may also transform rapidly over time. Moreover, the four segments in agriculture (farming, forestry, animal husbandry, and fisheries) have different production processes and techniques, so the aggregated production function of agriculture may vary across provinces. Compared with existing studies, which usually assume a fixed production function, this paper allows a varying coefficient production function that can better capture the structure change in the six reform periods over the past four decades. The empirical results show that the labor elasticity is decreasing, the fertilizer and machinery elasticities are increasing, and the land elasticity has a U-shaped curve across time. Moreover, technology and inputs are leading the growth alternatively in different reform periods.

1. Introduction

Remarkable agricultural growth has been witnessed in China due to the rural reforms implemented since 1978. The real growth rate in the Gross Value of Agricultural Output (GVAO) is 6.1% per year over the period of 1978–2015, compared with an average 2.5% increase in the socialist period (1949–1977). Several waves of institutional reforms and market deregulations in the supply side not only helped achieve tremendous improvement in productivity, but also overwhelmingly reshaped the agricultural process and production function of agriculture.

Farming, forestry, animal husbandry, and fisheries are the four segments in China's agricultural sector, each with its own production process. Therefore, the aggregated production function of agriculture also depends on the share by segment in each province. Chinese economic reform has improved living standards and food consumption. The demand for animal protein has increased rapidly and therefore raised the ratio of animal husbandry and fisheries in the agricultural sector, which also altered the shape of the agricultural production function.

To summarize, the fundamental reforms that have been implemented since 1978 have reshaped agricultural production from both the demand side and the supply side. The first puzzle is that the traditional method with a fixed production function assumption fails to capture the changing input-output relation across time due to rural reforms in China. To solve this issue, this paper employs a varying production function to better control the impact of remarkable agricultural evolution, which is not only important, but also necessary.

Another puzzle is the debate about China's agricultural productivity growth since the late 1990s. Some scholars (Dekle and Vandenbroucke, 2010; Pratt et al., 2008; Wang et al., 2013) assert that the productivity growth rate peaked in the late 1990s and then gradually lost its momentum. Other researchers (Chen et al., 2008; Chen, 2006a; Tong et al., 2009; Zhou and Zhang, 2013) point out that the significant slowdown had already happened in the late 1990s and subsequently rebounded.

This article analyzes China's rural reforms and agricultural revolution using a two-step approach. In the spirit of the varying coefficient model and stochastic frontier analysis, this article first develops a semi-parametric approach to estimate the time- and province-variant production function, as well as total factor productivity (TFP). In the second step, we analyze the changes in input elasticities and productivity in six reform periods to determine the impacts of different rural policies on China's agricultural sector.

This study makes three central contributions. Firstly, a semi-varying coefficient method is introduced to better capture the fundamental transition in China's agricultural sector. Secondly, this study not only estimates the productivity and efficiency changes, as in classic productivity analysis, but also the changes in input elasticities across provinces

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and time. Thirdly, this article further links the six rural reforms in China with agricultural production and contributes to the debate about China's agricultural productivity growth in the past 20 years.

The empirical results show that in 1978–2015: 1) the production function is indeed province- and time-variant, which reflects the fundamental transition of China's agriculture; 2) the labor elasticity is decreasing, the fertilizer and machinery elasticities are increasing, and the land elasticity has a U-shaped curve across time; and 3) China's agricultural productivity growth has obvious cyclical fluctuations and six cycles are witnessed. Moreover, the direction of changes in output and productivity has always been opposite in the past two decades, which indicates that technology and inputs are leading the growth alternatively in different reform periods. Finally, the input growth contributes more to the output in the current phase, which implies an extensive pattern of economic growth and that more technology innovation is needed to improve productivity.

The remainder of the article is structured as follows. Section 2 reviews China's six rural reform periods since 1978. Section 3 introduces the existing agricultural productivity analysis in China. Section 4 builds the theoretical model and Section 5 describes the data. Empirical results are presented and analyzed in Section 6. Section 7 concludes the article.

2. Agricultural policy reforms in China

Brümmer et al. (2006) divide China's rural reform from the late 1970s to the early 2000 into five phases: 1978–84, 1985–89, 1990–93, 1994–97, and post-1998. Zhang and Brümmer (2011) further add a sixth period that starts at 2004. This article follows this period division.

The first period (1978–84) is the transition from the collective system to a household-based farming system (Lin, 1992). The main content is the implementation of the household responsibility system (HRS), which endows farmers with the right to control their own production after fulfilling government procurement quotas. By the end of 1983, 98% of the production teams in China had adopted HRS (Lin, 1995). Decollectivization and decentralization in this phase diversified the rural economy and turned to economic incentives to spur growth (Oi, 1999). Many studies confirmed the essential success and achievements in this period.

The second period (1985–89) witnessed a two-tier system, including both market and planning factors. The government further liberalized agricultural pricing and marketing systems by allowing more products to trade in the market (Yao, 1994), except for some strategic products, such as grain and cotton (Zhang and Brümmer, 2011). The removal of legal restrictions on exchanges of inputs (on a limited basis) reduced resource misallocation (Lin, 1995). However, agricultural output growth slowed due to the rising production costs (Fan et al., 2002a) and the frequent adjustments of policies in favor of the market economy or planned economy (Brümmer et al., 2006). In contrast to the first phase, this regime received some criticism.

The third period (1990–93) further reformed the united procurement and marketing system. In order to avoid government failure due to information problems, China substituted a centrally planned system and governmental interference by functioning market forces and solutions. By the end of 1993, over 90% of all agricultural products were sold at market-determined prices (Fan et al., 2002a). However, the market reform was not fully complete because of the segmentation of regional markets and the isolation of domestic markets (Brümmer et al., 2006). Moreover, the acceleration of rural industry absorbed agricultural resources, such as labor, land and capital.

The fourth period (1994–98) began with tax system reform, which increased state funds for agriculture and the capability of "industry nurturing agriculture." The government was able to raise procurement prices for grain by 40% in 1994 and by another 42% in 1996, which narrowed the procurement/market price gap and stimulated agricultural production. The extension of land contracts and the awareness of farmers' use rights encouraged more investment in land (Lambert and Parker, 1998). Moreover, the self-sufficiency policies at the regional level forced relatively developed regions to produce enough food to feed themselves.

The fifth period (1998–2003) can be regarded as an integration of rural development with the overall economic reforms (Zhang and Brümmer, 2011). The government implemented a new series of procurement and marketing reforms in 1998, aiming to relieve the financial burden of the grain support program. However, the dilemma of the State-owned grain enterprises caused many problems. China's World Trade Organization (WTO) accession in 2001 brought a reduction in protection policies and the quota procurement system was finally eliminated in the same year. At the end of this period, the free grain market was brought to most regions of China.

The sixth period (2004-present) was focused on the so-called "three nongs" (agriculture, farmers, and the countryside) issues. The trade status of agricultural commodities in China switched from a surplus to a deficit in 2004 (Chen et al., 2008), which called attention to food security. Since that same year, the government has highlighted the rural reforms in its first annual document, aiming to raise agricultural production capacities and increase farmers' income (Wang et al., 2013). In 2004, China began a nationwide push to abolish agricultural taxes; they were totally eliminated in 2006 (Lohmar et al., 2009). In 2005, a central land policy was stipulated to preserve at least 1.8 billion mu (120.6 million hectares) of arable land (Chien, 2015). The rural reforms in recent years are in a more comprehensive and sophisticated framework.

3. Agricultural productivity analysis in China

Thanks to the fundamental reforms and rapid growth, more and more scholars are paying attention to the productivity analysis in China's agriculture sector (e.g. Huang and Rozelle (1996); Cao and Birchenall (2013)). Lin (1992) discusses the price reforms, the institutional reforms, and the market and planning reforms during the first two regimes. He employs both a traditional production function and a stochastic frontier function to evaluate the contributions of rural policies to China's agricultural productivity growth. Using the province-level panel data from 1970 to 1987, he finds that 40% of the output growth was attributable to the introduction of the HRS during the first reform phase. The important impact of HRS and the rapid growth in productivity in 1978–84 are supported by many other studies (e.g., Mcmillan et al. (1989); Wen (1993); Fan et al. (2002b, 2004)).

Most of these studies also agree on the significant slowdown in agricultural growth in the second period. For example, Carter and Estrin (2001) claim that the productivity growth rate was 8.1% in the first phase, and declined to 2.4% in the second phase. Some (Fan, 1991; Fan et al., 2004; Lin, 1992; Mcmillan et al., 1989) believe that the decollectivization of farms in the first period could only provide a one-time productivity gain, which inevitably vanished in the second period. Others (Huang, 1998; Sicular, 1995) attribute the decline to the government's failure in market liberalization after 1984.

A new wave of literature studies China's agricultural productivity growth in the 1990s and the 2000s. Although most of these researchers find that the productivity growth rebounded in the early 1990s, as compared with the second period, the changes since the late 1990s are controversial. Some scholars (Dekle and Vandenbroucke, 2010; Pratt et al., 2008; Wang et al., 2013) assert the productivity growth rate peaked in the late 1990s and then gradually lost its momentum. Other researchers (Chen et al., 2008; Chen, 2006b; Tong et al., 2009; Zhou and Zhang, 2013) argue that the significant slowdown actually happened in late 1990s and rebounded afterwards. In terms of the last regime, from 2004 to the present, Wang et al. (2013) find that the growth rate further declined, while Zhou and Zhang (2013) argue that the growth rate has rebounded once again.

