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Interaction and Non-neutral Effects of Factors in Chinese Wheat Production

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Abstract:

In this paper we examine the role of the interaction between labour productivity and the use of factors in explaining the recent (1998-2007) 11% decline in wheat production in China. We employ a non-neutral stochastic production frontier approach that enables us to identify the interaction and non-neutral effects of factors that are used in wheat production. For regional level wheat production in China we find that identifying the technical inefficiency effects and the non-neutral effects of factors assist big time in explaining the recent decline in wheat production. A higher level of labour productivity can stimulate efficiency gains in production, but adding more labour to the workforce or adding to the stock of machinery power can depress this potential marginal efficiency gain. We also find significant marginal efficiency gain of land reforms that add to the stock of cultivable land. Our results indicate that future agricultural reforms in China should address the incentive scheme for labour.

JEL Codes: N55, O13, O53, Q12.

Keywords: China, Stochastic Frontier, Factor Interaction, Non neutrality, Agriculture, Wheat Production.

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1 Introduction

According to the United States Department of Agriculture (USDA) 2008 data China is one of the largest producers of wheat in the world accounting approximately 17% of the world's wheat production[2]. But for the decade following the most recent agricultural reform in 1998 when the government took over the control of agricultural prices, wheat production in China has suffered a major decline. During 1998-2007 the countrywide average growth rate of total wheat production in China was -11%. In this paper we examine the role of labour productivity and the use of agricultural inputs as well as the effect of the interaction between these two in explaining the reasons behind this decline in wheat production in China. We use regional level wheat production data in order to identify the correspondence between labour productivity and regional level technical efficiency of wheat production in China in a stochastic production frontier where factors of wheat production have interaction and non-neutral effects.

We follow Huang and Liu (1994)'s modeling approach in order to capture the interaction effect of labour productivity and other inputs in a non-neutral production frontier. Typically in a neutral production frontier it is implicitly assumed that changes in technical efficiency are either autonomous or induced by the changes in the characteristics that are specific to regions. In a neutral production frontier variations in technical efficiency are therefore completely independent of the variations in the use of factors or the interactions among region-specific characteristics and the use of factors. When considering the determinants of technical efficiency it is important to recognize that time-varying technical efficiency may also respond to the variations in the use of factors and the interaction or cross effects of factors and productivity of factors. In this paper this is the key idea underlying the use of a non-neutral frontier.

Our key hypothesis here is that the recent decline in wheat production in China can be explained through a thorough analysis of region-specific underutilization of capacity, i.e. an analysis of regional level technical inefficiency in wheat production. The non-neutrality assumption allows us to model interaction effects between labour productivity and other factors of wheat production. For this we employ a translog (i.e. Transcendental logarithmic) production frontier where we identify the significance of the interaction effects of factors. We then examine the significance of the non-neutrality of these factors in determining the technical efficiency of wheat production.

Our study primarily belongs to the tradition of studies that examine technical efficiency

[2] India, USA and the European Union are the other largest producers of wheat, see USDA Wheat database for details.

of production using the stochastic production frontier approach. This approach was indepedently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). Important contributions in this spirit include Forsund et al. (1980), Cornwell et al. (1990), Bauer (1990), Battese and Coelli (1992, 1995), Sharma and Leung (1998), Jha and Rhodes (1999), Karagiannis and Tzouvelekas (2005) and Selim (2010). In this paper we extend these studies and the approach in general by introducing the computational technique for examining the interaction effects of labour productivity and the use of factors. This technique identifies the signs of the effects and therefore can assist one in explaining the policy implications of this approach in general.

None of the aforementioned previous studies examine agricultural production in China within a stochastic production frontier framework. Some important studies such as McMillan et al. (1989), Lin (1992), Zhang and Carter (1997) and Patel and Selim (2010) examine the effects of rural reforms on Chinese agricultural productivity, but they do not examine the technical inefficiency effects or the cross marginal effects at a regional level. In this paper we make a significant contribution to this particular literature by extending these works in a number of ways. We employ the stochastic frontier approach and establish the correspondence between regional level technical efficiency and growth in regional level total factor productivity of wheat production. For this we examine productivity and technical efficiency in a dataset that covers the most recent agricultural reform period, something which apart from Patel and Selim (2010) no other studies cover. Our study also identifies the level and the direction of the cross marginal effect of labour productivity and other factors of agricultural production in China, something which is not covered by these studies. This study therefore adds a completely new perspective of looking into the effect of policy reforms in Chinese agriculture.

Our results suggest that the underutilization of productive capacity at a regional level (or more simply the inefficiency in production) that apparently resulted in the negative growth rate of wheat production in China stems from the interaction of low labour productivity and the use of the factors. We capture these cross marginal effects by modeling the interactions between marginal wage and the factors of production as determinants of technical inefficiency. We find that such interactions significantly affect the regional level technical efficiency of Chinese wheat production. Our results also suggest that a higher level of labour productivity can stimulate gains in the efficiency of production, but adding more labour to the workforce or adding to the stock of machinery power can depress this potential marginal efficiency gain. We find significant marginal efficiency gain of land reforms that add to the stock of cultivable land. One of the key policy implications of these results is that agricultural reforms in China should address the incentive scheme for labour. Rather than subsidizing factor prices (e.g. the eighties' reforms) or supporting or regulating the output prices (e.g. the most recent reforms), reforms should provide clear incentives for training and formalizing the rural labour market.

2 A Model for Technical Inefficiency Effects

The stochastic frontier production function approach assumes that there is potential technical inefficiencies in production which can be captured by the deviation of observed output from the maximum feasible output. Consider a standard stochastic frontier model within a panel data framework:

$$\ln q_{it} = f(\ln x) + \varepsilon_{it} - \varphi_{it} \tag{1}$$

where q_{it} denotes the observed level of output of region $i = 1, \ldots.., N$ in year $t = 1, \ldots, T$, x represents an input vector, ε_{it} is a symmetric and normally distributed random error which represents the factors that cannot be controlled by the farmers, measurement errors in the dependent variable and ommitted explanatory variables, and φ_{it} are non-negative random variables that account for technical inefficiency (or underutilization of capacity) in production. The series of ε_{it} is independent of φ_{it}, and it has a zero mean and a constant variance equal to σ_ε^2. The series of φ_{it} is assumed to be independently and identically distributed and truncations (at zero) of the distribution $\mid N\left(\varphi_{it}, \sigma_\varphi^2\right) \mid$. This standard distribution allows for a wide range of distributional shapes[3].

If the technical inefficiency effects are significant in this model, the proportion of total variation from the frontier level of output in (1) that is accounted for the variation in φ_{it} will be large and statistically significant. More specifically, following Battese and Coelli (1995) one can estimate the parameter $\gamma \equiv \frac{\sigma_\varphi^2}{\sigma_\varphi^2 + \sigma_\varepsilon^2}$ in order to determine the source of variation in production and the extent of the impact of technical inefficiency effects as compared to random shocks (e.g. weather effects). A high (low) value of γ would imply that most of the variation from the frontier level of output is due to technical inefficiency effects (random shocks).

