Induced Bias of Technological Change in Agriculture and Structural Transformation: A Translog Cost Function Analysis of Chinese Cereal Production

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ABSTRACT

It is always controversial how China succeeded in maintaining a high degree of cereal self-sufficiency rate during its rapid structural transformation. This study attempts to address this question by examining the factor inputs and biased technological changes in Chinese cereal production. We estimate a translog cost function and deduce the biased technological changes in cereal production. The results suggest that Chinese cereal production has made adjustments in factor input and adopted various biased technologies to respond to its structural transformation and changes in the prices of factors. A shift from labor-using to labor-saving technology promotes its labor transfers across sectors. The technology of strong land- and fertilizer-using has replaced that of land- and fertilizer-saving to offset the effect of losing labor and to support China's cereal production. And the technology of capital-saving is being utilized to save agricultural surplus for its structural transformation.

Keywords: cereal production, translog cost function, technological change

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1. Introduction

China's achievement in maintaining food supply is remarkable. Most praise has focused on the fact that China succeeded in feeding the largest population (1.4 billion) as well as maintaining a high food self-sufficiency rate.[1] However, it is more important to note that such an achievement in food supply has taken place in the context of China's rapid structural transformation and economic growth. That is to say, China succeeded in maintaining a high food self-sufficiency rate while transferring large amounts of resources, such as labor (Zhao, 1999; Cai and Wang, 2008; Cai, 2010; Dong et al., 2018) and land (Yang and Li, 2000; Mullan et al., 2011; Wang et al., 2019), from the agricultural sector to the non-agricultural sector. In that sense, when attempting to explain China's fabulous achievement in domestic food production and supply, it is necessary and important to examine its inner linkage with the transfers of factors among sectors along with China's structural transformation.

Unfortunately, most studies only focus on China's food production per se but ignore its close relationship with China's structural transformation. For example, Gong (2020) argues that increased input was likely the dominant driver behind China's agricultural growth. Lin (1992) believes that the implementation of the household responsibility system contributed to more than half of China's achievement in food production by assessing the effect of decollectivization, price adjustment, and other reforms during 1978-1984. McMillan et al. (1989) and Fan et al. (2004) further prove that rural economic reforms piloted growth of China's agricultural production during 1978-1984. However, the impact of economic reforms on China's agricultural productivity has greatly diminished since the mid-1980s (McMillan et al., 1989; Lin, 1992; Kalirajan et al., 1996; Fan, 1997; Fan et al., 2004; Chen et al., 2008; McArthur and McCord, 2017; Shen et al., 2019; Wang et al., 2019). Thus, a recent wave of literature focuses on identifying the major determinants of total factor productivity (TFP) growth to account for China's food production from the perspective of TFP growth (Chen et al., 2008; Li et al., 2008; Gong, 2018 and 2020; Wang et al., 2019).

Considering that few studies have succeeded in linking China's food production with its simultaneous structural transformation, this paper provides the first empirical examination of the link between China's food production and its structural transformation by measuring the induced bias of technological change in China's agricultural sector. More specifically, it attempts to estimate a translog cost function of food production to investigate the transition of the induced bias of technological change in Chinese agriculture caused by China's structural transformation and the consequent changed prices of factor inputs.

Although the methodology has been widely used in analyzing the agriculture of many developed countries[2], there is rare research applying it to the agriculture of developing

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[1] In the mid-1990s, China adopted a food security strategy that equates food security to self-sufficiency in staple foods. The self-sufficiency target of 95% for such main crops as rice, wheat, maize, and soybeans was established in 1996. This target has been achieved over the past two decades, except for soybeans (Ito and Ni, 2013; Ghose, 2014).

[2] Nghiep (1979) applies it to examine the technological changes in prewar Japanese agriculture. Lopez (1980) and Clark and Youngblood (1992) estimate the translog cost function for Canadian agriculture separately. Glass and McKillop (1989) estimate a two-output cost function model to investigate Northern Ireland agriculture. Binswanger (1974b), Ray (1982), and Moss et al. (2003) estimate the translog cost function for the agriculture of the U.S.,

countries including China. We suppose the primary reason for such scarcity of empirical studies in this field is that data on the price of production factors, especially on the price of capital input in agricultural production, is difficult to obtain in developing countries.

To fill such a gap and estimate the translog cost function for Chinese agriculture, this study collects the cost-benefit data of China's cereal production and constructs price series of primary factor inputs. Then, by modeling the translog cost function into the constructed dataset, it measures the changes in the induced bias of technological change in Chinese cereal production resulting from the changes in relative prices of factor inputs. Our estimate results suggest that China's cereal production has adopted a model of labor- and capital- saving, land- and fertilizer-using technology during 1975-2017.

This finding can be taken as strong evidence on how China's structural transformation has shaped the technological adoption in its agricultural production and how it succeeded in achieving a high degree of food self-sufficiency in the context of rapid structural transformation. Essentially, structural transformation makes labor and land expensive relatively while making capital and fertilizer cheap relatively. This explains why China cereal production tends to adopt a technology of labor-saving and fertilizer-using. Nevertheless, the finding that it tends to use a technology of capital-saving and land-using seems inconceivable. Especially, the adoption of capital-saving is directly opposite to findings in other countries, such as the U.S. and Japan (Binswanger, 1974b; Kawagoe et al., 1986; Kuroda, 1988; Archibald and Brandt, 1991). However, once familiar with China's land policy and its capital market, there is no wonder such findings were made. On the one hand, China has always adopted an active policy of cultivated land protection, and due to China's land tenure system, cultivated land cannot be circulated or changed at will, especially in terms of cereals. On the other, in terms of capital, the tendency of capital-saving technology is mostly due to the lack of agricultural investments and capital flows from the agricultural sector to the non-agricultural sector, which is another consequence of China's structural transformation.[3] We believe these findings will be a great supplementary to the existing literature.

The remainder of this article is structured as follows. Section 2 introduces the cereal production in China. Section 3 describes the methodology and data used in this study. Section 4 summaries the estimation process and reports the results. Section 5 discusses and concludes the findings.

2. Cereal Production in China

In China, cereal grains consist of cereals, tubers, and beans, and the three main cereals refer to rice, wheat, and maize. Figure 1 shows the changes in the composition of yield and sown areas of China's main cereals production from 1952 to 2017. Firstly, we find that China's cereal yield is growing steadily except for significant declines in 1960-1962 and 2000-2003. These falloffs result from political mistakes (the Great Leap Forward) and the drastic reduction of arable land, respectively. In contrast, the sown

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respectively. Kawagoe, Otsuka, and Hayami (1986) employ the two-level constant elasticity of substitution production function to account for the different mechanisms between Japanese agriculture and U.S. agriculture.

[3] Dong's study (2021) measures the scale of capital flows between the agricultural and non-agricultural sectors in China and proves that a considerable amount of agricultural surplus has been transferred to the non-agricultural sector in China from 1952 to 2018.

area is slowly decreasing though there has been a rebound recently. The cereal yield trends and its sown area imply that cereal yield per unit area is increasing in China.