In terms of the estimation methods, Wu (2011) surveys 74 studies published from the 1990s onwards that focus on estimating total factor productivity in China. He finds that conventional production function is

(39 times), stochastic frontier analysis (22 times), and data envelopment analysis (15 times) are the three most widely used methods. Early studies (Fan and Pardey, 1997; Lin, 1992; Mcmillan et al., 1989) prefer to use conventional production function to estimate productivity. The second wave of studies adopts stochastic frontier analysis (SFA) (Brümmer et al., 2006; Carter and Estrin, 2001; Fan, 1991; Wu, 1995) and data envelopment analysis (DEA) (Chen et al., 2008; Liu et al., 2015; Mao and Koo, 1997) to decompose the total factor productivity into technical changes and efficiency changes. Both SFA and DEA estimate a production frontier that represents the highest attainable outputs given inputs. The shift of the frontier across time shows the technical changes, while the vertical distance between a unit's outputs and the frontier represents the technical efficiency of that unit. SFA assumes the production frontier follows some functional form, such as Cobb-Douglas or Translog, and allows a stochastic term to capture the noise. DEA is a deterministic model and the formation of the production function is relaxed to avoid rigid functional forms.

To summarize, previous literature agrees on the productivity change in the first three periods, but has different opinions on the last three periods. Moreover, only a few studies include an estimation of productivity in the 2010s. This article adopts stochastic frontier analysis for the following reasons: 1) it can decompose the total factor productivity and is therefore better than the conventional production function methods; 2) it allows a stochastic term to capture the noises, which is very necessary because random shocks (e.g., weather) affecting the agricultural production process are a big concern. Moreover, the varying coefficients stochastic frontier model uses semi-parametric techniques to relax the fixed functional form with a time- and province-variant frontier concern. In other words, the frontier still follows some function form, but its shape varies across time and provinces.

4. Model

This model includes two steps. Firstly, a varying coefficient stochastic frontier model is used to estimate production function (frontier), as well as the total factor productivity. Secondly, the growth of the estimated input elasticities and total factor productivity are regressed on reform period dummy variables respectively and other variables to show the achievements and changes in each of the six reform periods, all other things being equal.

4.1. Production function and productivity growth

4.1.1. Stochastic frontier analysis

The stochastic frontier production function model is proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) in the form:

$$Y_i = X_i'\beta + \nu_i - u_i, \quad i = 1, \ldots, N,$$

where Y_i and X_i are the vectors of output and inputs in logarithms of unit i, respectively. ν_i accounts for measurement errors, which is usually assumed to follow a normal distribution. u_i is a non-negative random variable representing technical inefficiency, which is assumed to follow a variety of distributions, including half-normal distribution (Aigner et al., 1977), normal truncated distribution (Stevenson, 1980), and gamma distribution (Greene, 1990).

Schmidt and Sickles (1984) proposed a panel stochastic frontier model in the form:

$$Y_{it} = \alpha + X_{it}'\beta + \nu_{it} - u_i = \alpha_i + X_{it}'\beta + \nu_{it}, \quad i = 1, \ldots, N, t = 1, \ldots, T \tag{1}$$

The fixed effects or random effects methods, as well as many other approaches (e.g., Kumbhakar (1990), Cornwell et al. (1990), Battese and Coelli (1992), Lee and Schmidt (1993), Kneip et al. (2003), and Sickles (2005)), can be used to estimate α_i under different conditions. Since the coefficients β are fixed, the conventional stochastic frontier model in Eq. (1) is denoted as single frontier method.

4.1.2. Varying coefficient model

In Eq. (1), $\beta = (\beta_1, \ldots, \beta_p)$ vectors the constant elasticity for each of the p inputs. However, the fundamental rural reforms overwhelmingly reconstruct China's agricultural sector, which may not only shift the production function (i.e., change productivity), but also change the shape of the production function.

Hastie and Tibshirani (1993) first introduce the Varying Coefficient Model (VCM), where the coefficients are nonparametric functions of some "threshold" variables θ. The original model has the form

$$y = x_1 h_1(\theta_1) + \ldots + x_p h_p(\theta_p) + \varepsilon,$$

where $\theta_1, \ldots, \theta_p$ change the coefficients of $x_1, \ldots, x_p$ through unspecified functions $h_1(\cdot), \ldots, h_p(\cdot)$. The coefficients are nonparametric functions that are not constant, hence the name "varying/smooth coefficient model." This method is first utilized to model time-variant coefficient functions for censored data in survival analysis.

A few research studies in production analysis have utilized the spirit of the varying coefficient model. Sun and Kumbhakar (2013) and Zhang et al. (2012) use a varying coefficient production function to study the Norwegian forest industry and China's high-tech industry, respectively. However, they adopted a conventional production function, rather than the stochastic frontier model. Some examples of the "threshold" variables include R&D spending, tax rate, firm size, firm age, etc. (Kumbhakar and Sun, 2013). Gong (2017) employs a varying coefficient production function to study the efficiency of oilfield service companies, where revenue shares by segment are treated as the "threshold" variables.

In terms of China's agricultural sector, Fan and Pardey (1997) use a varying coefficient production function to estimate productivity growth from 1965 to 1993. However, the coefficients of inputs are only linear functions of time, rather than unspecified nonparametric functions, such as the one in Hastie and Tibshirani (1993). As a result, the speed of the changes in production function is fixed across time, which fails to capture the heterogeneous changes in different reform periods.

Besides the time trend, another package of possible "threshold" variables that Fan and Pardey (1997) overlooked is the structure of the agricultural sector, which is the ratio/share of the four segments: farming, forestry, animal husbandry, and fisheries. Since the techniques utilized in the four segments of agriculture are different, the production function is segment-specific. However, it is difficult to conduct a productivity analysis for each of the four segments separately due to the lack of segment-level input data. Moreover, the existence of joint inputs is also a problem. For example, rice field pisciculture is a popular ecological agriculture mode in some parts of China where rural households raise fish in paddy fields. For these families, it is hard to separate its labor force and land between farming and fisheries. As a result, it is better to assume the aggregated production function of agriculture is not equal to any of the four segment-specific production functions, but is instead a combination of them.

This article uses output value shares by segment as the weight index to capture the heterogeneous agriculture structure across provinces, which measures the frequency of using every segment-specific technique in a province. Intuitively, if there is a dominant segment in a province, then the aggregated production function of that province is likely to be close to the production function of the dominant segment, as this province uses the production technique from this segment more frequently. Since using multiple techniques jointly can lead to nonlinear spillover effects caused by shared R&D investment, joint inputs, and so on, we cannot simply take the weighted average of the segment-specific production functions. Hence, nonparametric functions $h(\cdot)$ are used to control the nonlinear effects of output value shares by segment, which are also regarded as "threshold" variables.

This article generates a partial linear semi-varying coefficient stochastic frontier model to estimate the agricultural production function, where the time variable and the output value shares by segment are treated as "threshold" variables and the frontier has a Cobb-Douglas (C-

D) form:

$$y_{it} = \alpha_{it} + \sum_{k=1}^{p} \beta_{it}^{k} x_{it}^{k} + \tau Z + \nu_{it} - u_i = h_0(\theta_{it}) + \sum_{k=1}^{p} h_k(\theta_{it}) x_{it}^{k} + \tau Z + \nu_{it} - u_i, \tag{2}$$

where y_{it} is output, x_{it}^k is the k-th input, and $h_k(\theta_{it})$ is a nonparametric function to estimate the varying elasticity of the k-th input β_{it}^k. $\theta_{it} = (t, w_{it}^1, w_{it}^2, w_{it}^3, w_{it}^4)$ where w_{it}^1, w_{it}^2, w_{it}^3, and w_{it}^4 measure the output value of farming, forestry, animal husbandry, and fisheries for province i at time t, respectively. The intercept, $h_0(\theta_{it})$, is also assumed to be a nonparametric function of the "threshold" variables. Z vectors a group of year dummy variables, which controls the production frontier change over time. τ vectors the coefficients of the year dummy variables. $\exp(\nu_{it})$ is the stochastic component that describes random shocks affecting the production process, where ν_{it} is assumed to be normally distributed with a mean of zero and a standard deviation of σ_ν, and $TE_i = \exp(-u_i)$ denotes technical efficiency defined as the ratio of observed output to maximum feasible output. This study uses the popular "Error Components Frontier" (Battese and Coelli, 1992) with time-invariant efficiencies to estimate u_i and TE_i. Since the coefficients of the Cobb-Douglas production function are non-parametric functions, Eq. (2) is a semi-parametric production frontier model.

Suppose provinces use one input to generate one output in Segments A and B in a simplified model. Fig. 1 compares the conventional single frontier method with the varying coefficient method: 1) the left figure visualizes the conventional single frontier method. The x- and y-axes represent the province-level input and output, respectively. The vertical distance of a province's allocation to the fixed frontier is the province-level inefficiency. That is, all provinces compete with each other directly; 2) the right figure shows that the shape of the production frontier varies according to the share of the output from Segment B in a province. This approach considers the heterogeneity across segments. Provinces share the same frontier and are directly compared to derive efficiency if and only if they have the same ratio of output values from Segments A and B.

4.1.3. Estimation strategy

Fan et al. (1996) propose a method, known as semi-parametric frontier analysis, that allows for white noise and needs no specified functional form of the production frontier:

$$y = f(x) + \varepsilon = f(x) + \mu + v - u,$$

where $f(x)$ is a semi- or nonparametric production function, u is a non-negative technical inefficiency term and v is a statistical noise term. μ is the mean of u. Hence, $\varepsilon = \mu + v - u$ has a zero mean.

A two-step approach is utilized to solve this semi-parametric frontier analysis. In the first step, the residuals $\hat{\varepsilon}$ is derived from the semi- or nonparametric regression $y = f(x) + \varepsilon$. In the second step, the residual is decomposed as $\hat{\varepsilon} = \mu + v - u$ using the conventional stochastic frontier model. As Henningsen and Kumbhakar (2009) point out, the unavailability of software in earlier years prevented empirical studies from using this method. In recent years, however, the accessibility of software packages (e.g., Hayfield and Racine (2008), Hastie and Tibshirani (1990), Stasinopoulos and Rigby (2007) and Coelli et al. (2012)) have made it easier to use semi-parametric frontier analysis.