In a translog stochastic non-neutral frontier the interaction effects of factors are captured in the production frontier, while the non-neutral effects of factors are captured in a model that explains the technical inefficiency effects. This specification has been used in Karagiannis and Tzouvelekas (2005) and Selim (2010) which examine the technical inefficiency effects in sheep farming in Greece and rice cultivation in Bangladesh, respectively.

[3] If one assumes that the distribution of φ_{it} is half normal that has a mode at zero (or it is exponential), one would be implicitly assuming that a high proportion of regions are perfectly efficient. We choose the more general distribution assumption because we keep the analysis open to allow for a wide range of distributional shapes including nonzero modes.

For the purpose of a general demonstration, consider a standard two factor translog production frontier:

$$\ln q_{it} = \delta_0 + \delta_1 \ln x_{1it} + \delta_2 \ln x_{2it} + \delta_{11} (\ln x_{1it})^2 + \delta_{22} (\ln x_{2it})^2 + \delta_{12} (\ln x_{1it}) (\ln x_{2it}) + \varepsilon_{it} - \varphi_{it} \quad (2)$$

The interaction effect of the two factors is captured by the parameter δ_{12}, and the importance of this effect can be found in the (post estimation) computation of the elasticity of output with respect to individual factors:

$$\widehat{\zeta}_{1it} = \widehat{\delta}_1 + 2\widehat{\delta}_{11} \ln x_{1it} + \widehat{\delta}_{12} \ln x_{2it} \quad (3a)$$

$$\widehat{\zeta}_{2it} = \widehat{\delta}_2 + 2\widehat{\delta}_{22} \ln x_{2it} + \widehat{\delta}_{12} \ln x_{1it} \quad (3b)$$

The elasticity estimates $\widehat{\zeta}_{1it}$ and $\widehat{\zeta}_{2it}$ are therefore variable, and the elasticity of output with respect to one factor depends crucially on the level of the other factor. From an empirical point of view this specificaton is therefore useful if one is interested in identifying how factors interact within a production process. Moreover for regional level data this specification can assist in understanding the cross effects of the use of the factors of production.

The non-neutrality of these factors within the same framework are captured in a model that explains the technical inefficiency effects in production. In such a model technical inefficiency of a region (at any year t) is assumed to depend on a set of variables that describe some characteristics that are specific to that region (at t), and another set of variables that include the interactions between one or more variables of the first set with the factors x_1 and x_2. For instance if v is the vector of explanatory variables for the technical inefficiency model and ψ is the vector of parameters associated with v, the technical inefficiency model is:

$$\varphi_{it} = v_{it}\psi + \widetilde{v}_{it}\widetilde{\psi} + \ell_{it} \quad (4)$$

where ℓ_{it} are independently distributed random variables that are obtained by truncation of the normal distribution with mean zero and variance equal to σ^2_ℓ, such that φ_{it} is non-negative, and the vector $\widetilde{v}_{it}$ includes interaction of some of the v_{it} and the factors x_{1it} and x_{2it}[4]. The non-neutral effects of factors therefore are the ones that are based on the hypothesis that factors are important not only for production but also for the way they are used and for their interaction effect with one or more determinants of technical inefficiency. This approach was primarily proposed by Huang and Liu (1994), but the underlying intuition was hinted in Forsund et al. (1980) and in Bauer (1990).

[4] For instance if the hypothesis is that v_3 has interaction effect with the factors of production, the explanatory variables that represent these interactions are $v_{3it} (\ln x_{1it})$ and $v_{3it} (\ln x_{2it})$.

2.1 The Empirical Model

In this paper we use a four-factor translog production frontier in order to capture the interaction and non-neutral effects of factors of wheat production. This particular specification does not impose the assumptions about constant elasticity of production or constant elasticity of substitution between inputs. We use wheat production related data for 30 regions of China over the period 1997-2006 in order to estimate:

$$\ln q_{it} = \beta_0 + \sum_j \beta_j \ln x_{jit} + \sum_j \beta_{jj} \left(\ln x_{jit}\right)^2 + \sum_j \sum_k \beta_{jk} \left(\ln x_{jit}\right)\left(\ln x_{kit}\right) + \varepsilon_{it} - \varphi_{it} \tag{5}$$

where for region i in year t, q_{it} denotes the observed quantity of wheat produced, and x_{jit} is a vector of factors of wheat production. We assume that the production of wheat requires four factors, namely, labour (n), machinery power (m), land (l) and chemical fertilizer (f). The subscript j (and k) therefore refers to a factor, and $j = n, m, l, f$ (same for k)[5].

As is clear by now, the advantage of using this translog production frontier specification (instead of using a Cobb-Douglas production frontier) is that once we estimate (5) we can clearly identify the importance of the interaction effects of the factors as well as the levels of these interactions. For instance, the (post estimation) elasticity of wheat output at any year t with respect to the $j-th$ factor is:

$$\eta_{jt} = \beta_j + 2\beta_{jj} \ln x_{jt} + \sum_{k \neq j} \beta_{jk} \ln x_{kt} \tag{6}$$

This way we are able to identify what proportion of the elasticity of wheat output with respect to factor j is contributed by its interaction with factor k, $k \neq j$. In our model the elasticity of wheat output with respect to each factor j has three such interaction effects. Determination of the degree of returns to scale for this translog production frontier requires the $\beta_j s$, the $\beta_{jj} s$ and the interaction effects. For instance, the constant returns to scale (CRTS) assumption, i.e. $\sum_j \eta_j = 1$ in (5) imposes a number of linear restrictions on the

[5] For instance, β_m is the coefficient of the explanatory variable $\ln m_{it}$, β_{mm} is the coefficient of the variable $\ln \left(m_{it}\right)^2$, and β_{mf} is the coefficient of the variable $\left(\ln m_{it}\right)\left(\ln f_{it}\right)$.

parameters of (5), which are:

$$
\begin{aligned}
\sum_j \beta_j &= 1; & \text{(7a)}\\
2\beta_{nn} + \beta_{nm} + \beta_{nl} + \beta_{nf} &= 0; & \text{(7b)}\\
\beta_{nm} + 2\beta_{mm} + \beta_{ml} + \beta_{mf} &= 0; & \text{(7c)}\\
\beta_{nl} + \beta_{ml} + 2\beta_{ll} + \beta_{lf} &= 0; & \text{(7d)}\\
\beta_{nf} + \beta_{mf} + \beta_{lf} + 2\beta_{ff} &= 0 & \text{(7e)}
\end{aligned}
$$

Following Huang and Liu (1994) we further assume that the technical inefficiency in (5) is a function of characteristics that are specific to regions, the use of factors, and interactions between some characteristics and the factors. Technical inefficiency in (5) is determined by two sets of variables, z_{it} and $\widetilde{z}_{it}$. The set z_{it} includes some regional characteristics that are hypothesized to influence the regional level efficiency in production. For this set we choose some characteristics which are not directly related to production of wheat but their variation can affect production. The set $\widetilde{z}_{it}$ represents the interactions between some of the z_{it} and the factors in the stochastic frontier. This way we introduce non-neutrality of technical inefficiency in our model. Simultaneously with (5) we estimate:

$$\varphi_{it} = z_{it}\mu + \widetilde{z}_{it}\widetilde{\mu} + A_t + \theta_{it} \tag{8}$$

where θ_{it} are unobservable random variables that are assumed to be independently distributed and are obtained by truncation of the normal distribution with mean zero and variance equal to σ_θ^2, such that φ_{it} is non-negative. The term $A_t = \sum_{t=2}^{T} \mu_t D_t$ where D_t are time dummies. The measure of technical efficiency for region i in year t is $\widehat{te}_{it} = e^{-\widehat{\varphi}_{it}}$, which is constrained to be between zero and one.