Secondly, the three main cereals clearly account for a vast majority of all types of cereals, both in terms of yield and area. Additionally, their percentages in total cereal yield and total cereal sown area have also been increasing in recent years. Thus, it is convenient and reasonable to investigate the production of the three main cereals instead of all types of cereals considering the inconsistent availability of data for all other cereal types across many years. This study will primarily focus on the production of the three main cereals in China.

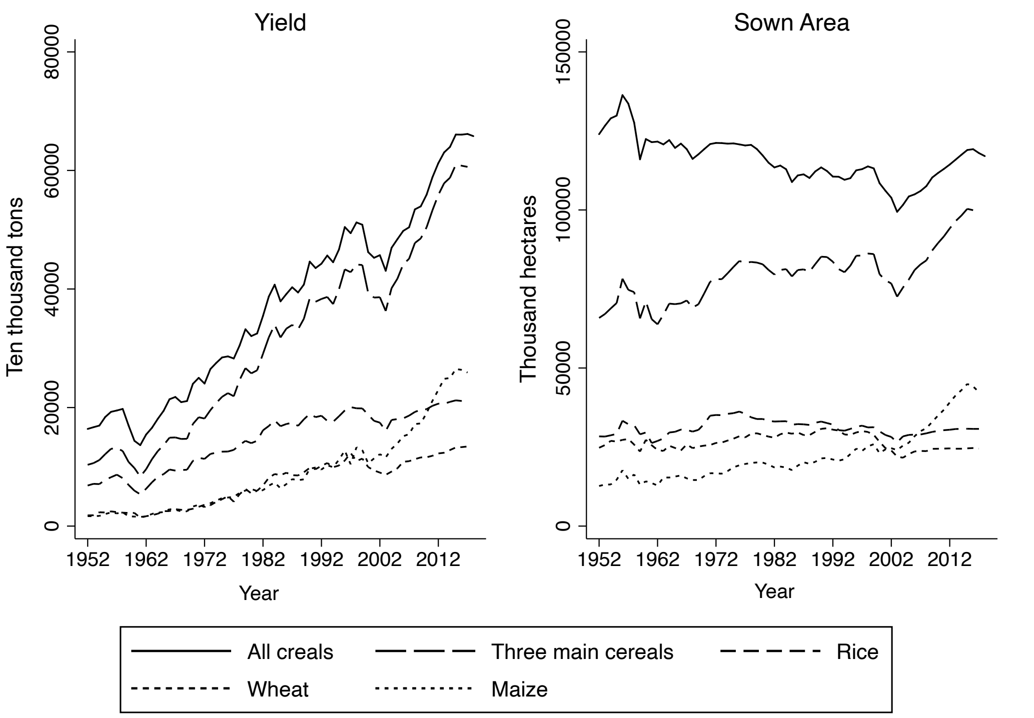

Figure 1. Composition of Main Cereals Production in China

Source: Data are from Database of National Bureau of Statistics of China.

Figure 2 summarizes the nominal prices and inputs volume of the four production factors - labor, capital, land, and fertilizer - in China's three main cereals from 1952.[4] Due to a lack of official data, the figures for capital and fertilizer only start from 1975.

Concerning factor prices, the nominal prices of all production factors rise except that of capital, which was rising before 1997 but fell away thereafter. Of the three nominal prices that keep increasing, the most rapid are labor wage and land rent, both of which have maintained a contemporary growth trend.

In responding to an escalating labor wage, labor days per mu[5] increased after 1952,

[4] We do not adopt the lending interest rates as capital price. Considering that the rural financial market is quite underdeveloped in China, the lending interest rate cannot reflect the changes in the actual price of capital service for agricultural production and will be a poor measure of capital price.

[5] Mu is a Chinese unit of area, which equivalent to 1/15 hectares.

peaked around 1977, and dropped thereafter. Corresponding to the falling capital price, the capital cost per mu tends to accelerate after the late 1990s. There was little overall change in land used for the three main cereals production from 1952 to the mid-1990s. However, with skyrocketing land rent, land input fell quickly around 2000 but rose back to previous levels quickly, implying rigid demand for land in Chinese cereal production. Besides, I speculate the steep rise in grain prices had influenced the upward trend of land used after the 2000s. Fertilizer input per mu increased annually until 1989, dropping suddenly when fertilizer prices began to rise. Subsequently, fertilizer input per mu has remained at a low level compared with before.

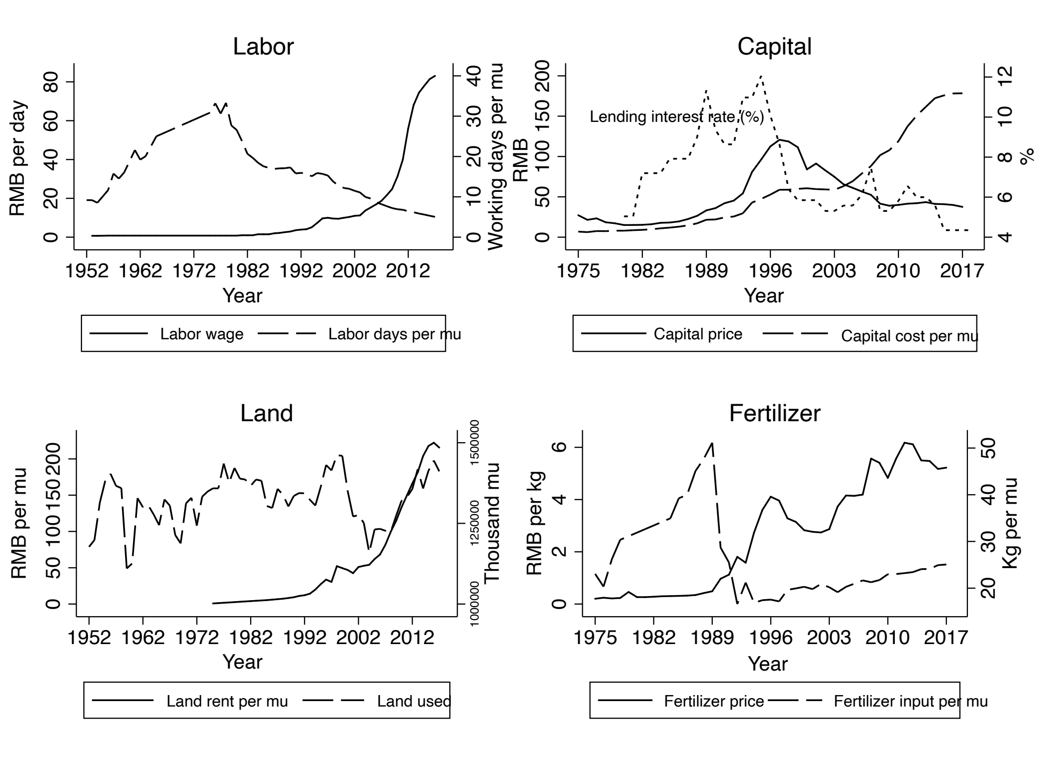

Figure 2. Nominal Prices and Inputs of Each Factor in the Three Main Cereals Production

Source: Calculated by the authors.