There are two nonparametric approaches to estimate the $h_k(\theta_{it})$ in Eq. (2), including the spline-based method (Ahmad et al., 2005; Hastie and Tibshirani, 1993) and the kernel-based method (Fan and Huang, 2005; Fan and Li, 2004; Hu, 2014; Su and Ullah, 2006; Sun et al., 2009). Kim (2013) prefers the spline method due to its flexibility to involve multiple smoothing parameters, while Fan and Zhang (2008) are in favor of the kernel-smoothing methods, since the varying coefficient model is a local linear model. However, the former may encounter computational challenges, while the latter may suffer from the "curse of dimensionality."

This study selects the penalized B-spline approach to estimate the production function for two reasons. Firstly, there are five "threshold" variables that will cause a "curse of dimensionality" if we use a kernel-based method. Secondly, Lu et al. (2008) present results on the strong consistency and asymptotic normality for penalized B-spline estimators of such a varying coefficient model.

4.2. Determinants of the changes in production

This article builds regressions to estimate the different impacts of the six rural reform periods on productivity growth and production function in Eqs. (3) and (4), respectively. It is worth noting that the dependent variables in Eqs. (3) and (4), the productivity growth and input elasticities, are derived from Eq. (2).

$$\Delta TFP_{it} = \alpha + \sum_{j=2}^{6} \delta_j PD_j + \sum_{j=2}^{4} \lambda_j w_{it}^j + \eta_1 irr_{it} + \eta_2 dis_{it} + \sum_{j=2}^{31} \rho_j D_j + \varepsilon \tag{3}$$

$$\beta_{it}^k = \alpha^k + \sum_{j=2}^{6} \delta_j^k PD_j + \sum_{j=2}^{4} \lambda_j^k w_{it}^j + \eta_1^k irr_{it} + \eta_2^k dis_{it} + \sum_{j=2}^{31} \rho_j^k D_j + \varepsilon^k, \forall k = 1, \ldots, p, \tag{4}$$

where ΔTFP_{it} is the growth rate of total factor productivity for province i at time t. The total factor productivity is derived by $TFP_{it} = h_0(\theta_{it}) + \tau Z - u_i$ in Eq. (2). β_{it}^k is the time- and province-variant coefficient for the k-th input to measure its elasticity for province i at time t, which is also

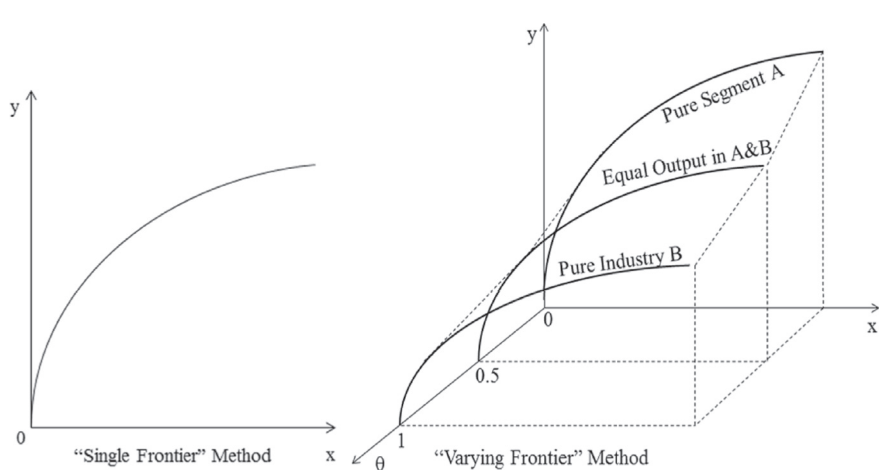

Fig. 1. Comparison of the frontier methods.

derived from Eq. (2). PD_j is the dummy variable of the j-th reform period. w_{it}^{j} is the output value share of the j-th segment. irr_{it} is the total sown area that is irrigated, in logarithms, and has been used as a productivity determinant (Chen et al., 2008). dis_{it} is the agricultural land area affected by natural disaster (primarily flood and drought), in logarithms, which may explain declines in output (Brümmer et al., 2006; Lambert and Parker, 1998). D_j is the provincial dummy variable for the j-th province.

5. Data

The data used in this study are provincial-level agricultural outputs and inputs of 31 provinces in mainland China for 1978–2015. This paper follows the traditional literature (e.g., Kalirajan et al. (1996), Chen (2006a), Zhou and Zhang (2013), and Liu et al. (2015)) in selecting inputs and outputs for the production function. The output variable is the deflated gross value of agricultural output (GVAO), which is defined as the sum of the total value of production from farming, forestry, animal husbandry, and fisheries (in billion CNY at 1980 constant prices). Inputs in the data set include four categories: labor, land, fertilizer and machinery. Labor is measured as the size of the labor force (in millions) in the primary industry. Land refers to the sown area (in million hectares) reflecting the actual utilization of the cultivated land. Fertilizer refers to the sum of the gross weight of nitrogen, phosphate, potash, and complex fertilizers (in million tons). Machinery is measured by the total power of agricultural machinery (in million kilowatts), which includes the total mechanical power of machinery used in the primary industry.

The output value share of the four segments in agriculture can be calculated, as the respective values of production from farming, forestry, animal husbandry, and fisheries are available. The total sown area that is irrigated and the agricultural land area affected by natural disaster are also observed. Most of the data are from *China Statistical Yearbook*. Some data are supplemented (e.g., the labor statistics in 2013–2015) and adjusted (e.g., data of Chongqing and Hainan) using the *China Compendium of Statistics 1949–2008* and the provincial-level statistical yearbooks.

Table 1 summarizes provincial-level inputs and outputs in China's agricultural sector. The first two rows provide the average provincial-level inputs and outputs in 1978 and 2015, respectively. The next six rows list the average annual growth rate of inputs and outputs for each of the six reform periods. The average gross value of agricultural output increased almost eight-fold, from 6.2 billion in 1978 to 48.3 billion in 2015, both at 1980 constant prices. The output real growth rate was 6.1% in the first period and then decreased to 1.3% in the second period, before it peaked in the third and fourth periods. The output growth rates in the fifth and sixth periods were maintained at around 4%.

In the labor market, the average size of the labor force in the primary industry increased around 1.5% per year in the 1980s and then maintained the same size in the 1990s. Since 1999, the agricultural labor force has decreased by around 1% per year due to migration inspired by the economic boom in secondary and tertiary industries. Overall, the average provincial-level labor force in the primary industry decreased from 9.3 million in 1978 to 8.7 million in 2015. The sown land area increased by 10% over 37 years, from 4.9 million hectares in 1978 to 5.4 million hectares in 2015. However, the changes in land varied across periods: area decline happened in the first period and then remained stable in the second and third periods; a significant increase was witnessed in the fourth period, followed by a 0.7% annual fallback in the fifth period, before rising again in the sixth period due to specific land policies. The amount of chemical fertilizer used tripled in the period of 1978–2015. The rapid growth started in the second period and stayed at a high level above 5% until the end of the fourth period. In the last two periods, the growth rate of fertilizer was about 2% per year. The total power of agricultural machinery in 2015 was more than eight times higher than it was in 1978, which was the fastest growth by far among the four inputs. The annual growth rate of machinery was always above 5%, except in the third period.

6. Estimation results

This empirical study applies the described models to the balanced panel of 31 provinces over a period of 37 years from 1978 to 2015. Before estimating the production frontier as introduced in Section 4, this paper discusses two potential problems and the method to test them.

The first problem is the endogeneity inherent in the production function, as input decisions might be made when some information is available from the decision-making unit but unobserved by outliers such as economists. Appendix A reviews the methods to deal with the endogeneity problem in the production function and provides the endogeneity test for our dataset. The result indicates that all four inputs (labor, land, fertilizer, and machinery) are exogenous.

The second problem is whether provinces with the same portfolio across segments share the same frontier. In our model, the technology is assumed to be segment-specific and hence provinces with different portfolios across segments are allowed to have different frontiers. However, the frontiers may be different even if two provinces have the same portfolio but do not share the same segment-specific technology. Appendix B further discusses this issue. The result shows that provinces do share the same segment-specific technology and hence this issue is not problematic in this case.

Solving these two problems, this study estimates the production frontiers, technical changes, provincial-level efficiencies, and total factor productivity using the varying coefficient stochastic frontier analysis in Eq. (2), and then predicts the different impacts of the six rural reform periods on productivity growth and production function using conventional OLS regressions in Eqs. (3) and (4).

6.1. Production frontiers

The varying frontier model in Eq. (2) estimates time- and province-variant elasticities for each of the four inputs (i.e., $\beta_{it}^{k} \forall k = 1, 2, 3, 4$). Fig. 2 illustrates the average elasticities for the four inputs across time. Five vertical lines in each graph divide the 37 years into the six reform periods. It is worth noting that 95% confidence intervals are also given in Fig. 2 (the dotted lines) by employing Efron's nonparametric bias-

Table 1
Summary statistics.

		GVAO	Labor	Land	Fertilizer	Machinery
		billion CNY	million	million hectares	million tons	million kilowatts
Annual Value	1978	6.2	9.3	4.9	0.6	3.9
	2015	48.3	8.7	5.4	1.9	36.0
Annual Growth Rate	Period I (1978–1984)	6.1%	1.6%	−0.7%	−0.1%	8.6%
	Period II (1985–1989)	1.3%	1.5%	0.4%	7.0%	7.5%
	Period III (1990–1993)	7.1%	0.0%	−0.1%	6.7%	3.5%
	Period IV (1994–1998)	9.6%	−0.1%	1.2%	5.3%	7.5%
	Period V (1999–2003)	3.9%	−1.1%	−0.7%	1.7%	5.4%
	Period VI (2004–2015)	4.2%	−1.2%	0.7%	2.4%	5.2%

Note: GVAO refers to gross value of agricultural output in billion CNY at 1980 constant prices.