2.2 Hypotheses

Our key two hypotheses are that the technical inefficiency effects are there and that they are significant. This is equivalent to assuming that the estimated γ and the parameters of model (8) together are significantly different from zero. For this we test the null hypothesis involving the linear restriction $\gamma = \mu = \widetilde{\mu} = \mu_t = 0$, where μ, $\widetilde{\mu}$ and μ_t are vectors of parameters for (8). Rejection of this null hypothesis would imply that the technical inefficiency effect are important in determining the deviation of observed wheat output from the potential maximum level. We also perform a joint significance test for all parameters of (8), i.e. the null hypothesis involving linear restriction $\mu = \widetilde{\mu} = \mu_t = 0$, a joint significance test for the time dummies, i.e. the null hypothesis involving linear restriction $\mu_t = 0$, and a joint significance test for the non-neutrality assumption, i.e. the null hypothesis involving linear restriction $\widetilde{\mu} = 0$. The last of these tests is important in assessing the importance of the non-neutrality assumption, and rejection of the null hypothesis for this test would imply that there are significant interaction effects between the factors of production and the characteristics of the regions.

We test the null hypothesis of CRTS in the translog production frontier (5) by testing the set of linear restrictions as in (7). Rejection of this hypothesis would imply that wheat production function in China does not exhibit constant returns to scale. In addition to this, we test if a non-neutral translog production frontier is the correct specification. This is done by testing the non-neutral translog production frontier against a simple neutral Cobb-Douglas production function specification. We set the null hypothesis that involves linear restrictions $\beta_{jj} = \beta_{jk} = \widetilde{\mu} = 0;\ j \neq k$. Failure to reject this null hypothesis would imply that the non-neutral translog production frontier can be rejected in favour of a simple neutral Cobb-Douglas production function.

Given the specification in (8), if the variance of φ_{it} depends on the characteristics that are specific to regions, the resulting estimation would lead to downward (upward) bias in the estimates of technical efficiency for relatively smaller (larger) regions. For this reason we conduct a formal test for heteroscedasticity for model (8). We assume that the possibility of heteroscedasticity in model (8) may arise because of the explanatory variables that belong to the set z. Following Karagiannis and Tzouvelekas (2005) we assume that the variance function is exponential, which takes the form:

$$\ln \sigma^2_{\varphi it} = \xi_0 + \xi z_{it} \tag{9}$$

where ξ is a vector of parameters attached to the variables in the set z. We perform a test on the null hypothesis of homoscedasticity, i.e. $\xi = 0$. We test these null hypotheses using a generalized likelihood ratio statistic, where the test statistic follows approximately a chi-square distribution with degrees of freedom equal to the number of restrictions in the null hypothesis, provided that the null hypothesis is true, and a mixed chi-square distribution when the null hypothesis involves $\gamma = 0$[6].

[6] Critical value for 5% level of significance for the tests that involve $\gamma = 0$ are collected from table 1 of Kodde and Palm (1986).

3 Data

We use a panel of 30 regions of China for the period 1997-2006 for the estimation of (5) and (8). Our main data source is the Statistical Yearbook published by the National Bureau of Statistics, China (SYB, CBNS)[7]. This is the primary source for Chinese agricultural data published by the Economic Research Service at the United States Department of Agriculture (ERS, USDA), but for provincial level data the ERS, USDA reports data from 2000. This is also the primary source for the data published by *All China Data* at the China Data Center of the University of Michigan, Ann Arbor[8]. Summary statistics of the data including the description of variables are presented in table 1 (in appendix A).

The output of wheat is the total wheat production measured on an annual basis in 1000 tons. The total area of cultivated land and sown area for wheat are both in 1000 hectares. Agricultural employment is in 10000 persons[9]. The machinery data is the total power of agricultural machinery (in 10000 kw) used in farming, forestry, animal husbandry, and fishery, including ploughing, irrigation and drainage, harvesting, transport, plant protection and stock breeding. Fertilizer data is the quantity of chemical fertilizer (in 10000 tons) applied in agriculture during the year, including nitrogenous fertilizer, phosphate fertilizer, potash fertilizer, and compound fertilizer. We convert the output and input data in per hectare form, i.e. we first compute the proportion of total cultivated land that is cultivated for wheat production. We use this proportion to derive output of wheat per hectare, power of machinery per hectare and chemical fertilizer per hectare. The labour data is converted in the form of person days per hectare. This is calculated by multiplying the labour force by the ratio of the total sown area of wheat and the total area of cultivated land, and then dividing the result by three hundred (the number of working days in one year).

For the estimation of (8), we choose a number of variables which represent particular characteristics of the regions. One of our key hypotheses in this paper is that labour productivity plays a major role in determining the deviation of observed output from the frontier level of output. We choose farmers' wage in order to proxy for labour productivity. This variable belong to the set z, and belongs as an interacting variable for the factors in set $\widetilde{z}$.

[7] The SYB published by the CBNS reports regional data for 31 regions, but we choose 30 of them. We leave out the region Hainan because for this region we find many missing values. In figure 2 and figure 6 in appendix B of this paper we present some important results for the regional level where one can find the names of the regions.

[8] *http://chinadataonline.org/*, this online data archive publishes provincial level data for 20 provinces of China. The ERS, USDA data can be obtained from *http://www.ers.usda.gov/Data/China/*, and SYB, CBNS data that we use are available online in *http://www.stats.gov.cn/english/statisticaldata/yearlydata/* under the subject heading *Agriculture*.

[9] This agricultural labour force refers to the total labourers who are directly engaged in production of farming and receive remuneration payment or earn business income in the farming sector.

The wage data as reported in SYB, CBNS is the average annual wage of a representative agricultural worker in money terms. This average wage is the average annual payment to a representative worker engaged in any activities that involve farming, forestry, animal husbandry and fishery. For the estimation of (8) this data is divided by three hundred in order to derive the average per day wage rate for a representative farmer.

The other variables that we use in the set z for model (8) include two characteristic dummy variables, the percentage of population that has access to tap water (as a proxy for the level of well being), average temperature in celsius (as a proxy for climate condition), bullock in 10000 heads (as an inverse proxy for rainfall), and the percentage of total land area that is affected by natural disaster (as a proxy for natural disasters). The two characteristic dummy variables that we use account for the shift in the mean level of technical inefficiency for categories of the level of illiteracy and the land altitude from the sea level. According to the United Nations Development Program (UNDP) Report 2009, China's *literacy* rate is 93.3%. We assign value 1 for the regions that have illiteracy rate higher than 10% (well above the national average illiteracy rate), and 0 for the regions that have illiteracy rate less than 10% (approximately within the national average illiteracy rate). The other dummy variable assigns the value 1 for the regions having land level altitude that is above 2000 meters from the sea level (high lands), and 0 for the regions for which the land level altitude is within 2000 meters from the sea level.