3. The Translog Cost Function for Cereal Production

3.1. Model specification

The input amount of production factors will vary along with the changes in the price of each factor, and production technology will change accordingly. To capture the mechanisms of those changes, we explore a translog cost specification in this study to estimate the elasticities of substitution between pairs of inputs and thereby to measure the induced bias of technological change in China's cereal production.

The translog specification of the dual cost function is proposed to measure technological change biases (Christensen et al., 1973; Berndt and Christensen, 1973; Binswanger 1974a and 1974b), which has the general form of

$$C = f(Q, P, T), \quad (1)$$

where C is cost of cereal production, Q is cereal output, P is the price of input, and T is an index of time.

Mathematically, letting c_t be the minimum cost of producing a given amount of cereal output q_t, with given input price, p_{it}, of input i, a second order Taylor-series expansion of equation (1) becomes

$$\ln c_t = \alpha_o + \alpha_q \ln q_t + \sum_i \alpha_i \ln p_{it} + 1/2\beta_{qq} (\ln q_t)^2 + 1/2 \sum_i \sum_j \beta_{ij} \ln p_{it} \ln p_{jt} + \sum_i \gamma_{iq} \ln p_{it} \ln q_t + \delta f(t), \quad (2)$$

where t is an annual index of time. This translog cost function allows arbitrary and variable elasticities of substitution among input factors. This form can also be used to approximate any one of the known costs and production functions with the proper set of constraints on its parameters, which includes[6]

i) Equality of the cross derivatives (symmetry constraint):

$$\beta_{ij} = \beta_{ji}, \qquad \text{for all } i,\ j,\ i \neq j. \quad (3)$$

ii) Linear homogeneity in input prices:

$$\sum_i \alpha_i = 1;\ \sum_i \alpha_{ij} = 0;\ \sum_j \alpha_{ij} = 0; \quad \text{for all } i,\ j,\ i \neq j. \quad (4)$$

iii) Monotonicity (using Shephard's lemma):

$$\frac{\partial \ln c_t}{\partial \ln p_{it}} = \alpha_i + \sum_j \beta_{ij} \ln p_{jt} + \gamma_{iq} \ln q_t \geq 0, \quad i = 1, \ldots, n. \quad (5)$$

Furthermore, equation (5) can be rewritten as

$$\frac{\partial \ln c_t}{\partial \ln p_{it}} = \frac{\partial c_t}{\partial p_{it}} \cdot \frac{p_{it}}{c_t} = s_{it}, \quad (6)$$

where s_{it} is the cost share of input i.

iv) Concavity in input prices:

$$\frac{\partial^2 c_t}{\partial p_{it} \partial p_{jt}} < 0. \quad (7)$$

Under those constraints, the Allen partial elasticities of substitution can be computed as

$$\sigma_{ijt} = \frac{\beta_{ij}}{s_{it} s_{jt}} + 1, \qquad \text{for all } i \neq j. \quad (8)$$

and

$$\sigma_{iit} = \frac{1}{s_{it}^2} (\beta_{ii} + s_{it}^2 - s_{it}), \qquad \text{for all } i, \quad (9)$$

where σ_{ij} is partial elasticities of substitution. The cross- and own- partial elasticities of demand for input i can be separately computed as

$$\epsilon_{ijt} = \sigma_{ij} \cdot s_{jt}, \qquad \text{for all } i \neq j. \quad (10)$$

and

$$\epsilon_{iit} = \sigma_{ii} \cdot s_{it}, \qquad \text{for all } i. \quad (11)$$

3.2. Data

[6] Refer to Christensen et al. (1973) and Binswanger (1974a, 1974b).

Annual data used for estimation are obtained from the *National Cost and Profit of Agricultural Products Materials Compilation*, compiled by the Prices Division of the National Development and Reform Commission. They include national-level figures of outputs and inputs per mu in the production of the three main cereals for the period 1975-2017.[7] The total nominal cost is measured by the annual production cost per mu (RMB per mu) for the three main cereals consisting of labor cost, capital cost, land cost, and fertilizer cost. The total real cost per mu is the deflated figures of the total nominal cost per mu (at 2010 prices) by the price index of agricultural production materials. The aggregate output of the three main cereals is measured by the annual production per mu (kg per mu) of each cereal. The inputs costs are measured as follows:

(i) The nominal labor cost is measured by the sum of home labor cost per mu and employed labor cost per mu[8], while the real labor cost is the deflated figures (at 2010 prices) of the nominal labor cost by China's consumer price index.

(ii) The nominal capital cost consists of leasing and operating expenses[9] (involving mechanical operation fees, drainage fees, and animal power fees), repair and maintenance fees[10], and deprecation of fixed assets. And the real capital cost is the deflated figures (at 2010 prices) of the nominal capital cost by China's price index of fixed assets formation.

(iii) The nominal land cost is measured by the land cost per mu (consisting of lent-land rent and self-land rent)[11]. And the real land cost per mu is the deflated figures (at 2010 prices) of the nominal land cost by China's index of secondary industry.

(iv) The nominal fertilizer cost is measured by the fertilizer fee per mu. The real fertilizer cost per mu is the deflated figures (at 2010 prices) of the nominal fertilizer cost by the fertilizer price index.

The real cost share of each input factor can be obtained by dividing the real cost of each input factor per mu to the total real cost per mu. The prices of the four inputs are measured as follows:[12]

(i) The labor input price is measured by the average labor day wage for each year, and then deflated by the consumer price index (at 2010 prices).

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[7] We use the aggregated figures of the three main cereals, including outputs and inputs published by the *National Cost and Profit of Agricultural Products Materials Complication*.

[8] The official data of labor cost per mu from 1975 to 1989 are missing due to a lack of figures of employed labor cost per mu. We replace the figures of labor cost per mu with those of home labor cost, assuming the employed labor cost per mu is zero for those years. This assumption is reasonable considering the official figures of labor cost per mu are equal to those of home labor cost per mu from 1990 to 1997, implying that before 1997 there was almost no employed labor cost in the three main cereals production.

[9] The official data of leasing and operating expenses per mu from 1975 to 1989 are missing except the years of 1978, 1985, and 1988. Therefore, we replace the missing values with the sum of mechanical operation fees, drainage fees, and animal power fees according to its definition.

[10] The official data of repair and maintenance fees from 1975 to 1989 are lacking barring 1978, 1985, and 1988. The missing values from 1975 to 1984 are calculated as $v_{t-1} = v_t - (v_{1985} - v_{1978})/7$, where v is value and t denotes year. Similarly, the missing values in 1986 and 1987 are calculated as $v_{t-1} = v_t - (v_{1988} - v_{1985})/3$, where v is value and t denotes year. Finally, we replace the figure in 1989 with the average of 1988 and 1990.

[11] The official data of land cost per mu from 1975 to 1989 are missing except for 1978, 1985, and 1988. We recalculate the missing values of those years with the same method as we used to deal with the missing values of repair and maintenance fees.

[12] The data on the consumer price index, the index of the secondary industry, the price index for investment in fixed assets, the price index for means of agricultural production, and the fertilizer price index are from the national database of the Chinese National Bureau of Statistics. The data on the price index of fixed assets formation are from Dong's study (2018).

(ii) The capital input price is calculated through dividing national total capital cost to produce the three main cereals by the number of tractors used in production. It is then deflated by the price index of fixed assets formation (at 2010 prices).