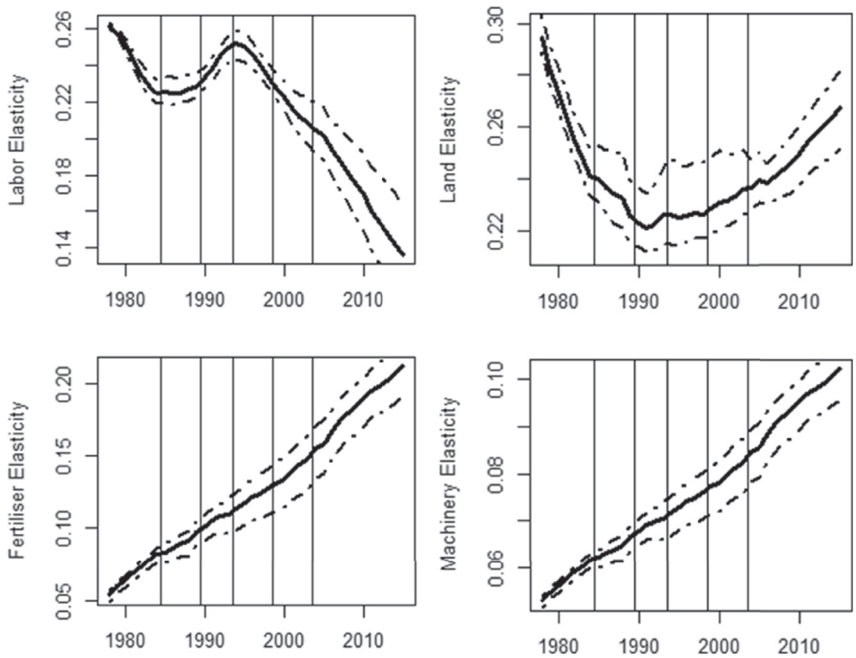

Fig. 2. Average elasticities of the four inputs across time.

corrected and accelerated (BCa) bootstrap method with 10,000 replications (Briggs et al., 1999).

The upper left graph shows that labor elasticity decreased in the first period, stayed flat in the second period, rebounded in the third period, and finally declined continuously in the last three periods, indicating less of a contribution of labor input to output with other things being equal. The upper right graph shows that land elasticity dropped significantly in the first two periods, remained at the bottom in the third and fourth periods, and then gained momentum in the last two periods, which implies that the marginal productivity of land has been increasing since the 1990s, if holding other factors fixed. The lower left and right graphs provide the changes in elasticities for fertilizer and machinery, respectively. Both are continuously increasing during the six periods, showing that these two inputs are more crucial to agricultural outputs over time. To summarize, the changes in labor and land elasticities are significantly different, while the changes in fertilizer and machinery elasticities are indifferent across periods. Considering also the changes in quantity of these inputs, this article concludes the following: 1) the contribution of labor to agricultural production is declining; 2) the marginal productivity of land experienced a U-shape curve; and 3) the increasing contributions of fertilizer and machinery to agricultural production are robust.

Fig. 3 provides the average elasticities for the four inputs across provinces. The upper 10 provinces are the western region of China (Western China), the middle nine provinces are the central region of China (Central China), and the lower 12 provinces are the eastern region of China (Eastern China). On the one hand, the intra-regional comparison shows: 1) all four input elasticities are consistent across provinces in Western China; 2) five lower provinces have similar input elasticities while the other four provinces are slightly different in Central China; and 3) the differences in input elasticities are relatively large for provinces in Eastern China. On the other hand, the inter-regional comparison shows that the fertilizer and machinery elasticities are larger on average in the central and western regions, while the labor and land elasticities are larger on average in the eastern region.

6.2. Technical changes and efficiency

The production frontiers also shift vertically across time, which is affected by technology, market, and other time-variant factors. A greater intercept in the production function implies higher attainable productivity when holding inputs fixed. The changes in intercept measure the technical changes. Fig. 4 shows the technical changes in 1978–2015, which measure the highest attainable output in a certain year compared with the highest attainable output in 1978. Five vertical lines divide the 37 years into the six reform periods. It can be seen that the highest attainable output has grown almost five-fold in 37 years, indicating rapid technical growth. However, such growth does not occur at the same pace across time. Slow growth and even some declines are witnessed in the entire second reform period, as well as at the beginning of the first and fourth periods.

The production frontier represents the highest attainable production, which is not achieved by most provinces. Technical efficiency, on the other hand, measures how close each province is to the frontier. Fig. 5 ranks the average technical efficiency for the 31 provinces in mainland China. The top 12 provinces all achieve an average efficiency beyond 90%, followed by 10 provinces with efficiency between 80% and 90%, while the remaining nine provinces have low efficiency, under 80%. In Fig. 5, we also find that the high efficiency provinces are mainly located in the eastern and central regions, while the low efficiency provinces are mainly located in the western and eastern regions.

6.3. Growth in total factor productivity

The average total factor productivity growth rate across time is given in Fig. 6. There are obvious cyclical fluctuations in productivity growth, which includes six cycles in the past four decades. The cutline between reform periods is either in the peak or valley of a cycle, indicating different policies and the impacts of various waves of reforms. The growth rate increased dramatically during the first period but declined rapidly in the second period. Productivity skyrocketed at the beginning of the third period, but soon fell back to regular speed. Negative growth is witnessed in the beginning of the fourth period but momentum was gained year by year. The trend in the fifth period is analogous to the one in the third period. In the last but longest period, the volatility is much smaller, but we still witness cyclical fluctuations, with two valleys in 2007 and 2011, when zero growth occurred. Robustness checks of the estimated total factor productivity can be found in Appendix C, where more reasons to adopt varying coefficient model are discussed.

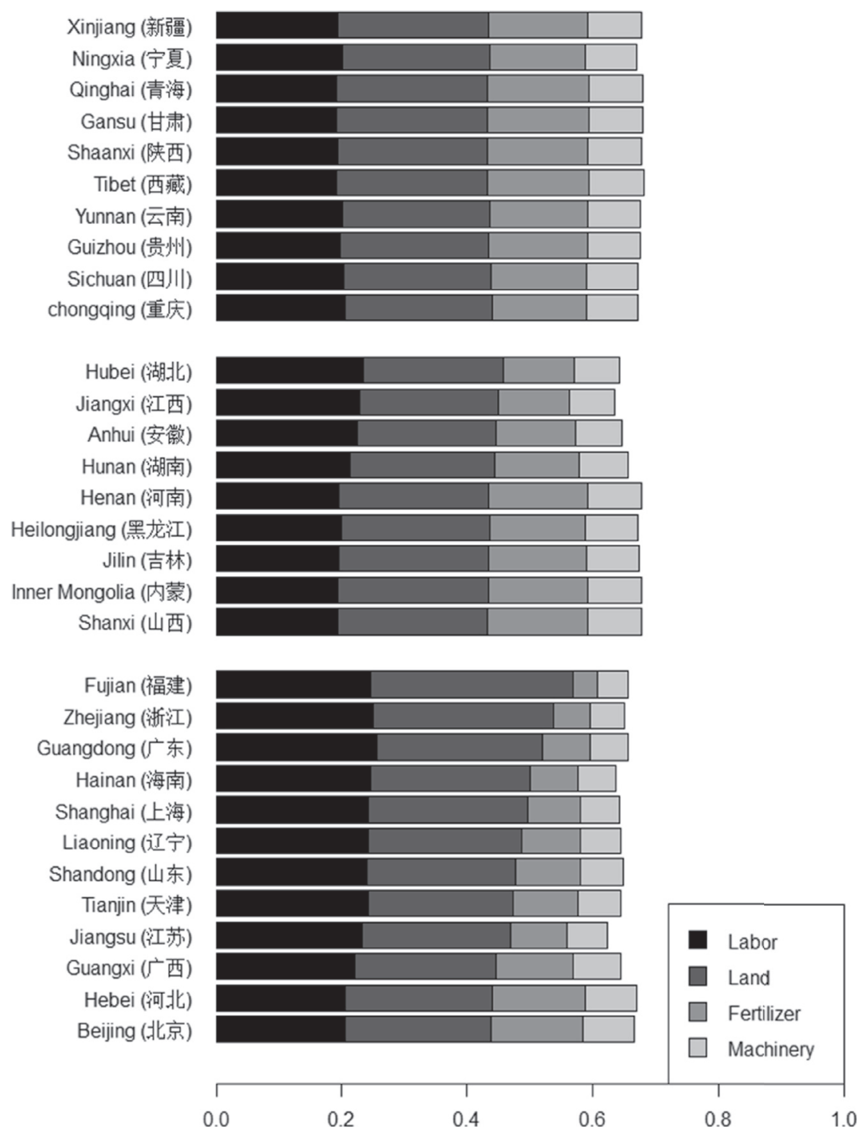

Fig. 3. Average elasticities of the four inputs across provinces.

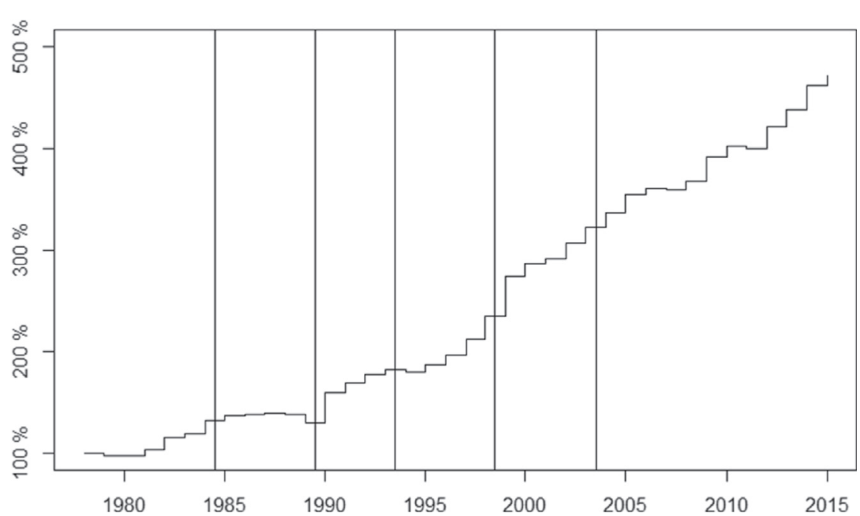

Fig. 4. Technical changes in the six reform periods.

