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ESTIMATING CROP-SPECIFIC PRODUCTION TECHNOLOGIES IN CHINESE AGRICULTURE: A GENERALIZED MAXIMUM ENTROPY APPROACH

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ABSTRACT

A Generalized Maximum Entropy (GME) approach is adapted to empirically estimate crop-specific production technologies in Chinese agriculture. Despite a modest behavior assumption about equal marginal returns of non-land inputs among crops, this method does not require price information, which is usually distorted in a centrally planned economy such as China. Multi-output technologies for seven regions over more than two decades are estimated, and input allocations for each province are recovered simultaneously. The estimated multi-output production technology and input allocations imply that China may have greater grain production potentials than previously thought.

CONTENTS

ESTIMATING CROP-SPECIFIC PRODUCTION TECHNOLOGIES IN CHINESE AGRICULTURE: A GENERALIZED MAXIMUM ENTROPY APPROACH

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1. INTRODUCTION

One of the most difficult problems associated with the estimation of agricultural production function is that crop-specific input usage is generally not available. In the past, there have been several approaches in estimating crop-specific inputs (Just, Zilberman, and Hochman, 1983; Shumway, Pope, and Nash, 1984; Shumway, 1988; Just et al., 1990; Lence and Miller, 1998a, 1998b). A classical approach is to use the relationship between input allocations and production parameters under the assumption of profit maximization (Shumway, Pope, and Nash; Just et al.). However, this assumption is often rejected by empirical production analysis (Love, 1999). Moreover, in many centrally planned economies, both prices and quantities of inputs and outputs are heavily regulated and distorted by the government, making it even more difficult to recover input allocations based on price information and the standard profit-maximization assumption. A more practical approach is to assume that input allocations follow some behavior rules such as equal fixed inputs per unit of activity (Just et al.). In other words, some restrictive assumption about production technology has to be imposed.

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More recently, Lence and Miller proposed a Generalized Maximum Entropy (GME) approach to estimate multi-output production function and to recover input allocations simultaneously. This approach does not require behavioral assumptions, but does accommodate nonsample information about plausible factor share allocations. Using Monte Carlo simulations, Lence and Miller show that this approach has better performance relative to other methods. But so far, no empirical application of this method has been seen to our knowledge. It is not clear whether this method can be adapted to an empirical production analysis in recovering input allocation information.

The objective of this study is to empirically estimate production functions and to recover the input allocations in Chinese agriculture simultaneously, using the GME approach. There are several reasons for choosing China. Firstly, China is the largest grain producer, as well as the largest consumer in the world. Even a small change either in grain production or consumption will have a large impact on the world grain market. As the significant differences among projections for China's future food balance are primarily due to the disagreement in the supply side, i.e., future potential of grain production (Fan and Agcaoili-Sombilla, 1997), it is crucial to identify grain production technology correctly.

Over the last decade, there have been a few empirical studies estimating grain production or yield functions for Chinese agriculture (Lin, 1992; Huang and Rozelle, 1995; Wu and Meng, 1995; Zhang and Carter, 1997). Due to lack of crop-specific input information, all these studies had to make some strong assumptions about input use. Huang and Rozelle (1995) and Wu and Meng (1995) use total inputs for agriculture to estimate the grain yield function or production function, respectively. As we know, the input use of grain is very different from that of other crops. For example, grain production may use less labor and fertilizer than cash crops. Lin derived labor use for crop production based on the shares of output values of crops in total agricultural output value. The underlying assumption of this method is that labor elasticities are the same for crops and noncrops.

Zhang and Carter generated labor and fertilizer inputs for grain production using provincial labor and fertilizer input shares from the Provincial Production and Cost Survey, and applying them to the county-level data. However, the reliability of the survey data has been questioned by Colby, Crook, and Webb (1992) for its extremely small sample size, e.g., only six households surveyed in Shanxi Province in 1984 and for nonrandomness of the sample. As a result, due to lack of crop-specific input information, previous estimates of grain production functions for Chinese agriculture might be biased because grain production technologies may differ sharply from other crops and the changes in input shares may vary across regions and over time. Consequently, any projections on China’s grain supply based on these parameters are also likely to be biased.

The second reason for choosing China is that, until at least recently, it had been a typical, centrally planned economy, which provides a testing ground for other centrally planned economies that could use the same procedure for recovering their input allocations. Input allocations in these countries’ agriculture may provide important information for U.S. agricultural trade, as these countries represent potentially large trading partners for U.S. agricultural products. Understanding crop-specific technology is key to analyzing the comparative advantage of individual crop and potential trading patterns in the future.