4 Estimation, Computations and Analysis of Results

We use maximum likelihood estimation technique. The summary of the results from the stochastic frontier estimation is presented in table 2 in appendix A. We report the explanatory variables, their coefficient estimates and the t-ratios associated with these estimates. Except for the coefficient estimate for log of fertilizer, all other coefficient estimates of the stochastic frontier model are significantly different from zero. The translog production frontier specification is primarily justified by the statistical significance of the parameter estimates of β_{jj} and β_{jk}, which account for the second order effects and the factor interaction effects, respectively. The wald test for the joint significance of all the parameters in the model imply that they are jointly statistically significant.

The signs of the estimated parameters say little unless we compute the elasticity of wheat output with respect to individual inputs. These are computed using (6), and the histogram of the computed elasticity measures are presented in figure 1 in appendix B. In the same set of figures we present the histogram of the computed returns to scale in wheat production in China. The full panel mean {standard deviation} of the elasticity of wheat output with respect to labour, machinery power, land and chemical fertilizers are equal to $-1.011\,\{0.925\}\,,0.809\,\{0.830\}\,,0.514\,\{0.854\}$ and $0.694\,\{1.34\}$, respectively, and the full panel mean measure of the returns to scale is equal to 1.007 implying that wheat production in China at the regional level is characterized by constant returns to scale.

The summary of the results from the estimation of the technical inefficiency model (8) is also presented in table 2 in appendix A. Together with the parameter estimates and the associated standard errors, we report the estimated parameter γ and the log of the likelihood function. Only three of the time dummies are statistically significant. Based on likelihood ratio test the model without time dummies is not preferred over the model with time dummies, and therefore the results that we report are for the model with time dummies.

Except for the interaction of log of fertilizer and wage, the explanatory variables that account for the non-neutrality assumption in (8) are individually statistically significant. We also find significant marginal effects of illiteracy, land altitude, living conditions (proxied by access to tap water) and climate condition (proxied by average temperature) on the technical inefficiency of the regions. Better living conditions and higher temperature have a negative marginal impact on technical inefficiency, while more illiteracy and higher altitude of land adds to mean technical inefficiency of regions[10].

We perform a number of diagnostic tests and robustness tests, and their summary is in table 3 in appendix A. We use the generalized likelihood ratio test method in order to test the set of linear restrictions for the validity of the stochastic frontier approach, the validity of the technical inefficiency model, the aggregate returns to scale, the choice of translog functional form (against a Cobb Douglas functional form), the non-neutrality assumption in determination of technical inefficiency, heteroscedasticity and the joint significance of the tiime dummies in (8).

The first null hypothesis in table 3 which specifies that the inefficiency effects are absent is strongly rejected at the 5% level. The second null hypothesis that states that the inefficiency effects are not stochastic is also strongly rejected. The same holds for the third null hypothesis that states that the inefficiency effects are not a linear function of all the determinants considered in model (5). We fail to reject the null hypothesis of constant returns to scale in wheat production. We reject the null hypothesis of Cobb-Douglas production function specification at 5% level, which again justifies the choice of the translog production

[10] See http://www.asiaone.com/News/Latest+News/Asia/Story/A1Story20100421-211539.html for April 21, 2010 Reuters report that explains how low temperature has affected in a decline in wheat production in China.

frontier specification. This result also justifies our assumption that there is significant factor interaction effects in regional level wheat production. The hypothesis that the non-neutrality assumption in technical inefficiency model is invalid is also rejected at 5% level. There is no evidence of heteroscedasticity in our estimation of the technical inefficiency model, and the time dummies are jointly statistically significant.

The histogram of the estimated technical efficiency levels for the full panel is presented in figure 1 in appendix B. The technical efficiency estimates has a minimum of 34% and a maximum of 96%, and the mean and variance of these estimates for the full panel are 90% and 0.0045, respectively. The estimated technical efficiency for individual regions for the full sample period are presented in figure 2 in appendix B, and a summary of the descriptive statistics related to these measures is presented in table 4 in appendix A.

4.1 Marginal inefficiency effects

It is quite clear that there are significant interaction effects across the factors of wheat production and there is non-neutrality in the determination of technical inefficiency of the regions. In figure 3 in appendix B we present the scatter plots of the (computed cross section means of) elasticity measures for labour, machinery power, land and chemical fertilizer. These suggest that the elasticity of wheat output with respect to labour is always negative. This finding acts as our key motivation in including a proxy for labour productivity and interaction of the factors of production with labour productivity as explanatory variables in the technical inefficiency model. We derive the marginal inefficiency effect of labour productivity (MIE_w) by partially differentiating (8) with respect to wage, i.e.

$$MIE_{wit} = \mu_w + \mu_{wn} \ln n_{it} + \mu_{wm} \ln m_{it} + \mu_{wl} \ln l_{it} + \mu_{wf} \ln f_{it} \tag{10}$$

where μ_w is the parameter associated with wage in (8), and μ_{wj}, $j = n, m, l, f$ are the parameters associated with the interaction variables in (8). In addition, considering the non-neutrality of factors of wheat production we compute the second order cross marginal inefficiency effects of all four factors, where

$$\frac{\partial MIE_{wit}}{\partial n_{it}} = \mu_{wn} \left(\frac{1}{n_{it}} \right) \tag{11a}$$

$$\frac{\partial MIE_{wit}}{\partial m_{it}} = \mu_{wm} \left(\frac{1}{m_{it}} \right) \tag{11b}$$

$$\frac{\partial MIE_{wit}}{\partial l_{it}} = \mu_{wl} \left(\frac{1}{l_{it}} \right) \tag{11c}$$

$$\frac{\partial MIE_{wit}}{\partial f_{it}} = \mu_{wf} \left(\frac{1}{f_{it}} \right) \tag{11d}$$

We use the full panel data in order to compute the first order marginal inefficiency effect of wage (as in (10)) and the second order cross marginal inefficiency effects of the factors of wheat production (as in (11)). The scatter plot for these measures (mean of cross sections) are presented in figure 4 in appendix B. Their histograms and summary statistics are in figure 5 in the same appendix[11]. These suggest that higher level of wage (i.e. higher labour productivity) generally reduces technical inefficiency, but this effieincy gain is depressed by the use of more workers or more machinery power. The marginal gain in efficiency which can be attributable to higher labour productivity is excelled by the use of more cultivable land or chemical fertilizers. There is clear evidence of efficiency gains from higher wage over the years 1999-2005, and simultaneously for the same years we find that this gain continues to be depressed by more use of machinery power and workers.

These results suggest that agricultural policy reforms that introduce better land reforms and land management system and more competitive market for chemical fertilizers contribute to the rate of labour productivity-led marginal efficiency gain. However, any additional labour or allowing the existing labour force to use more machinery power depresses this rate. Given the agricultural policy reform history in China, our findings imply that rather than providing input subsidy or output price support, future reforms should put more emphasis on providing incentives to enhance labour productivity and encouraging formalization of the agricultural labour market.

4.2 Total factor productivity and technical efficiency at the regional level

We compute the total factor productivity (TFP) at the regional level using the standard Solow residual approach, given the translog production frontier (5). The regional TFP measures in this study therefore includes the second order effects and the interaction effects of the factors of wheat production. We also compute the growth rate in regional level TFP and the growth rate in regional level technical efficiency, and their trends for the full sample period are presented in figure 6 in appendix B[12]. For the full panel the correlation coefficient of these two growth rates is equal to 0.23.