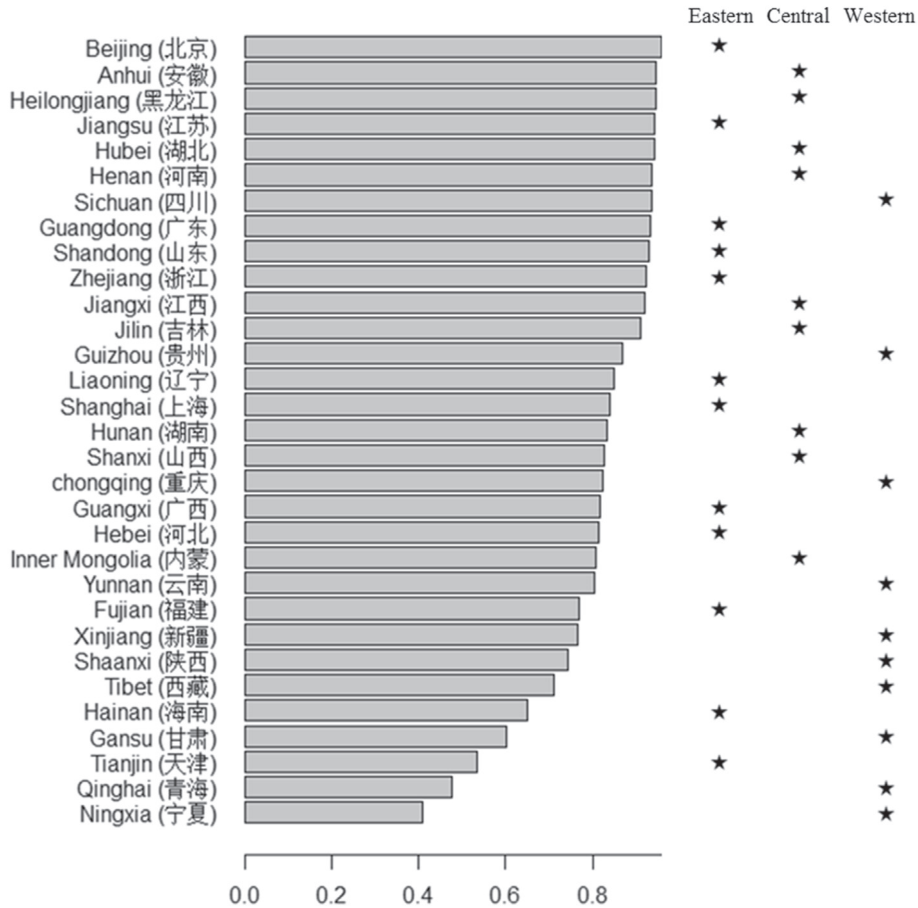

Fig. 5. Ranking of the average technical efficiency across provinces.

6.4. Components of frontier and TFP changes

The most important question this article seeks to answer regards the impacts of the six waves of rural reforms on agricultural production and productivity growth. How did these periods, along with a series of policies, reshape the production frontier and productivity growth in China's agricultural sector? Table 2 reports the estimated results in Eqs. (3) and (4), which is a second-step regression after estimating Eq. (2). Since the first period has been well-studied and highly praised by many scholars, this article uses this period as the base and estimates the impacts of other periods compared to this first regime. The first column in Table 2 presents the TFP determination results in Eq. (3), while the next four columns in Table 2 present the elasticity determination for the four inputs in Eq. (4), respectively.

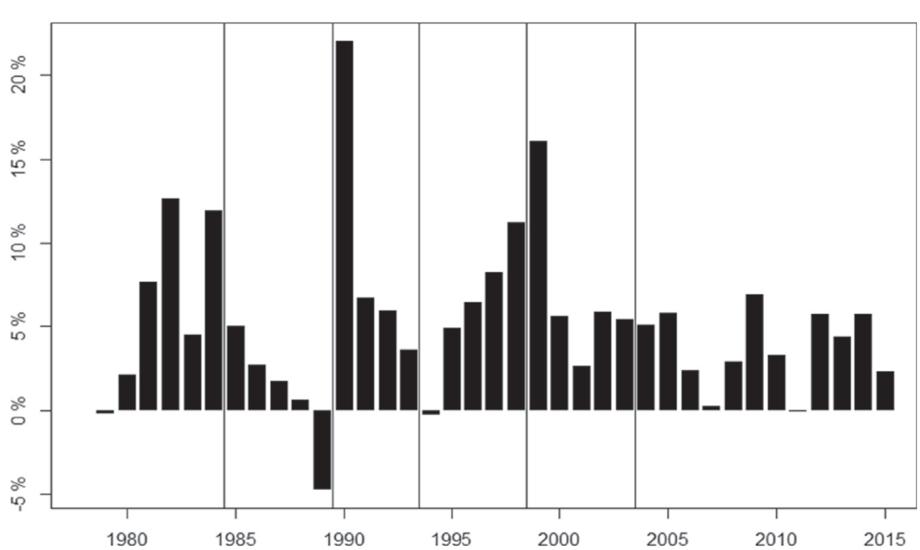

Fig. 6. Growth rate of total factor productivity across time.

Table 2
Regression results.

	Productivity Change	Frontier Change			
	ΔTFP_{it}	β^1_{it}	β^2_{it}	β^3_{it}	β^4_{it}
	TFP	Labor	Land	Fertilizer	Machinery
	(1)	(2)	(3)	(4)	(5)
PD_2	−0.050***	−0.027***	−0.024***	0.033***	0.010***
	(0.006)	(0.004)	(0.003)	(0.001)	(0.0004)
PD_3	0.037***	−0.015***	−0.032***	0.057***	0.018***
	(0.006)	(0.004)	(0.004)	(0.002)	(0.001)
PD_4	0.006	−0.021***	−0.024***	0.081***	0.025***
	(0.007)	(0.004)	(0.004)	(0.002)	(0.001)
PD_5	0.016*	−0.050***	−0.015**	0.107***	0.033***
	(0.008)	(0.005)	(0.004)	(0.002)	(0.001)
PD_6	−0.021**	−0.092***	0.001	0.149***	0.046***
	(0.007)	(0.005)	(0.004)	(0.002)	(0.001)
w^2_{it}	0.130	−0.252***	0.082	0.071**	0.022**
	(0.081)	(0.054)	(0.048)	(0.022)	(0.007)
w^3_{it}	−0.040	0.058**	−0.024	−0.025**	−0.008**
	(0.031)	(0.021)	(0.018)	(0.008)	(0.003)
w^4_{it}	−0.048	0.344***	−0.324***	−0.495***	−0.154***
	(0.051)	(0.033)	(0.030)	(0.014)	(0.004)
irr_{it}	0.011	−0.040***	0.028***	0.016***	0.005***
	(0.007)	(0.005)	(0.004)	(0.002)	(0.001)
dis_{it}	−0.005*	0.004*	0.001	−0.005***	−0.002***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.0002)
α	0.018	0.436***	0.100***	0.019	0.043***
	(0.041)	(0.028)	(0.024)	(0.011)	(0.003)
D_j	yes	yes	yes	yes	yes
R^2	0.28	0.66	0.51	0.96	0.96

Note: Significant at: *5, * *1 and * * * 0.1 percent; Standard error in parentheses.

6.4.1. *Reform periods*

The first column in Table 2 shows that the TPF growth rate in the second period was 5% lower than in the first period, which is close to the decline in output growth shown in Table 1 (4.8%). The rising production costs and the frequent adjustments of policies in favor of the market economy or planned economy discussed in Fan et al. (2002a) and Brümmer et al. (2006) are the main reasons for this slowdown. However, the growth rate of the third period rebounded dramatically and achieved a 3.7% higher growth rate than in the first period. This TFP growth rate is larger than the difference in output growth (1%), indicating a larger contribution of technical improvement than the input growth in the third period. The major political drivers in this regime are the reforms of the united procurement and marketing system. China substituted a centrally planned system and governmental interference with functioning market forces and solutions. By the end of 1993, over 90% of all agricultural products were sold at market-determined prices, which avoids government failure and boosts the production and exchange of agricultural products. The market system reduces resource misallocation and improves production even with the same amount of resources, which leads to growth in productivity.

Section 3 of this article introduces the debate of whether the productivity growth peak occurs in the third or fourth period. Although the output growth in the fourth period is 2.5% higher than that in the third period (shown in Table 1), our estimation result shows that the productivity growth rate in the fourth period fell back to the level of the first period, which is more than 3% lower than the level in the third period. Therefore, the peak of output growth occurs in the fourth period, but the peak of TFP growth occurs in the third period, which supports the findings of Chen (2006b), Chen et al. (2008), Tong et al. (2009), and Zhou and Zhang (2013). The lower productivity growth in the fourth period compared with the third period is due to the vanished productivity benefit from marketing reforms. As mentioned, over 90% of all agricultural products were sold at market-determined prices at the end of the third period, which leaves less space to improve in the fourth period. Although productivity grows less rapidly than in the third period, it is close to the speed of the successful first period, which confirms the great achievement in the fourth period. Moreover, the significantly higher growth rate in output than in productivity in the fourth period implies an extensive pattern of economic growth where the contribution of input growth (especially fertilizer and machinery) outweighs that of technical growth. The dramatic growth in inputs is encouraged by the reforms during the period. Firstly, China started tax system reform, which increased state funds for agriculture and the capability of "industry nurturing agriculture." The government was able to raise procurement prices for grain by 40% in 1994 and by another 42% in 1996, which stimulated agricultural production and input investments. The extension of land contracts and the awareness of farmers' use rights studied in Lambert and Parker (1998) also encouraged more investment in land. Moreover, the self-sufficiency policies at the regional level forced relatively developed regions to produce enough food to feed themselves, which also increased input investments in these regions.