The next section discusses the model specification and shows how a behavioral assumption is accommodated within the GME model. The third section reports estimation results. Concluding remarks and policy implications are provided in the final section.

2. MODEL SPECIFICATION

The agricultural sector in China produces a great number of products including major staples like rice, wheat and corn; major livestock products such as meat, wool, and dairy products; and horticultural and fishery products. Three aggregate outputs (grain crops, cash crops, and other agricultural activities) and five inputs (land, labor, chemical fertilizer, machinery, and draft animals) are considered in our analysis, based on both data availability and the desire for comparison with other studies. The production values of the above three outputs are measured in constant 1980 prices. A panel dataset including 25 provinces over the period 1975-96 is constructed from various governmental sources. In order to minimize the heterogeneity problem inherent in Chinese agricultural production across regions, China is divided into seven production regions, following Fan (1991), which takes into account the availability of the agricultural data, the geographical features, and the current social and economic conditions. A detailed description about data sources, coverage, and regional classification is provided in Appendix A.

To adapt the GME approach to the empirical analysis, the following Cobb-Douglas production function is used to represent the multi-input, multi-output technology[1]:

$$\ln(Y_{ikt}) = \alpha_{1kt}^{(r)} * \ln(A_{ikt}) + \sum_{j=2}^{5} \alpha_{jkt}^{(r)} * \ln(f_{jkt}^{(r)} * X_{ijt}) + c_{kt}^{(r)} + \varepsilon_{ikt} \, , \qquad (1)$$

and

$$\sum_{k=1}^{3} f_{jkt}^{(r)} = 1 \qquad (2)$$

for any t and j>1, where i = 1–25 represents the 25 provinces; k=1, 2, and 3 refers to grain crops, cash crops, and other agricultural activities, respectively; t denotes the year of 1975-1996 (t=1 if year=1975; t=22 if year=1996); r=1 to 7 represents northeast, north, northwest, central, east, south, and southeast regions; and j=2 to 5 denotes the input uses of labor, chemical fertilizer, machinery, and draft animals, respectively. The parameter $f_{jkt}^{(r)}$ defines the share of input j in production k at time t; Y_{ikt} is province i's production value of the kth output at time t, which is expressed in 1980 constant prices; A_{ikt} represents the ith province's land use for the kth output at time t; X_{ijt} refers to the total use of input j by province i at time t, which is known; $\alpha_{jkt}^{(r)}$ is the input j's production elasticity for crop

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[1] Based on our classification of the three major activities, the interdependence among the activities is mainly through inputs instead of outputs. Therefore, the technical interdependence term, which appears in Lence and Miller's specification, is not included in our specification. Translog production function and alternative error structures are also tried, but the increase in unknown parameters would greatly complicate the nonlinear optimization problem. Furthermore, most of previous studies in Chinese agriculture use the C-D functional form (Fan 1991, Lin 1992, Rozelle and Huang 1996, Fan and Pardey 1997, and Carter and Zhang 1997).

k at time t in region r for j>1, while $\alpha_{1kt}^{(r)}$ is production elasticity of land for crop k at time t; and $c_{kt}^{(r)}$ is a common intercept for output k at time t in region r. Disturbance is represented by ε_{ikt}.

Land allocations (planted areas for various activities) are known, but nonland input uses are observed only at the aggregate level, not at the crop-specific level. Therefore, the parameters in (1) cannot be estimated by the standard econometric technique because multiple solutions exist due to the unknown nonland input allocations $f_{jkt}^{(r)}$. However, the GME method can solve this kind of underdefined problem.

The entropy concept was formalized by Shannon (1947), with his assertion that the "information" received by one event E_i is equal to $-\ln p_i$, for a given set of n events E_1, E_2, …, E_n with probabilities p_1, p_2, …, p_n. The entropy is defined as the expected information value, $-\sum p_i \ln p_i$. Jaynes (1957a, 1957b) expanded this definition as a maximum principle to choose an unknown distribution of probabilities from given moment constraints. The philosophy of maximum entropy can be stated in two principles: 1) use all the information available, and 2) do not assume (or use) any information not available. Golan, Judge, and Miller (1996) further generalized the maximum entropy method to solve many standard and ill-posed econometric problems by reparameterizing real value unknowns in terms of probabilities. Lence and Miller demonstrated the usefulness of the GME method in estimating multi-output production function and recovering unknown input allocations. The basic idea of the GME is to transform all real-value parameters into a probability form.