The growth of TFP of wheat production at the regional level shows considerable amount of variation, both across regions and over the sample period. The mean growth rate of TFP is negative during the period 1999-2003, which can be attributable to the loss in productivity following the introduction of the more regulated *grain self-sufficiency* regime. The data suggests that for the full sample period (i.e. 1997-2006) only 4 out of the 30 regions have

[11] In figure 4 and 5 the measures of (11a-d) are labelled as MIEN2, MIEM2, MIEL2 and MIEF2, respectively.

[12] In figure 6 the growth rate of TFP is labelled as G_TFP and the growth rate of Technical Efficiency is labelled as G_TE.

experienced positive growth in wheat production. Immediately following the introduction of the grain self-sufficiency system there is a huge drop in wheat production in all regions. All 30 regions suffered negative growth of wheat production during 1999-2003. The average growth rate of the total quantity of wheat produced in these 30 regions of China during the full sample period was -6.2%, and for 1999-2003 this growth rate was -22%.

As in figure 6, this evidence is clearly supported by our computed growth rates in the regional level TFP. Mean TFP growth rate reaches a very high level in 2004 and after that it drops again, which can be due to a random shocks to the economy. During the same time period except for region 4, 6 and 14 (which are Fujian, Guangdon and Inner Mongolia) our results do not indicate any drastic changes in the technical efficiency of regions or in its growth rate. We find that for 10 out of the 30 regions (including Beijing) that we consider the TFP growth rate has a sudden rise in 2004, while for 8 others this rise is observed in 2005.

5 Concluding Remarks

The most recent major reform in Chinese agriculture is the introduction of the grain self-sufficiency system in 1998, through which the government took over the full control of the agricultural output and input prices. Data suggests that following this reform wheat production in China continued to suffer huge declines. Prior to this reform, several other reforms were undertaken in order to introduce incentives for farmers to produce more. Overall the history of agricultural reforms in China suggests that apart from the state-owned enterprise reform (in the nineties) the government did not explicitly introduce any reforms which improves the productivity of agricultural labour.

In this paper we show that in order to indentify the primary reasons behind the most recent decline in wheat production in China, it is necessary to identify the interaction and the non-neutral effects of factors that are used for producing wheat. Modelling the technical inefficiency effects with the non-neutral effects of factors enables us to clearly identify that one of the most important reasons behind the most recent decline in wheat production is the lack of government initiative to improve labour productivity. Our results imply that higher labour productivity can stimulate efficiency gains in wheat production, but simply increasing the quantity of labour or machinery can depress the rate of labour productivity-led efficiency gain in production. These results indicate that in future agricultural reforms in China that aim to increase the level of output and productivity should emphasize on the incentive scheme for labour.

With the introduction of the grain self-sufficiency system in 1998, the government of China has committed to improving the rural distribution system, strengthening agricultural service system and devising a farmland protection system. Our findings suggest that the government should put more emphasis on reforms that introduce a better incentive package for farmers to improve their productivity. A flat subsidy to wages does not serve this purpose, because such policies are essentially associated with misreporting of working hours. The government may consider abolishing the regulations in the labour market which in turns would enable markets to determine agricultural wage in a more competitive manner. In addition, it may consider registration schemes for farm income and alternative schemes that absorbs the unpaid or less than optimally paid surplus workers (e.g. family members at work).

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Appendix A: Tables.

Table 2: Summary of results from translog non-neutral stochastic frontier estimation

	Variable/Intercept	Parameter	Estimate	t-ratio
Production Frontier	Intercept	β_0	2.256	1.91**
	$\ln(n)$	β_n	-3.702	-4.013***
	$\ln(m)$	β_m	2.036	2.043**
	$\ln(l)$	β_l	3.732	6.772***
	$\ln(f)$	β_f	1.948	0.668
	$\ln(n) * \ln(n)$	β_{nn}	0.197	1.778*
	$\ln(m) * \ln(m)$	β_{mm}	-0.430	-4.891***
	$\ln(l) * \ln(l)$	β_{ll}	0.154	2.112**
	$\ln(f) * \ln(f)$	β_{ff}	1.007	6.813***
	$\ln(n) * \ln(m)$	β_{nm}	-0.359	-2.716***
	$\ln(n) * \ln(l)$	β_{nl}	1.233	1.752*
	$\ln(n) * \ln(f)$	β_{nf}	-0.887	-2.085**
	$\ln(m) * \ln(l)$	β_{ml}	0.161	1.943**
	$\ln(m) * \ln(f)$	β_{mf}	0.647	3.379***
	$\ln(l) * \ln(f)$	β_{lf}	-1.779	-4.512***
Technical Inefficiency Model	Intercept	μ_0	-0.103	-0.532
	w	μ_w	0.012	1.61*
	$w * \ln(n)$	μ_{wn}	-0.0000014	-2.27**
	$w * \ln(m)$	μ_{wm}	-0.0000012	-3.012***
	$w * \ln(l)$	μ_{wl}	0.0000008	1.808*
	$w * \ln(f)$	μ_{wf}	0.0000005	0.573
	bl	μ_{bl}	0.0000004	0.055
	ad	μ_{ad}	0.0201	2.615***
	ld	μ_{ld}	0.0097	1.624*
	tw	μ_{tw}	-0.0011	-2.518***
	tmp	μ_{tmp}	-0.0016	-4.316***
	ds	μ_{ds}	-0.0002	-1.031
	$Time\ dummies$	μ_2	-0.022	-0.011
		μ_3	0.973	0.766
		μ_4	0.096	1.001
		μ_5	-0.861	-2.011**
		μ_6	0.122	0.989
		μ_7	0.118	2.915***
		μ_8	-0.341	-0.917
		μ_9	0.913	1.602*
		μ_{10}	-0.457	-0.936
	γ		0.891	7.122***
	$\ln(likelihood)$		30.23	

Note: ***, ** and * imply statistically significant at 1%, 5% and 10% level.

Table 3: Summary of likelihood ratio tests.

	Null Hypothesis	log of likelihood	Test Statistic	Critical Value at 5% level	Decision
1	$\gamma = \mu_0 = \mu_w = \mu_{wn} = ... = \mu_{10} = 0$	9.08	42.3	21.1	Reject Null
2	$\gamma = 0$	26.03	8.41	5.13	Reject Null
3	$\mu_w = \mu_{wn} = ... = \mu_{10} = 0$	10.064	40.32	31.4	Reject Null
4	$\sum \eta_j = 1$	25.79	8.88	11.1	Accept Null
5	$\beta_{jj} = \beta_{jk} = \mu_{wj} = 0; j \neq k$	11.67	37.12	23.7	Reject Null
6	$\mu_{wn} = \mu_{wm} = \mu_{wl} = \mu_{wf} = 0$	20.01	20.43	9.49	Reject Null
7	$\xi_w = \xi_{bl} = ... = \xi_{ds} = 0$	28.635	3.19	7.81	Accept Null
8	$\mu_2 = \mu_3 = ... = \mu_{10} = 0$	19.08	22.3	16.9	Reject Null