After the rapid growth in the third and fourth periods, the output growth rate decreased from 9.6% to 3.9% in the fifth period. In Table 1, we can see that labor and land inputs decreased, while the growth in fertilizer and machinery inputs decelerated sharply. The TFP growth in this period, however, is higher than in the previous period, which avoids a more severe crash in agricultural production. The reforms of state-owned grain enterprises and reduction of protection policies due to WTO accession during the period help eliminate less productive capacity, which impedes the excessive growth in inputs and concentrates more on productivity-derived growth. In this period, China focused more on quality instead of quantity in the agricultural sector in order to face the challenge and competition brought by globalization.

Although the growth rates in land and fertilizer inputs increased in the sixth period, the lower productivity growth prevents the production growth from rising. The trade status of agricultural commodities in China switched from a surplus to a deficit in 2004, which called attention to food security (Chen et al., 2008). Therefore, the government requires sufficient agricultural products even if they are not productive and competitive, which raises input growth but lowers the average productivity as a result. Moreover, China began a nationwide push to abolish agricultural taxes in 2004 (Lohmar et al., 2009) and stipulated a central land policy to preserve at least 1.8 billion mu (120.6 million hectares) of arable land in 2005 (Chien, 2015). These policies, similar to those that relate to finance and land in the fourth period, also encourage more investment in agricultural inputs, which brought us back to the extensive pattern of economic growth as reflected in our estimation results.

To summarize, the cyclical fluctuations in TFP growth are verified, with other things being equal. The third and fifth reform periods witnessed a higher TFP growth than the successful first reform period. The TFP growth rate has slowed down in recent years, meaning that more effective agricultural policies are needed. It is worth noting that input growth and productivity growth alternately lead output growth period by period.

In terms of the input elasticities, columns (2)–(5) verify the trends shown in Fig. 2, after holding other things equal: 1) labor elasticity is decreasing all the way, except for a fleeting comeback in the third period; 2) land elasticity has a U-shaped curve where the value hits the bottom in the third period and then rises gradually to the level of the first period in recent years; and 3) the elasticities of both fertilizer and machinery are increasing in all six periods. The acceleration of rural industry and urbanization absorbed high quality agricultural resources including labor and land, which decreased the two elasticities in earlier years. In terms of land, the extension of land contracts in the fourth period and the central land policy to preserve at least 1.8 billion mu (120.6 million hectares) of arable land in the sixth period help improve land elasticity and hence achieve the U-shaped curve. Without protection policies, more productive and highly educated laborers left agriculture, which leads to decreasing labor elasticity. Thanks to the reforms in the finance and tax system, farmers have more funding to buy fertilizer and machinery as well as more knowledge on how to use them efficiently, which results in increasing fertilizer and machinery elasticity.

The varying elasticities and quantities of inputs across time jointly affect the contribution of inputs to outputs: 1) the decreasing labor force in agriculture reduces its contribution to production, which is further weakened due to decreasing labor elasticity after six waves of reforms; 2) declining land elasticity is once analogous to the case for labor, but then recovers in both elasticity and quantity; and 3) the increasing elasticities of fertilizer and machinery, along with their growth in quantities, generate spillover effects, which further expand their contribution to a higher agricultural output level.

6.4.2. Structure of the agricultural sector

Besides the effect of reform periods, output value shares by segment are also used as "threshold" variables to model the varying elasticities of inputs. Therefore, it is worth testing the effects of the agricultural structure. Because the share of farming in most provinces is decreasing, due to the higher demand for meat and fish, this article uses it as the base and estimates the changes in productivity and frontier when other segments replace the market share of farming. Column 1 in Table 2 shows that any change in agricultural output structure will not significantly change the TFP growth, indicating that all four segments achieved balanced productivity growth. However, the changes in agriculture structure do affect the production frontier significantly based on Columns (2)–(5) in Table 2, which provides crucial evidence to support the concern of segment-specific production function and the necessity of the varying coefficient approach. Compared with farming, labor input is less important in forestry activities, but more important in the other two segments especially for fisheries. For land utilization, the forestry segment requires more land, while the fisheries segment is less land-intensive. Moreover, fertilizers and machinery are mainly used in farming and forestry activities.

6.4.3. Irrigation and natural disasters

Some scholars (Brümmer et al., 2006; Chen et al., 2008; Lambert and Parker, 1998) believe the area that is irrigated and the area that is affected by natural disasters may influence the agricultural production process. Our estimation result shows that more natural disasters will decrease the TFP growth rate, but the effect of irrigation on TFP growth is insignificant. To some extent, the effect of irrigation is opposite to the influence of natural disaster, as the former is often designed and constructed to prevent the occurrence and damage of the latter. This is reflected in Table 2, where the coefficients of these two variables have opposite signs in all five columns. When more irrigation facilities are established, the same amount of land, fertilizer, and machinery can convert to more output, respectively. At the same time, fewer laborers are needed in more irrigated areas. On the contrary, more natural disasters will weaken the effectiveness of land, fertilizer, and machinery, but the contributions of labor will be more highlighted.

7. Conclusion

A series of fundamental and market-oriented reforms since 1978 have dramatically reshaped China's agricultural sector. This article aims to better capture such structural changes using a varying coefficient production model where the shape of the production function is province- and time-variant. We further analyze the transition in agriculture production in the six rural reform periods.

The empirical results show that labor elasticity is decreasing, fertilizer and machinery elasticities are increasing, and land elasticity has a U-shaped curve over time. Moreover, China's agricultural productivity growth has obvious cyclical fluctuations and six cycles are witnessed in the past four decades. Finally, the third and fifth reform periods (1990–93 and 1998–2003) achieved higher productivity growth than the well-studied and highly praised first reform period (1978–84), whereas the second and sixth reform periods (1985–89 and 2004-present) experienced low growth. Currently, the input growth contributes more to the output, which implies an extensive pattern of economic growth; more technology innovation is needed to improve productivity.

Appendix E. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jdeveco.2017.12.005.

Appendix A. Endogeneity problem

Endogeneity inherent in production function is a problem, as input decisions might be made when some information is made available by the decision-making unit (DMUs) but is unobserved by the economists (Ackerberg et al., 2015). A classic method to deal with the endogeneity problem in the production function is to employ the two-step approach proposed by Olley and Pakes (1996), which utilizes observed investment to "control" for unobserved productivity shocks (efficiency). This idea is extended in Levinsohn and Petrin (2003) by using intermediate inputs rather than investment to solve the simultaneity issue, since the latter is not available in many datasets. However, the coefficients of the exogenous inputs may not be identified due to the collinearity problems in both of the two aforementioned approaches (Ackerberg et al., 2015).

Since the investment and intermediate data are incomplete in the dataset, this paper uses another method, the popular instrumental variables (IV) estimation, to solve the endogeneity problem. For stochastic frontier analysis, Amsler et al. (2015) introduce how to deal with the endogeneity problem using the IV approach. Firstly, a control function method (also called the residual inclusion method) can help test the exogeneity of the inputs using t-tests for the significance of the reduced form residuals. Then, a Corrected Two-Stage Least Square (C2SLS) can be adopted in the Cobb-Douglas (C-D) model, while a control function method can be adopted in the Transcendental Logarithmic (T-L) model. This paper employs the method proposed in Amsler et al. (2015). In terms of the instrument variables, Levinsohn and Petrin (2003) suggest using lagged values of inputs employed.

Using the control function method in Amsler et al. (2015), Table A.1 indicates that all four inputs (labor, land, fertilizer, and machinery) are exogenous, as the coefficients in rows 5–8 are all statistically insignificant.

Table A.1
Endogeneity test results.

Variable	Coefficient	Standard Error
Labor	0.182***	(0.033)
Land	0.381***	(0.046)
Fertilizer	0.089***	(0.022)
Machinery	0.076***	(0.022)

(*continued on next page*)

Table A.1 (*continued*)

Variable	Coefficient	Standard Error
c.Labor	−0.062	(0.102)
c.Land	−0.042	(0.121)
c.Fertilizer	0.023	(0.030)
c.Machinery	−0.138	(0.071)
Year Effects	controlled	
Province Effects	controlled	
Intercept	1.211***	(0.098)

Note: Significant at: *5, **1 and *** 0.1 percent; Standard error in parentheses.

Appendix B. Whether provinces with the same structure have different frontiers

We assume the technology is the same in the same segment in the same year across provinces. In most literature, we assume all the decision-making units (DMUs) share the same frontier and the distance to the frontier is explained by technical inefficiency. It is possible that DMUs do not share the same frontier as they may have different access to advanced technology. If this is the case, a metaproduction function is usually used to investigate DMUs in different groups that may not have the same technology (Battese and Rao, 2002).

The metaproduction function was first established by Hayami (1969) and Hayami and Ruttan (1970), and it is treated as the envelope of commonly conceived neoclassical production functions (Hayami and Ruttan, 1971). This method is attractive theoretically since the producers in the same group have potential access to the same technology, but technology gaps exist across groups. It is worth noting that the technology gaps among different groups in the original metaproduction studies are often caused by geographic reasons. The metafrontier methodology is then introduced in stochastic frontier analysis, which is an overarching function that envelopes all the frontiers of groups using different technologies (Battese et al., 2004).

However, both metaproduction and metafrontier methods are mostly used across countries rather than within a country in aggregated-level analysis. For example, Mundlak and Hellinghausen (1982) and Lau and Yotopoulos (1989) adopt metaproduction to compare agricultural productivity across countries, while Gunaratne and Leung (1996) and Sharma and Leung (2000) both use the stochastic metafrontier model to estimate the efficiency of aquaculture farms in South Asian nations. The reason is that the spread of technology is usually restricted and blocked at the national border by import and export policies and regulations. Such restriction within a country is difficult, especially in recent years.

Empirically, this paper tests if the frontiers for western, central, and eastern regions of China are different. This division is widely applied when it comes to classifying provinces in China, both economically and geographically. Note that the production determination regressions in Eqs. (3) and (4) are established to estimate the impacts of rural reform periods on frontiers. In order to check the heterogeneity in agricultural production across regions, this paper replaces province dummy variables with region dummy variables in Eqs. (3) and (4), and the regression results are reported in Table B.1. The coefficients of the two region dummy variables are all statistically insignificantly different from zero in the first two columns and last two columns, indicating that TFP growth rate, labor elasticity, fertilizer elasticity, and machinery elasticity are all region-invariant when other things are being controlled. For land elasticity in column 3, the coefficients of the region dummies are economically insignificant, as a change of 0.0185 or 0.009 is relatively small compared with the average land elasticity of 0.242. To summarize, both productivity and frontier have no change or negligible change across regions. As a result, it is unnecessary to assume different technology by region in the same segment.