(iii) The land input cost is measured by the nominal land cost per mu, and then deflated by the index of secondary industry (at 2010 prices).

(iv) There is no official data on fertilizer prices. We calculate the fertilizer price through dividing the nominal fertilizer fee per mu (RMB per mu) by the fertilizer input per mu (kg per mu).[13] It is then deflated by the fertilizer price index (at 2010 prices).

4. Empirical Results

4.1. Estimates for the translog cost function

The translog cost function should be estimated as a system of equations. That means, if estimating the translog cost function of the three main cereals, equation (2), on its own, it is likely that parameter estimates will be inefficient due to the high correlation between the explanatory variables (Glass and McKillop, 1989). A better way is that equation (2) is estimated jointly with the cost share equations of each input, equation (6).

Before proceeding, the symmetry constraint, the linear homogeneity constraint, and the monotonicity constraint are assumed and forced into the estimated system. Thus, there is no necessity to test them separately. However, the translog function's concavity is data dependent; hence concavity cannot be guaranteed when using the usual estimation produce. Unfortunately, our data does not satisfy the concavity constraint.[14] We impose local concavity into our model to solve this problem.[15] After repeated trials, we select the observation of 1975 as the normalization point and use feasible generalized nonlinear least squares regression to estimate. The results of three-stage regression and Zellner's seemingly unrelated regression, in which concavity is not imposed, are also reported.

In terms of the setting of neutral technological change, most studies involve an index of time directly in their estimation models (Binswanger, 1974b; Ray, 1982; Glass and McKillop, 1989; Archibald and Brandt, 1991). We conduct the estimates with and without a time index separately. It is worth noting that a new method of introducing Kalman filter into translog function is proposed (Jin and Jorgenson, 2010; Jorgenson et al., 2013). This method uses latent variables instead of a constant time trend to describe the technological change rate. We also adopt this method for comparison.

Table 1 summarizes the results. Overall, our models perform remarkably well, especially with local concavity imposed. It is noteworthy that the models without the

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[13] The official data of fertilizer input per mu are missing from 1979 to 1983. The missing values from 1979 to 1983 are calculated as $v_{t-1} = v_t - (v_{1984} - v_{1978})/6$, where v is value and t denotes year.

[14] A necessary and sufficient condition for concavity is that the Hessian matrix of the cost function must be negative semi-definite. The test process can refer to Baum and Linz (2009).

[15] Several solutions exist to cope with this problem. One way is to impose global curvature restrictions (Wiley et al., 1973; Diewert and Wales, 1989 and 1995). However, imposing global restrictions on the translog cost functions will destroy flexibility property. Another option is to impose concavity locally at a chosen reference point (Diewert and Wales, 1989; Ryan and Wales, 2000; Chua et al., 2005). This method does not destroy the flexibility of the functional form. Moreover, imposing local concavity at one point will lead to concavity satisfaction at most or all data points (Ryan and Wales, 2000; Sauer et al., 2006; Hussain and Bernard, 2016).

trend item perform better than those with the trend item for all methods. It seems involving a time trend into the estimation of the translog cost function is not a good choice in China's case.

Given that imposing local concavity uses the rescaled data, it makes no sense to compare the coefficients directly. What we are principally concerned with is to obtain as accurate estimation results as possible to estimate partial elasticities of substitution as well as price elasticities of demand for input and thus to deduce the biased technological change. Here, Model 5, with local concavity imposed and with no time trend item, has the smallest AIC and BIC, which also performs better in R^2. Hence, we adopt the estimation results of Model 5 for the following analysis. When estimating neutral technological change, we also include the estimation results of Kalman Filter Estimation (Model 7) to compare the findings using Solow residuals method with those using the latent variable method.

Table 1. Estimated Coefficients of the Translog Cost Function

	Three-stage regression		Zellner's seemingly unrelated regression		Feasible generalized nonlinear least squares regression (local concavity imposed)		Kalman Filter Estimation
	Without time-trend	With time-trend	Without time-trend	With time-trend	Without time-trend	With time-trend	With latent variable
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
α_q	-4.572**	-9.518***	-1.974*	-2.382**	-0.340***	-0.252**	3.016
	(-2.234)	(-2.446)	(-1.118)	(-1.112)	(0.088)	(0.100)	(-2.786)
α_l	1.161***	1.205***	1.124***	1.136***	0.503***	0.502***	0.930***
	(-0.190)	(-0.185)	(-0.156)	(-0.156)	(0.008)	(0.008)	(-0.166)
α_k	0.809***	0.858***	0.944***	0.921***	0.233***	0.232***	0.424*
	(-0.226)	(-0.211)	(-0.17)	(-0.172)	(0.007)	(0.007)	(0.224)
α_h	-1.073***	-0.989***	-0.964***	-0.919***	0.081***	0.082***	-0.764***
	(-0.194)	(-0.185)	(-0.104)	(-0.108)	(0.006)	(0.006)	(0.145)
α_f	0.102	-0.074	-0.104	-0.138	-0.012	-0.022	0.411
	(-0.317)	(-0.283)	(-0.195)	(-0.194)	(0.035)	(0.035)	(-0.281)
β_{qq}	0.716*	1.710***	0.268	0.356*	0.871***	0.839***	-0.580
	(-0.377)	(-0.438)	(-0.186)	(-0.187)	(0.310)	(0.302)	(-0.480)
β_{ll}	0.119***	0.121***	0.125***	0.126***	0.130***	0.130***	0.107***
	(-0.008)	(-0.008)	(-0.006)	(-0.006)	(0.007)	(0.007)	(0.008)
β_{kk}	-0.007	-0.010	-0.005	-0.003	0.010	0.008	0.012
	(-0.010)	(-0.009)	(-0.007)	(-0.007)	(0.007)	(0.007)	(-0.010)
β_{hh}	0.170***	0.158***	0.192***	0.192***	0.191***	0.192***	0.147***