Table 4: Descriptive statistics of Technical Efficiency Estimates

Technical Efficiency	Mean	St. Dev.	Observations
$[20\%, 40\%)$	0.348	–	1
$[60\%, 80\%)$	0.705	0.072	14
$[80\%, 100\%)$	0.912	0.038	285
All	0.900	0.067	300

Table 1: Variables and their summary statistics (30 regions, 1997-2006)

Variable	Description	Mean	St. Dev	Min	Max
Output (q)	Total yield of wheat (1000 tons)	1449.37	3260.82	0.030	17271.96
Labour (n)	Agricultural employment (10000 persons)	282.70	548.91	0.855	5193.69
Machinery (m)	Total power of agricultural machinery (10000 kw)	521.24	984.02	2.507	4854.93
Land (l)	Total area of land sown for wheat (10000 Hectares)	384.92	957.03	0.012	11771.28
Fertilizer (f)	Total quantity of chemical fertilizer (10000 tons)	39.28	68.32	0.270	332.26
Wage (w)	Average annual wage of agricultural workers (yuan)	6686.74	3653.48	3327.00	36056.83
Bullock (bl)	Cattle & Buffaloe (10000 heads)	391.26	287.81	6.100	1191.65
Altitude Dummy (ad)	1 if region has ≥ 2000 meters altitude from the sea level, 0 otherwise	—	—	—	—
Illiteracy Dummy (ld)	1 if region has illiteracy rate that is $\geq 10\%$, 0 otherwise	—	—	—	—
Tap Water Access (tw)	% of regional population who have access to tap water	96.173	4.213	71.00	100.00
Temperature (tmp)	Average annual temperature (in degree celsius)	14.984	4.333	4.340	26.347
Disaster Affected Area (ds)	% of total area affected by disaster	57.75	13.087	0.004	79.60

Appendix B: Figures

Figure 1: Histogram and descriptive statistics of elasticity, returns to scale and technical efficiency.

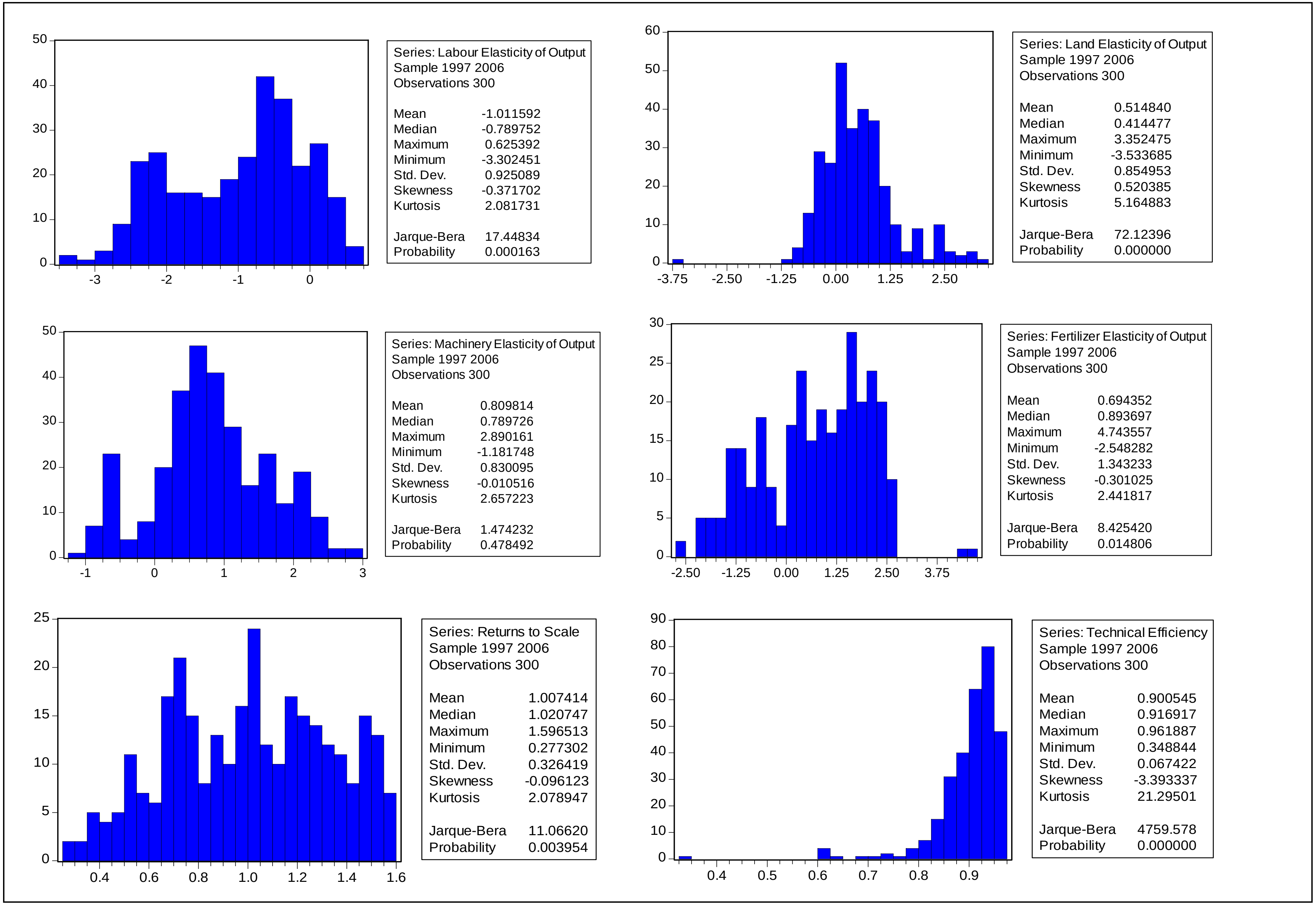

Figure 2: Technical efficiency for individual regions, 1997-2006.