Table B.1
Regression results.

	Productivity Change			Frontier Change	
	ΔTFP_{it}	β_{it}^1	β_{it}^2	β_{it}^3	β_{it}^4
	TFP	Labor	Land	Fertilizer	Machinery
	(1)	(2)	(3)	(4)	(5)
eastern	−0.001	−0.002	0.0185***	−0.002	−0.0006
	(0.002)	(0.003)	(0.000)	(0.001)	(0.000)
western	−0.003	−0.004	0.0090**	0.0005	0.0002
	(0.005)	(0.003)	(0.003)	(0.001)	(0.0003)
$PD_2 - PD_6$	controlled	controlled	controlled	controlled	controlled
$w_{it}^2 - w_{it}^4$	controlled	controlled	controlled	controlled	controlled
irr_{it}	controlled	controlled	controlled	controlled	controlled
dis_{it}	controlled	controlled	controlled	controlled	controlled
α	0.108***	0.252***	0.243***	0.074***	0.059***
	(0.016)	(0.011)	(0.011)	(0.004)	(0.001)

Note: Significant at: *5, * *1 and * * * 0.1 percent; Standard error in parentheses.

Appendix C. Reasons for using the varying coefficient C-D model

C.1 Traditional analysis is invalid

Theoretically, the motivation for using the varying coefficient model is introduced in the first three paragraphs of the paper: 1) several waves of institutional reforms and market deregulations have reshaped China's agriculture and hence the input-output relation may vary across time; and 2) the difference and change in the structure of the sector (ratios of the four segments) can also change the aggregated input-output relation because the relation is segment-specific, which leads to province-variant input elasticities. If the true input-output relation is indeed fixed as the traditional analysis assumed, we should find stable estimations using the varying coefficient model, rather than those with great variation in Figs. 2 and 3 (we add 95% confidence intervals in Fig. 2 by employing Efron's nonparametric bias-corrected and accelerated (BCa) bootstrap method with 10,000 replications

(Briggs et al., 1999)). More specifically, the first argument (time-variant coefficients) is verified as the lines in Fig. 2 are not flat, and the second argument (province-variant coefficients) is verified since the coefficients vary across provinces in Fig. 3. Therefore, we do not use the traditional analysis.

C.2 The varying coefficient C-D model is robust

However, the proof of the invalid fixed input-output relation assumption only goes against the utilization of the traditional analysis, not verifying the accuracy of our varying coefficient model. In order to check the robustness of our estimation, this paper introduces two more models for comparison.

Firstly, this paper assumes that the functional form follows the Transcendental Logarithmic (T-L) model rather than the Cobb-Douglas (C-D) model to see if the result varies. The semi-varying coefficient stochastic frontier model with T-L form is

$$y_{it} = h_0(\theta_{it}) + \sum_{k=1}^{p} h_k(\theta_{it}) x_{it}^k + 0.5 \sum_{k=1}^{p} \sum_{l=1}^{p} h_{kl}(\theta_{it}) x_{it}^k x_{it}^l + \tau Z + \nu_{it} - u_i \tag{C.1}$$

Although semiparametric techniques are utilized in varying coefficient models, both C-D and T-L models require assumption of the formation of the production function. This paper therefore introduces a third approach to further relax this assumption. The problem of a nonparametric method that avoids rigid functional forms is that it can violate economic theory and lead to an implausible prediction. This dilemma is tackled by a semiparametric model, subject to some restrictions suggested by economic theory. Diewert and Wales (1987) emphasize that production functions are monotone increasing and concave with respect to inputs. Monotonicity guarantees that companies produce more with more inputs, while concavity guarantees decreasing marginal products when input increases. Wu and Sickles (2013) develop a semi-parametric function $\xi(\cdot)$ with monotonicity and concavity restrictions:

$$\xi(x) = \int_0^x \exp\left(\int_0^s - g(h(w))dw\right)ds,$$

where global monotonicity is achieved since the positive exponential function embedded in the integral transformation guarantees a non-negative first derivative $\xi'(x) = \exp(\cdot) \geq 0$. Concavity is obtained after $g(x) = x^2$ in the second integral is assumed, which ensures that the second derivative $\xi''(x) = \xi'(x)[= -g(h(w))] \leq 0$. Then, this study opts to use the spline method to model $h(w)$ nonparametrically. Specifically, truncated power series splines $\phi(x) = (1, x, \ldots, x^p, (x-k_1)_+^p, \ldots, (x-k_M)_+^p)^T$ are employed, where $0 < k_1 < \ldots < k_M < 1$ are a series of knots of the spline basis functions, $(x)_+ = \max(x, 0)$, and p is a positive integer. Then $h(x) = c^T\phi(x)$ where c vectors the coefficients with a compatible dimension. Finally, this paper follows Gong (2016) to build a new semiparametric stochastic frontier production under shape constraints in the form:

$$Y_{it} = A \cdot \left[\prod_{k=1}^{M} \xi_k\left(X_{it}^k\right)\right] \cdot \exp(\tau Z) \cdot \exp(v_{it}) \cdot \exp(-u_t), \tag{C.2}$$

where $A = \exp(\alpha)$ is the intercept. $\xi_k(X_{it}^k)$ is a monotone increasing and concave function of the k-th input.

This paper uses the method in Eller et al. (2011) to check the robustness of our varying coefficient model with the C-D model. Table C.1 reports the estimation results of the OLS regressions, where the TFP of the varying coefficient C-D model (TFP^{CD}) is the independent variable, while the TFP of the varying coefficient T-L model (TFP^{TL}) and the TFP of the shape constraint model ((TFP^{SC}) are the dependent variables, respectively. The result verifies the robustness of our varying coefficient model with the C-D form. This table also calculates the correlation between the dependent variables and the independent variable. Both correlation coefficients in the table are above 0.7, which implies a strong uphill (positive) linear relationship across the estimation and again confirms the robustness.

Table C.1
Robustness of the efficiencies across models.

	TFP^{TL}	TFP^{SC}
TFP^{CD}	1.070***	1.034***
	(0.024)	(0.020)
Constant term	−0.207	1.534***
	(0.177)	(0.151)
Correlation	0.913	0.895

C.3 The Varying coefficient C-D model is better

To summarize, the results from the varying coefficient C-D model, the varying coefficient T-L model, and the semiparametric model under shape constraints are robust. This paper uses the varying coefficient C-D model rather than the other two, since it can easily derive the varying input elasticity that is needed in the second step analysis. Moreover, the robust result in the shape-constraint method that relaxes formation assumption further confirms the validity of using the simple C-D form. When formation assumption is valid, it is good to use the simple form for degree of freedom reasons.

References

Ackerberg, D.A., Caves, K., Frazer, G., 2015. Identification properties of recent production function estimators. Econometrica 83, 2411–2451.

Ahmad, I., Leelahanon, S., Li, Q., 2005. Efficient estimation of a semiparametric partially linear varying coefficient model. Ann. Stat. 258–283.