	(-0.010)	(-0.010)	(-0.003)	(-0.004)	(0.004)	(0.004)	(0.007)
β_{ff}	0.089***	0.074***	0.093***	0.092***	-0.002	-0.014	0.067***
	(-0.021)	(-0.018)	(-0.009)	(-0.009)	(0.052)	(0.049)	(0.018)
β_{lk}	0.034***	0.033***	0.029***	0.028***	0.039***	0.037***	0.038***
	(-0.006)	(-0.006)	(-0.004)	(-0.004)	(0.005)	(0.005)	(0.005)
β_{lh}	-0.107***	-0.108***	-0.098***	-0.098***	-0.099***	-0.096***	-0.108***
	(-0.006)	(-0.006)	(-0.003)	(-0.003)	(0.003)	(0.004)	(0.005)
β_{lf}	-0.046***	-0.046***	-0.055***	-0.056***	-0.023***	-0.022**	-0.037***
	(-0.011)	(-0.010)	(-0.006)	(-0.005)	(0.009)	(0.009)	(0.009)
β_{kh}	-0.023***	-0.023***	-0.040***	-0.042***	-0.041***	-0.041***	-0.030***
	(-0.007)	(-0.007)	(-0.003)	(-0.003)	(0.003)	(0.003)	(0.007)
β_{kf}	-0.004	-0.001	0.016**	0.017**	-0.012	-0.011	-0.020*
	(-0.011)	(-0.010)	(-0.007)	(-0.007)	(0.008)	(0.008)	(0.011)
β_{hf}	-0.039***	-0.027***	-0.054***	-0.053***	-0.001	-0.001	-0.009
	(-0.011)	(-0.010)	(-0.003)	(-0.003)	(0.006)	(0.006)	(-0.008)
γ_{lq}	-0.115***	-0.122***	-0.113***	-0.115***	-0.181***	-0.189***	-0.075***
	(-0.031)	(-0.030)	(-0.026)	(-0.026)	(0.036)	(0.037)	(0.027)
γ_{kq}	-0.098***	-0.105***	-0.112***	-0.107***	-0.064**	-0.062**	-0.039
	(-0.034)	(-0.032)	(-0.027)	(-0.027)	(0.031)	(0.031)	(-0.034)
γ_{hq}	0.164***	0.157***	0.139***	0.132***	0.025	0.016	0.128***
	(-0.030)	(-0.029)	(-0.017)	(-0.017)	(0.018)	(0.019)	(0.022)
γ_{fq}	0.050	0.071	0.085***	0.090***	0.020	0.075	-0.013
	(-0.049)	(-0.044)	(-0.031)	(-0.031)	(0.092)	(0.089)	(-0.042)
δ		-0.014***		-0.002*		-0.002*	
		(-0.004)		(-0.001)		(0.001)	

u							1.000
							(0.000)
α_o	17.843***	58.601***	10.284***	14.363***	0.099***	0.100***	-14.778***
	(-6.669)	(-12.506)	(-3.407)	(-3.96)	(0.019)	(0.020)	(0.107)
lnc: R^2	0.9448	0.9544	0.9369	0.9391	0.9830	0.9825	0.9872
sl: R^2	0.8261	0.8261	0.7854	0.7813	0.8678	0.8660	0.8259
sk: R^2	0.4694	0.4670	0.3584	0.3388	0.4387	0.4392	0.3649
sh: R^2	0.8988	0.9216	0.7865	0.7816	0.9286	0.9258	0.4303
AIC	-836.64	-822.27	-898.60	-898.71	-944.90	-944.49	-810.61
BIC	-810.22	-794.09	-872.18	-870.53	-907.92	-905.74	-778.91
Economies of scale							
Mean	1.31	0.54	1.45	1.36	1.01	0.92	1.14
Range	[1.07, 1.85]	[-0.01, 1.54]	[1.30, 1.79]	[1.19, 1.72]	[0.82, 1.36]	[0.73, 1.28]	[0.84, 1.40]

Note: 1. * indicates significant at 10% level; ** indicates significant at 5% level; *** indicates significant at 1% level.

2. Standard deviations are in parentheses.

3. The equation of s_f is dropped from the estimation system to avoid singularity because the sum of all cost shares is equal to one.

4. Model 1, Model 2, Model 3, Model 4, and Model 7 are estimated on the original data. Model 5 and Model 6 are estimated on the rescaled data (1975=1).

5. Model 5 and Model 6 use the iterative FGNLS estimator.

6. The degree of economies of scale is calculated and reported in the last two rows of table 1. Its calculation equation is $ES = 1 - (\alpha_q + \alpha_{qq} * lnq + \gamma_{lq} * lnl + \gamma_{kq} * lnk + \gamma_{hq} * lnh + \gamma_{fq} * lnf)$.

Figure 3 presents the observed and predicted figures of each input's cost share during 1975-2017 on the basis of the estimation results from Model 5. Obviously, they fit remarkably well. Of the four input factors, labor accounts for the largest percentage of total cost, around 40% in total. The second largest, land, is at about 30%, followed by capital, with 20%. The smallest is fertilizer, which constitutes only about 10%. Here, we can see that although many studies assert that fertilizer contributed most to Chinese agriculture's growth during the 1980s and 1990s (e.g., Lin, 1992), what really matter in cereal production might be labor and land, which when combined account for almost 80% of the total cost.

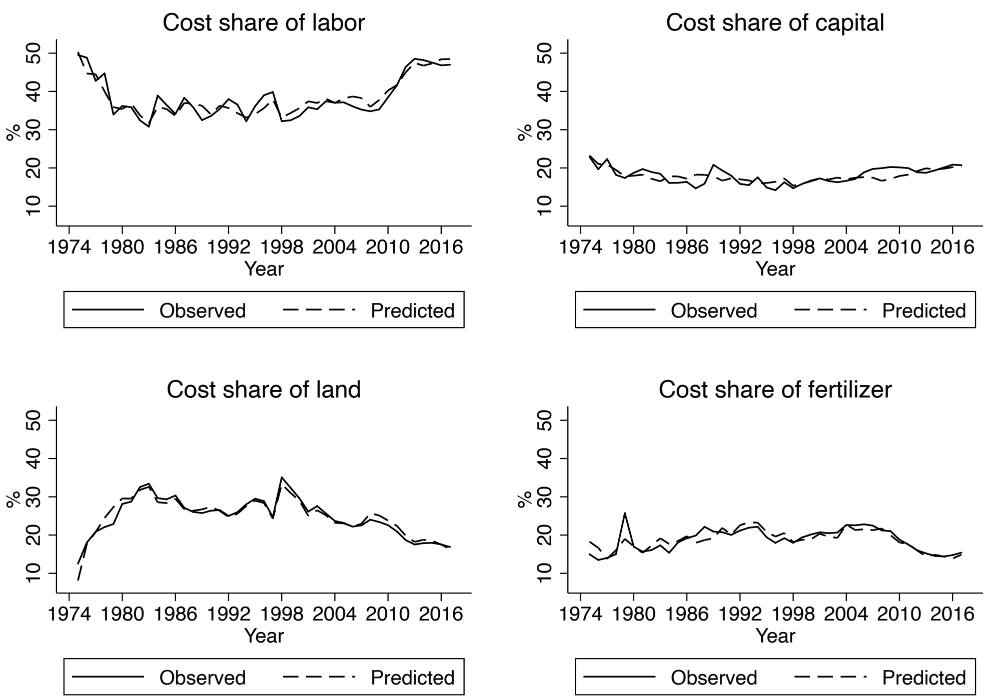

Figure 3. Observed and Predicted Cost Share of Each Input

Source: Calculated by the authors based on the estimation results of Model 5.

Note: The cost share of each input is calculated on the constant price (2010=1).

4.2. Partial elasticities of substitution between pairs of inputs

The calculation results of the partial elasticities of substitution between pairs of input factors are reported in table 2. A strong substitutability is exhibited between labor and capital ($\sigma_{lk} > 1$). A complement relationship is detected between labor and land ($\sigma_{lh} < 0$). Also, a weak substitutability relationship is detected between labor and fertilize ($0 < \sigma_{lf} < 1$)and between capital and fertilize ($0 < \sigma_{kf} < 1$).