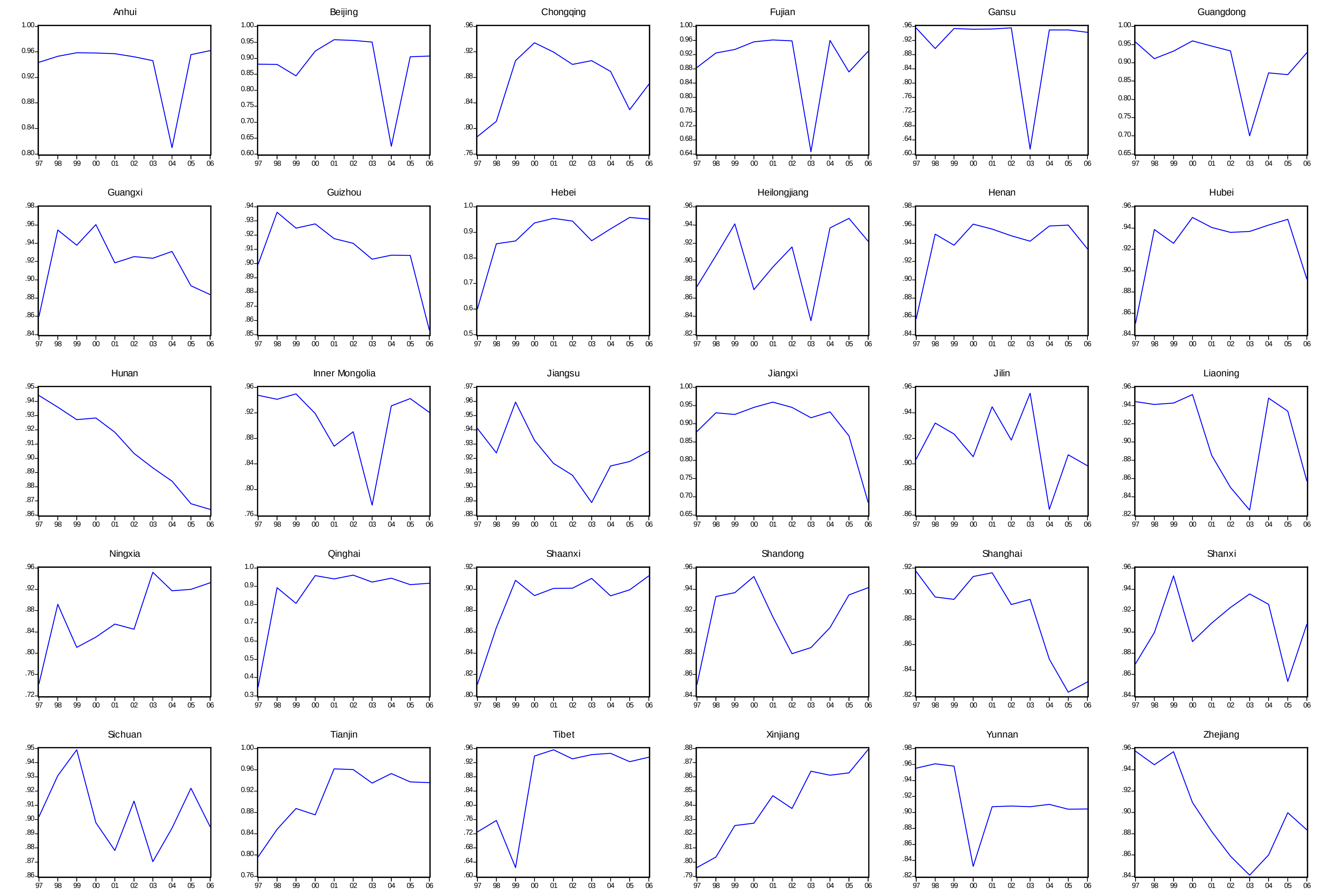

Figure 5: Histogram and descriptive statistics of marginal inefficiency effect and cross effects measures.

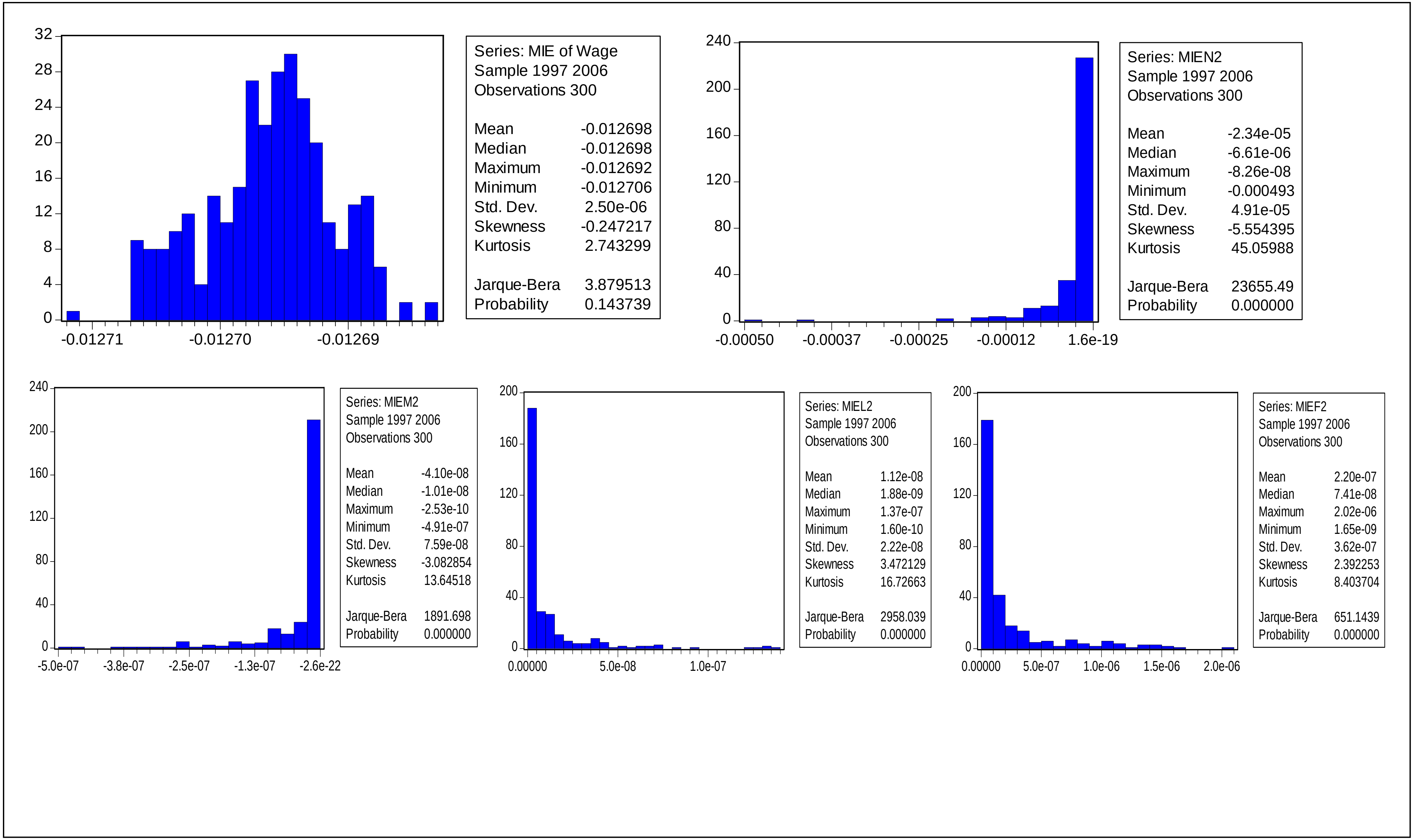

Figure 6: Growth in TFP and Growth in Technical efficiency for individual regions, 1997-2006.