Aigner, D., Lovell, C.A., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econom. 6, 21–37.
Amsler, C., Prokhorov, A., Schmidt, P., 2016. Endogeneity in stochastic frontier models. J. Econom. 190, 280–288.
Battese, G.E., Coelli, T.J., 1992. Frontier Production Functions, Technical Efficiency and Panel Data: with Application to Paddy Farmers in India. Springer, Netherlands.
Battese, G.E., Rao, D.P., 2002. Technology gap, efficiency, and a stochastic metafrontier function. Int. J. Bus. Econ. 1, 87–93.
Battese, G.E., Rao, D.P., O'donnell, C.J., 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. J. Prod. Anal. 21, 91–103.
Brümmer, B., Glauben, T., Lu, W., 2006. Policy reform and productivity change in Chinese agriculture: a distance function approach. J. Dev. Econ. 81, 61–79.
Briggs, A.H., Mooney, C.Z., Wonderling, D.E., 1999. Constructing confidence intervals for cost-effectiveness ratios: an evaluation of parametric and non-parametric techniques using Monte Carlo simulation. Stat. Med. 18, 3245–3262.
Cao, K.H., Birchenall, J.A., 2013. Agricultural productivity, structural change, and economic growth in post-reform China. J. Dev. Econ. 104, 165–180.
Carter, C.A., Estrin, A.J., 2001. Market reforms versus structural reforms in rural China. J. Comp. Econ. 29, 527–541.
Chen, P.C., Ming-Miin, Y.U., Chang, C.C., Hsu, S.H., 2008. Total factor productivity growth in China's agricultural sector. China Econ. Rev. 19, 580–593.
Chen, W., 2006a. Productivity growth, technical progress and efficiency change in Chinese Agriculture:1990-2003. China Railw. Sci. 16, 203–222.
Chen, W., 2006b. Productivity Growth,technical progress and efficiency change in Chinese Agriculture:1990-2003. China Railw. Sci. 16, 203–222.
Chien, S.S., 2015. Local farmland loss and preservation in China—a perspective of quota territorialization. Land Use Pol. 49, 65–74.
Coelli, T., Henningsen, A., Henningsen, M.A., 2012. Package 'frontier'. Technical Report, R.
Cornwell, C., Schmidt, P., Sickles, R.C., 1990. Production frontiers with cross-sectional and time-series variation in efficiency levels. J. Econom. 46, 185–200.
Dekle, R., Vandenbroucke, G., 2010. Whither Chinese Growth? A sectoral growth accounting approach. Rev. Dev. Econ. 14, 487–498.
Diewert, W.E., Wales, T.J., 1987. Flexible functional forms and global curvature conditions. Econometrica 55, 43–68.
Eller, S.L., Hartley, P.R., Medlock, K.B., 2011. Empirical evidence on the operational efficiency of national oil companies. Empir. Econ. 40, 623–643.
Fan, J., Huang, T., 2005. Profile likelihood inferences on semiparametric varying-coefficient partially linear models. Bernoulli 11, 1031–1057.
Fan, J., Li, R., 2004. New estimation and model selection procedures for semiparametric modeling in longitudinal data analysis. J. Am. Stat. Assoc. 99, 710–723.
Fan, J., Zhang, W., 2008. Statistical methods with varying coefficient models. Stat. Interface 1, 179.
Fan, S., 1991. Effects of technological change and institutional reform on production growth in Chinese agriculture. Am. J. Agric. Econ. 73, 266–275.
Fan, S., Pardey, P.G., 1997. Research, productivity, and output growth in Chinese agriculture ☆. J. Dev. Econ. 53, 115–137.
Fan, S., Zhang, L., Zhang, X., 2002a. Growth, Inequality, and Poverty in Rural China: the Role of Public Investments, pp. 417–419.
Fan, S., Zhang, L., Zhang, X., 2004. Reforms, investment, and poverty in rural China. Econ. Dev. Cult. Change 52, 395–421.
Fan, S.G., Zhang, X.B., Dong, X.Y., Song, S., Zhang, X., 2002b. Production and productivity growth in Chinese agriculture: new national and regional measures. Econ. Dev. Cult. Change 50, 819–838.
Fan, Y., Li, Q., Weersink, A., 1996. Semiparametric estimation of stochastic production frontier models. J. Bus. Econ. Stat. 14, 460–468.
Gong, B., 2016. Efficiency and Productivity Analysis of Multidivisional Firms. Department of Economics, vol. Ph.D. Rice University.
Gong, B., 2018. The shale technical revolution – cheer or Fear? Impact analysis on efficiency in the global oilfield service market. Energy Pol. 112, 162–172.
Greene, W.H., 1990. A gamma-distributed stochastic frontier model. J. Econom. 46, 141–163.
Gunaratne, L.H., Leung, P., 1996. Asian black tiger shrimp industry: a meta-production frontier analysis. The farm performance study on which these research papers were based was funded by the Asian Development Bank under RETA 5534, and implemented by the Network of Aquaculture Centres in Asia-Pacific in 1994-1995. In: Leung, PingSun, Sharma, Khem R. (Eds.), University of Hawaii at Manoa, Honolulu, Hawaii, USA, p. 55.
Hastie, T., Tibshirani, R., 1993. Varying-coefficient models. J. Roy. Stat. Soc. B 757–796.
Hastie, T.J., Tibshirani, R.J., 1990. Generalized Additive Models. CRC Press.
Hayami, Y., 1969. Sources of agricultural productivity gap among selected countries. Am. J. Agric. Econ. 51, 564–575.
Hayami, Y., Ruttan, V.W., 1970. Agricultural productivity differences among countries. Am. Econ. Rev. 60, 895–911.
Hayami, Y., Ruttan, V.W., 1971. Agricultural Development: an International Perspective. The Johns Hopkins Press, Baltimore, Md/London.
Hayfield, T., Racine, J.S., 2008. Nonparametric econometrics: the np package. J. Stat. Software 27, 1–32.
Henningsen, A., Kumbhakar, S., 2009. Semiparametric stochastic frontier analysis: an application to Polish farms during transition. In: European Workshop on Efficiency and Productivity Analysis (EWEPA) in Pisa, Italy, 24. June.
Hu, X., 2014. Estimation in a semi-varying coefficient model for panel data with fixed effects. J. Syst. Sci. Complex. 27, 594–604.
Huang, J., Rozelle, S., 1996. Technological change: rediscovering the engine of productivity growth in China's rural economy. J. Dev. Econ. 49, 337–369.
Huang, Y., 1998. Agricultural Reform in China. Cambridge University Press.
Kalirajan, K.P., Obwona, M.B., Zhao, S., 1996. A decomposition of total factor productivity growth: the case of Chinese agricultural growth before and after reforms. Am. J. Agric. Econ. 78, 331–338.
Kim, Y.-J., 2013. A partial spline approach for semiparametric estimation of varying-coefficient partially linear models. Comput. Stat. Data Anal. 62, 181–187.
Kneip, A., Sickles, R., Song, W., 2003. On Estimating a Mixed Effects Model with Applications to the U.S. Banking Industry. Mimeo, Rice University.
Kumbhakar, S.C., 1990. Production frontiers, panel data, and time-varying technical inefficiency. J. Econom. 46, 201–211.
Kumbhakar, S.C., Sun, K., 2013. Estimation of a flexible stochastic cost frontier model with environmental factors subject to economic constraints. In: European Economic Association & Econometric Society 2013 Parallel Meetings. Gothenburg, Sweden.
Lambert, D.K., Parker, E., 1998. Productivity in Chinese provincial agriculture. J. Agric. Econ. 49, 378–392.
Lau, L.J., Yotopoulos, P.A., 1989. The meta-production function approach to technological change in world agriculture. J. Dev. Econ. 31, 241–269.
Lee, Y.H., Schmidt, P., 1993. A production frontier model with flexible temporal variation in technical efficiency. The measurement of productive efficiency: Techniques and applications 237–255.
Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Rev. Econ. Stud. 70, 317–341.
Lin, J.Y., 1992. Rural reforms and agricultural growth in China. Am. Econ. Rev. 82, 34–51.
Lin, J.Y., 1995. Endowments, technology, and factor markets: a natural experiment of induced institutional innovation from China's rural reform. Am. J. Agric. Econ. 77, 231–242.
Liu, S.W., Zhang, P.Y., He, X.L., Jing, L., 2015. Efficiency change in North-East China agricultural sector: a DEA approach. Agric. Econ. 61, 522–532.
Lohmar, B., Gale, F., Tuan, F., Hansen, J., 2009. China's Ongoing Agricultural Modernization: Challenges Remain after 30 Years of Reform. Economic Information Bulletin - USDA Economic Research Service.
Lu, Q., Yang, C., Li, J., 2008. Rural-urban migration, rural household income and sustainable development in rural areas of China. Chin. J. Popul. Res. Envirn. 06, 70–73.
Mao, W., Koo, W.W., 1997. Productivity growth, technological progress, and efficiency change in Chinese agriculture after rural economic reforms: a DEA approach. China Econ. Rev. 8, 157–174.
Mcmillan, J., Whalley, J., Zhu, L., 1989. The impact of China's economic reforms on agricultural productivity growth. J. Polit. Econ. 97, 781–807.
Meeusen, W., Van den Broeck, J., 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. Int. Econ. Rev. 435–444.
Mundlak, Y., Hellinghausen, R., 1982. The intercountry agricultural production function: another view. Am. J. Agric. Econ. 64, 664–672.
Oi, J.C., 1999. Two decades of rural reform in China: an overview and assessment. China Q. 159, 616–628.
Olley, G.S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64, 1263–1297.
Pratt, A.N., Yu, B., Fan, S., 2008. The total factor productivity in China and India: new measures and approaches. China Agric. Econ. Rev. 1, 9–22.
Schmidt, P., Sickles, R.C., 1984. Production frontiers and panel data. J. Bus. Econ. Stat. 2, 367–374.
Sharma, K.R., Leung, P., 2000. Technical efficiency of carp pond culture in South Asia: an application of a stochastic meta-production frontier model. Aquacult. Econ. Manag. 4, 169–189.
Sickles, R.C., 2005. Panel estimators and the identification of firm-specific efficiency levels in parametric, semiparametric and nonparametric settings. J. Econom. 126, 305–334.
Sicular, T., 1995. Redefining state, plan and market: China's reforms in agricultural commerce. China Q. 144, 1020–1046.
Stasinopoulos, D.M., Rigby, R.A., 2007. Generalized additive models for location scale and shape (GAMLSS) in R. J. Stat. Software 23, 1–46.
Stevenson, R.E., 1980. Likelihood functions for generalized stochastic frontier estimation. J. Econom. 13, 57–66.
Su, L., Ullah, A., 2006. Profile likelihood estimation of partially linear panel data models with fixed effects. Econ. Lett. 92, 75–81.
Sun, K., Kumbhakar, S.C., 2013. Semiparametric smooth-coefficient stochastic frontier model. Econ. Lett. 120, 305–309.
Sun, Y., Carroll, R.J., Li, D., 2009. Semiparametric estimation of fixed effects panel data varying coefficient models. Adv. Econom. 25, 101–129.
Tong, H., Fulginiti, L.E., Sesmero, J.P., 2009. Chinese regional agricultural productivity: 1994-2005. Gen. Info. 14.
Wang, S.L., Tuan, F., Gale, F., Somwaru, A., Hansen, J., 2013. China's regional agricultural productivity growth in 1985–2007: a multilateral comparison. Agric. Econ. 44, 241–251.
Wen, G.J., 1993. Total factor productivity change in China's farming sector: 1952-1989. Econ. Dev. Cult. Change 42, 1–41.
Wu, X., Sickles, R., 2013. Semiparametric Estimations under Shape Constraints with Applications to Production Functions.
Wu, Y., 1995. Productivity growth, technological progress, and technical efficiency change in China: a three-sector analysis 1. J. Comp. Econ. 21, 207–229.

Wu, Y., 2011. Total factor productivity growth in China: a review. J. Chin. Econ. Bus. Stud. 9, 111–126.

Yao, S.J., 1994. Agricultural Reforms and Grain Production in China. Palgrave Macmillan, UK.

Zhang, R., Sun, K., Delgado, M.S., Kumbhakar, S.C., 2012. Productivity in China's high technology industry: regional heterogeneity and R&D. Technol. Forecast. Soc. Change 79, 127–141.

Zhang, Y., Brümmer, B., 2011. Productivity change and the effects of policy reform in China's agriculture since 1979. Asian Pac. Econ. Lit. 25, 131–150.

Zhou, L.I., Zhang, H.P., 2013. Productivity growth in China's agriculture during 1985–2010. J. Integr. Agric. 12, 1896–1904.