Table 2. Estimated Allen Elasticities of Substitution between Pairs of Inputs (Selected Years)

Year	σ_{lk}	σ_{lh}	σ_{lf}	σ_{kh}	σ_{kf}	σ_{hf}
1975	1.3305	-1.4096	0.7460	-1.1742	0.7269	0.9777
1980	1.6079	0.0574	0.6130	0.2259	0.6214	0.9744
1985	1.6145	0.0175	0.6421	0.1849	0.6462	0.9781
1990	1.6812	-0.0582	0.6860	0.1012	0.6822	0.9844
1995	1.7065	0.0016	0.6710	0.1178	0.6537	0.9829
2000	1.6570	0.0446	0.6524	0.1406	0.6275	0.9791
2005	1.5813	-0.1205	0.7129	-0.0228	0.6878	0.9836
2010	1.5375	-0.0301	0.6786	0.0343	0.6410	0.9772
2015	1.4129	-0.1275	0.6568	-0.1239	0.5925	0.9640
2017	1.3927	-0.2463	0.6759	-0.2389	0.6161	0.9664
Mean	1.5772	-0.0793	0.6680	0.0325	0.6473	0.9774

Source: Calculated by the authors based on the estimation results of Model 5.

4.3. Own- and cross- price elasticities of input demand

Table 3 provides the means of the estimated price elasticities of demand for each input. First, all own-price elasticities of demand have the expected sign except land. The positive sign of own-price elasticities of demand for land implies that the demand for land will increase even when its price goes up, showing that demand for land input is rigid in Chinese cereal production. It is because there is almost no substitute for land in production. We can also recall the findings from table 2. Of the four own-price elasticities of demand, the most sensitive is fertilizer while the least is land. This reflects that fertilizer is the most liquid in their market, while liquidity is poorest in land.

Table 3. Estimated Own- and Cross- Price Elasticities of Demand for Inputs (Means)

	Price of			
Demand for	Labor	Capital	Land	Fertilizer
Labor	-0.2729	0.6025	-0.0368	0.2576
Capital	0.2812	-0.7670	0.0034	0.1160
Land	-0.0113	0.0175	0.0640	0.2431
Fertilizer	0.1254	0.1218	0.1829	-0.8216

Source: Calculated by the authors based on the estimation results of Model 5.

Then, let us see the cross-price elasticities of demand. A positive sign of cross-price elasticities of demand shows a substitutability relationship between two input factors. A negative sign indicates a complement relationship between two input factors. It is noteworthy that labor appears to be a substitute for fertilizer. Our analysis used the data of commercial fertilizer. Once wages rise and labor becomes scarce, commercial fertilizer replaces traditional self-supplied fertilizer because the latter requires heavy labor input. Thus, we observe an increase in the demand for commercial fertilizer increases on account of rising labor wages. This phenomenon is also specified in other studies (Nghiep, 1979; Ray, 1982; Archibald and Brandt, 1991).

4.4. Measurements of induced bias in technological change

This section presents the derived series of biases in Chinese cereal production for the period from 1975 to 2017. The basic estimation for the biases is[16]

$$ds_i^* = ds_i - \sum_{j=1}^{3} \hat{\beta}_{ij} d\rho_j \tag{12}$$

where ds_i^* is the change in the share of factor i in the absence of ordinary factor substitution due to price change; ds_i is the actual total change in share of factor i, which includes the effects of the price change; $d\rho_j$ is the proportional change of the ratio of the price of factor i to the price of other inputs.

We compute series s_{it}^* which show how the shares would have developed after 1975 in the absence of factor price changes

$$s_{it}^* = s_{i,1975} + \sum_{t=0}^{T} \Delta s_{it}^* \tag{13}$$

The index of factor-using bias is calculated as

$$R_{it} = s_{it}^* / s_{i,1975} \tag{14}$$

which is in semilogarithmic scale.

The estimation results are shown in figure 4. The advantage of this expression is that the slopes of the lines in fact indicate technological biases of each input, which can be expressed in the form of

$$B_{it} = \frac{ds_{it}^*}{dt} \cdot \frac{1}{s_{it}^*} \tag{15}$$

while B_{it} is the bias in technological change. Technological change is i-saving at period t, if $B_{it} < 0$, neutral if $B_{it} = 0$, and i-using at period t, if $B_{it} > 0$. Furthermore, the position of the line shows the cumulative bias for each input in Chinese cereal production since 1975.

[16] Refer to Binswanger's study (p.971, 1974b) and Kawagoe et al.'s study (p.583, 1986).

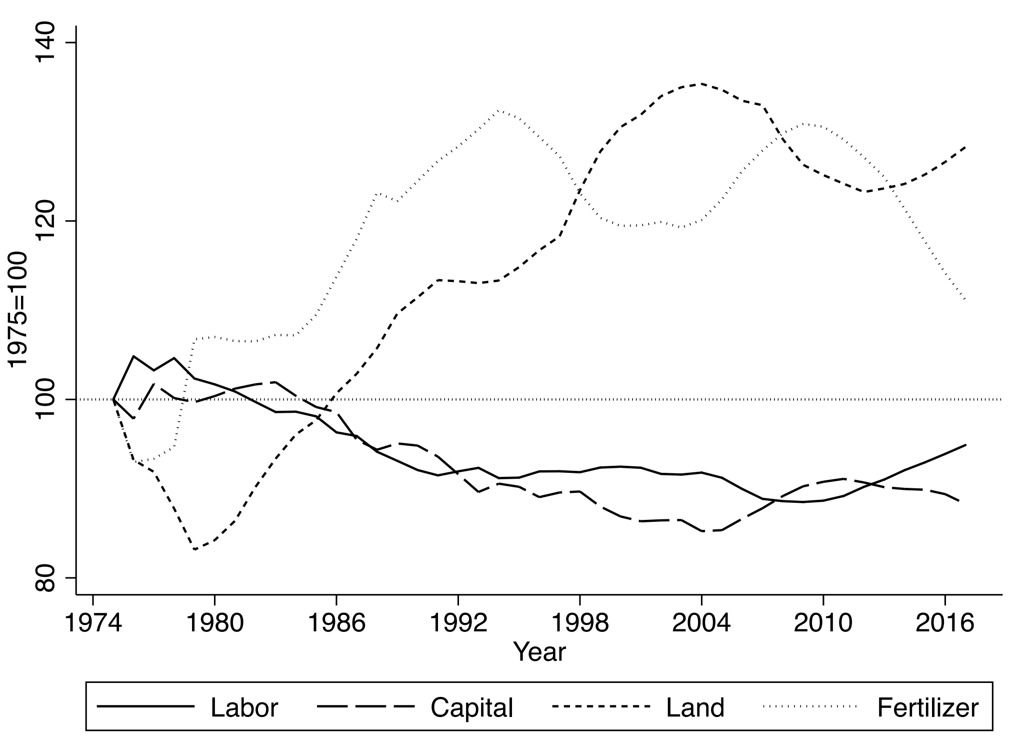

Figure 4. Cumulative Changes in Factor Shares Due to Biased Technological Change in Chinese Cereal Production: 1975=100

Source: Calculated by the authors and based on the estimation results of Model 5.

Note: The technological bias is calculated based on ten-year moving averages.