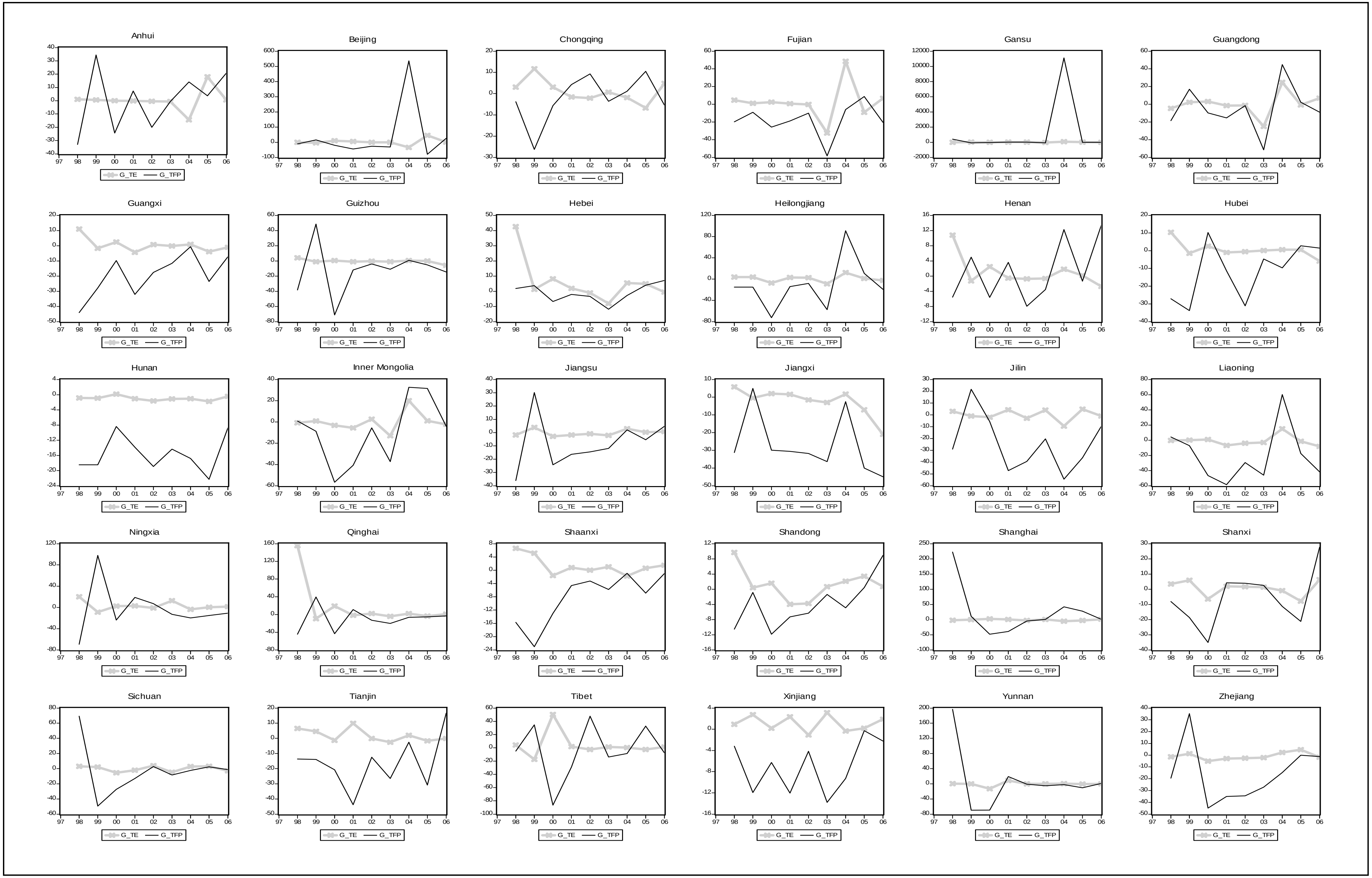

Figure 3: Scatter plots of the (computed cross section means of) elasticity measures for labour, machinery power, land and chemical fertilizer.

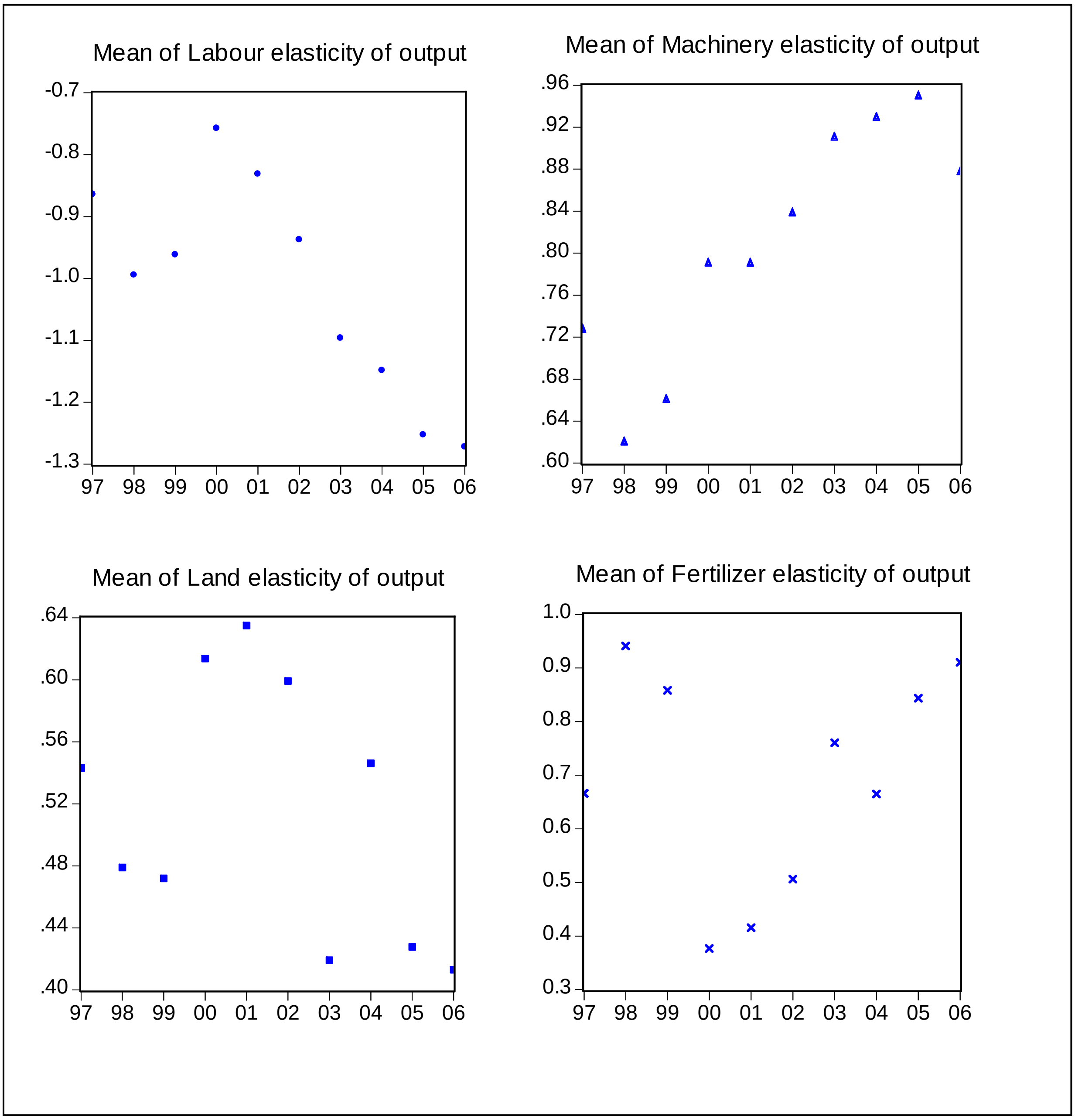

Figure 4: Plots for marginal inefficiency effect and cross effects measures (mean of cross sections).