Our results show that Chinese cereal production assumes a mode of labor- and capital- saving, land- and fertilizer-using technology during 1975-2017. Firstly, after the mid-1990s, China's cereal production began to adopt a technology of labor-saving. Before that, it had embraced one of labor-using. It is because labor transfers from the agricultural sector to the non-agricultural sector began in the l980s and accelerated in the mid-1990s. When labor became scarce and expensive, it had to tend to a technology of labor-saving to reduce cost. However, it is noteworthy that China likely adopts a weaker type of labor-saving technology than those observed in the U.S. and Japan.[17]

Secondly, China endorses a technology of capital-saving to produce its cereal, differing from the situation in developed countries.[18] This phenomenon can be explained by the scarcity of capital in China's agriculture. Prior to China opening its markets for foreign investors in the mid-1990s, its agriculture was obliged to save surplus for the development of its own industrial sector.[19] However, after China's economy succeeded in taking-off, it was difficult to reinvest the funds into its agriculture. Thus, there is no wonder that capital cannot be used intensively in China's cereal sector. Further proof lies in the rather low level of agricultural mechanization in

[17] Refer to the studies of Binswanger (1974b), Kawagoe et al. (1986), Kuroda (1988), and Archibald and Brandt (1991).

[18] U.S. agriculture and Japanese agriculture tend to adopt capital-using technology in production (Binswanger, 1974b; Kawagoe et al., 1986; Kuroda, 1988; Archibald and Brandt, 1991).

[19] Refer to Dong's study (pp. 63-103, 2018). A similar phenomenon has been found in Brazil by Bustos et al. (2020).

China. In terms of the number of tractors per 100 sq. km of arable land, the figure of China is about one-third that of the U.S. and one-twentieth of Japan.[20]

Thirdly, Chinese cereal production has adopted a technology of land-using from the late 1980s. As previously mentioned, China has been attempting to stabilize its arable land above a certain level. Although urbanization inevitably invaded its arable land, the area of land used in the three main cereals was for the most part kept stable. In other words, China sacrificed some other cereals to graduate the land used for production of its three main cereals (Recall figure 1). This guarantees the practicability to conduct the technology of land-using in China's cereal production.

Lastly, cereal production in China shows strong fertilizer-biased technological change after the mid-1980s. Before that, a form of fertilizer-saving was used. We can understand it in this way. The input market became available with China's marketization, and extensive use of chemical fertilizers became possible. Consequently, keeping a fertilizer-saving mode was no longer required. Moreover, considering fertilizer appears as a substitute for labor (see table 2), the adoption of fertilizer-using technology is also, comparatively, an aftereffect of labor migration.

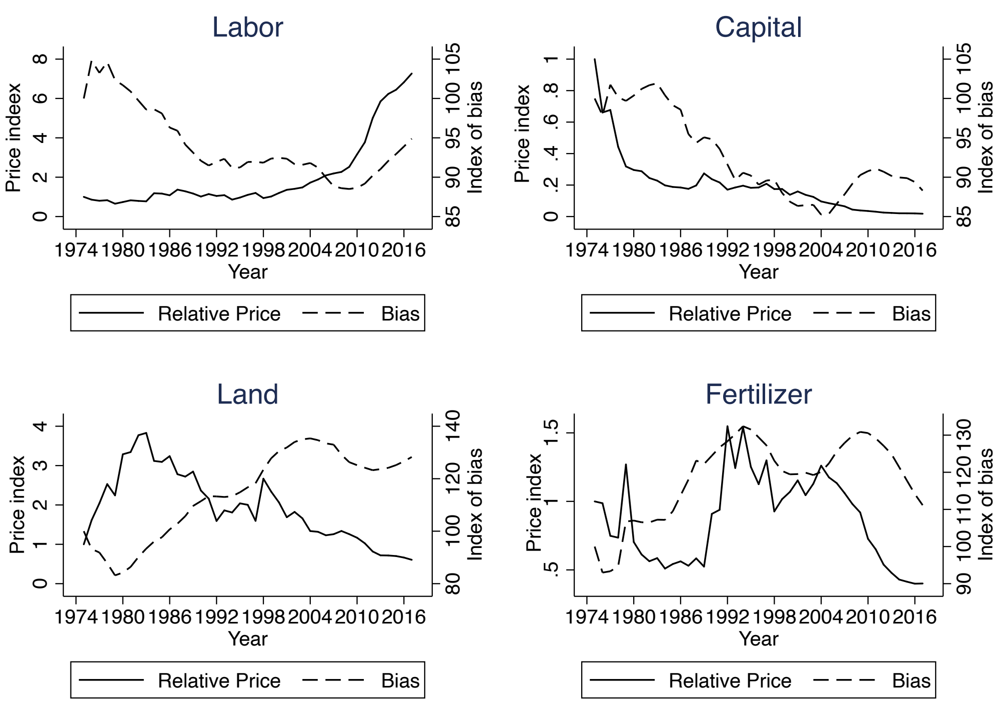

Figure 5. The Indexes of Factor Prices Relative to the Aggregate Input Price and the Indexes of Factor-using Biases in Technological Change

Source: Calculated by the authors and based on the estimation results of Model 5.

Figure 5 shows the indexes of factor prices relative to the aggregate input price and factor-biased technological changes for each input. In terms of relative factor price, the

[20] Data on tractors per 100 sq.km of arable land are from the database of World Bank.

use of capital and fertilizers, whose relative price is below one, is relatively cheap compared with labor and land, whose relative price exceeds one. This is by virtue of labor and land becoming scarce in agriculture as structural transformation and urbanization advance.

Intriguingly, capital relative price began to fall in the late 1970s and land relative price first dropped in the 1980s. The former is likely due to China's financial marketization while the latter might be linked to rapid flow-out of labor.

Our results also suggest that movements in the indexes of factor-biased technological changes are negatively associated with those of the relative factor prices for most input factors barring capital. In other words, once a factor becomes more expensive than others, China tends to adopt a technology of this factor-saving to reduce the cost. And vice versa. The only exception is capital. Even as the relative price of capital is declining and becomes much lower than the other factors, China's cereal sector still adopts a capital-saving technology. As previously discussed, this stems from the scarcity of capital in China's agriculture.

4.5. Measurements of neutral technological change

Neutral technological change in Chinese cereal production is estimated using the traditional Slow residuals method and Kalman Filter method, respectively (see figure 6). Our estimation results support the existing conclusion on the TFP in Chinese agriculture (Lin, 1992; McMillan et al., 1989; Fan et al., 2004; Chen et al., 2008), which addresses that TFP appeared rapid during 1978-1984 and has been sluggish since the mid-1980s.

And interestingly, we find that the figures based on the Kalman filter method seem more supportive. Normalized latent state, which represents the neutral technological changes, appears positive during 1978-1990, becomes negative between 1990 and 2008, and tends to rise thereafter. Wang et al.'s recent study (2019) reveals that China's agricultural TFP rebounds from a slower level and tends to grow faster since the late 2000s. Estimation results from Kalman filter support that assertion.

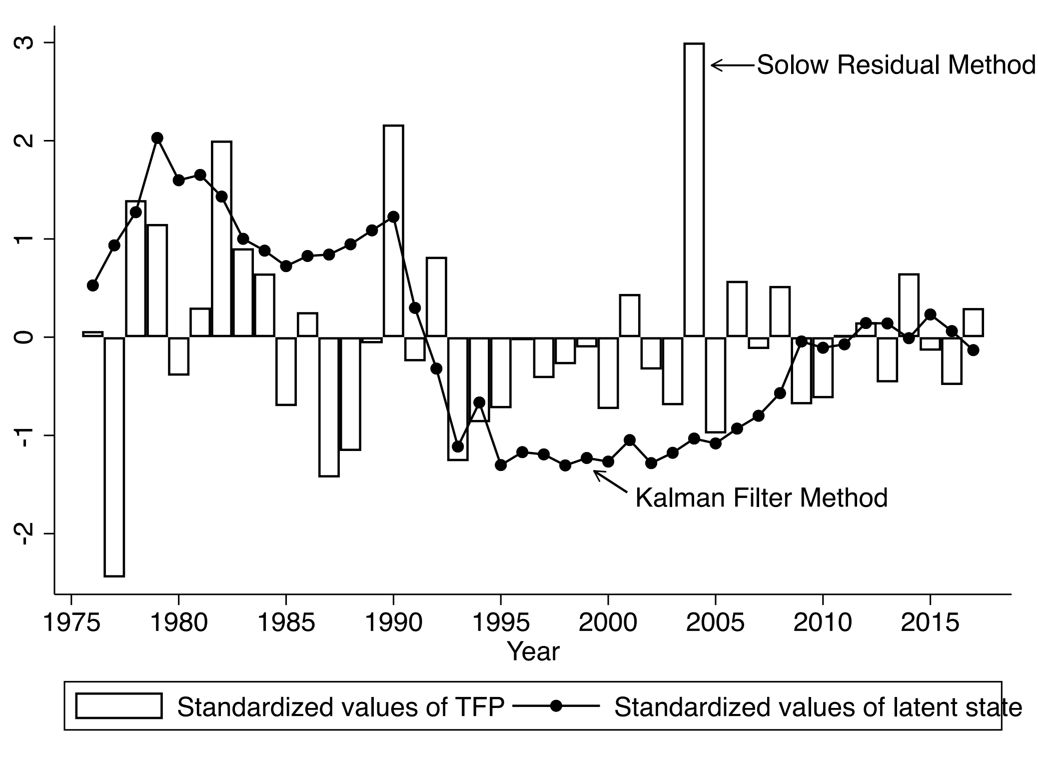

Figure 6. Neutral Technological Changes Based on Solow Residues and on Kalman Filter Method

Source: Calculated by the authors. The latent state is calculated from Model 7.

5. Conclusion

Adequate and stable food supply is the foundation of economic development (Lewis, 1954; Hayami, 2000). China's achievements in maintaining its agricultural production are impressive. Distinguished from the recent research fever on decomposing China's agricultural TFP to explain China's achievements in domestic food production and supply, our study focused on the changed factor prices and biased technological changes in cereal production and addressed what type of transition in the induced bias of technological change has taken place to maintain sufficient domestic cereal production and supply in the context of its rapid structural transformation.

Our estimation results suggest that the technological change in Chinese cereal production during 1975-2017 is biased toward saving labor and capital and using land and fertilizer. The findings basically mirrors those of other developed countries such as Japan and the U.S (Kawagoe et al., 1986; Kuroda, 1988) during their structural transformation period except as to the biased technology toward saving capital.

With China's rapid labor migration, labor becomes relatively expensive compared with other types of input factors (See Figure 5). Thus, China's cereal production tends to adopt technology of labor-saving. There is no wonder that numerous studies confirm and assert that the impact of labor input on China's agricultural output growth was minor, even negative after the 1980s (Lin, 1992; Dekle and Vandenbroucke, 2010; Huang et al., 2010; Yang and Lahr, 2010; Cao and Birchenall, 2013).

In fact, what interests us more is why a land-scarce country like China moves toward land-using technology but capital-saving technology, which seems to go against our common sense. On the one hand, the adoption of a biased technology toward land-using is largely due to China's land tenure system. In China, agricultural land is collectively owned, and thus, agricultural land cannot circulate freely. In addition, the increasing displacement of labor also makes it cheaper to till the unmarketable arable land. That also explains why the relative price of labor is higher than the relative price of land in China's cereal sector. Furthermore, China has always adopted an active policy of cultivated land protection. Combined, those factors make masses of land for cereal production available and make the need for changing toward to a land-saving technology less urgent.

On another, China's choice of adopting a biased technology toward using capital is primarily due to the capital flows from the agricultural sector to the non-agricultural sector, taking place during the whole period from 1952 to now. Although the finding significantly differs from those in Japan or in the U.S., which both tended to adopt a biased technology toward using capital during their transformation period, it conforms to China's reality. As known to all, China's economic reforms and opening up began in 1978, but in fact, the inflow of large-scale foreign investment started in the mid-1990s. Before that, China was a closed economy, and its funding for production was likely self-accumulated. Since the mid-1990s, when sizable foreign investment began to inflow to China, and since that time, its capital price began to fall (See figure 2). For that reason, China's agriculture had to contribute a considerable part of its surplus or savings to support China's industrial sector (Dong, 2021). Thus, for the observation period, we find China's cereal production adopts a biased technology toward saving capital rather than using it.

Thus far, we can conclude that with the adoption of such technologies in cereal production, China succeeded in achieving domestic sufficient cereal production and supply with little effect on transferring factor inputs from the agricultural sector to the non-agricultural sector and its rapid structural transformation. However, some hidden problems plague China's existing cereal production mode.

The first problem involves the input of capital. As previously mentioned, China endorses capital-saving technology in its cereal production. Given that capital is an important substitute for labor and there will be far less labor left for the cereal sector someday, the lack of capital-intensifying innovation will impede attempts to maintain its current output level. Even worse, the marginal productivity of fertilizer appears to have diminished already (Chen et al., 2008). Therefore, development of capital-based innovation is imperative for China, not optional. Considering China's current agricultural mechanization level, we believe there leaves a great possibility for improvements in terms of agricultural capital.

Another problem is that China lacks breakthrough technological progress in its agriculture. Our analysis provides another perspective for examining the contribution of TFP. Both the existing literature and our estimation show that neutral technological progress in China's cereal sector has been sluggish since the mid-1980s. Regardless of why TFP slows down (Chen et al., 2008; Shen et al., 2019; Gong, 2018 and 2020; Wang et al., 2019), further investment in research probing breakthrough technological innovation should be placed high on the agenda.

Our findings also provide some implications for other developing countries. In those countries, as in China, capital is relatively scarce. Accordingly, during the infancy of economic development, adopting capital-saving technology will benefit the growth of the entire economy. Since the capital required is relatively unavailable, sufficient labor and adequate land must be secured to support agricultural production, especially the land. As labor forces are increasingly transferred to the non-agricultural sector, the technology of capital-using (Pingali, 2007; Irmen, 2017) and labor-saving (Williamson, 1971; Irmen, 2017) will become vital because once the labor remaining in the agricultural sector is unable to produce sufficient output, increasing the capital input becomes necessary and lucrative.

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