Since the intercept and error terms are indistinguishable, we will first estimate them together and then recover the intercepts as mean values and error terms as mean deviations. Following Golan, Judge, and Miller (1994), we write the sum of intercept and error terms as a weighted average of known constant as follows:

$$c_{kt}^{(r)} + \varepsilon_{ikt} = \sum_{l=1}^{s} z_{kl} * w_{iktl} \tag{3}$$

Where { z_{kl} } is the parameter space that corresponds to the possible realizations of w_{iktl} and s is the number of elements in the parameter space. The weights w_{iktl} are treated as probabilities to be estimated. The vector of { w_{iktl} } satisfies the following properties of probabilities:

$$w_{iktl} \geq 0 \text{ and } \sum_{l=1}^{s} w_{iktl} = 1 \quad \text{for any i, k, and t.} \tag{4}$$

A review of existing literature on the estimations of Chinese agricultural production functions supports the hypothesis of constant return to scale in Chinese agriculture (Carter, 1995). Therefore, we impose the constant return to scale in our estimation:

$$\alpha_{jkt}^{(r)} \geq 0 \text{ and } \sum_{j=1}^{5} \alpha_{jkt}^{(r)} = 1 \text{ for any k and t.} \tag{5}$$

In principle, the parameters $\alpha_{jkt}^{(r)}$ can also be reparameterized in terms of probabilities. But if (5) holds, these parameters may be viewed as an unknown frequency distribution and be estimated directly.[2] The GME problem can be set up as maximizing the sum of the entropy in regard to the parameters of elasticities, error frequency, and input shares:

$$H^{(r)}(a,w,f) \equiv -\sum_{j=1}^{5}\sum_{t=1}^{22}\sum_{k=1}^{3}[a_{jtk}^{(r)}\ln(a_{jtk}^{(r)})] - \sum_{i\in r}\sum_{t=1}^{22}\sum_{k=1}^{3}\sum_{l=1}^{5}[w_{itkl}\ln(w_{itkl})] - \sum_{j=2}^{5}\sum_{t=1}^{22}\sum_{k=1}^{3}[f_{jtk}^{(r)}\ln(f_{jtk}^{(r)})] \quad (6)$$

subject to (1)–(5).

In addition, since noncrop production does not require fertilizer use, the fertilizer allocation and input elasticity for this output are set to zero. Because we do not have any prior information regarding the input allocations among crops, we choose a uniform distribution for the ex-ante shares, which is implied by the above objective function.[3]

Obviously the above specification does not assume any possible relationship between the production technology and input allocations. In a planned or transitional economy, farmers' decisions on land allocation and total input use are unlikely to be determined by pure economic factors due to the distorted price system and persistent administrative interventions by governments. But when land allocations and total input uses are given (often distorted by the government), we argue that farmers have the capacity and incentive to make rational decisions to allocate their nonland inputs among

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[2] We find that writing the parameters in terms of probabilities significantly increases computing time only without affecting our basic conclusions. So we opt to choose this simpler specification.

[3] As stated earlier, it is problematic to use national production and cost survey as prior information. So far, we have not found any other ex-ante input allocation information. If prior information is available, it can be accommodated into the objective function easily as cross entropy (see Lence and Miller for more details).

crops in an efficient way, such that their total output values are maximized. If this assumption holds, the marginal returns of nonland inputs among different agricultural activities must be equal, which can be expressed explicitly as follows:

$$\alpha_{j1t}^{(r)} * \frac{Y_{i1t}}{(f_{j1t}^{(r)} * X_{ijt})} = \alpha_{j2t}^{(r)} * \frac{Y_{i2t}}{(f_{j2t}^{(r)} * X_{ijt})} = \alpha_{j3t}^{(r)} * \frac{Y_{i3t}}{(f_{j3t}^{(r)} * X_{ijt})} \quad . \qquad (7)$$

The common term of total input X_{ijt} can be eliminated from the above constraint. Notice this assumption is a necessary, but not sufficient, condition for the standard profit maximization. The profit-maximization assumption requires not only that the marginal return of an input be the same across different crops, but also that it be equal to the input price. In addition, the total input uses are taken as given in our estimation, as opposed to being endogenously solved using input and output prices under a profit-maximization framework. The model may also be estimated by using conventional constrained maximum likelihood method with constraints (5) and (7). But one would have to restrict the parameters to be constant over time and across regions and make strong assumptions about the distribution of error terms, because otherwise, there are not enough degrees of freedom for estimation. In our case, since we are more concerned about the regional and temporal difference, the maximum entropy method is a more appropriate technique to deal with this kind of ill-posed question.

Due to lack of prior information about the distribution of the intercept, we use a two-stage method to determinate the parameter support space. First, we set s=5 and let the distribution of the error follow a symmetric distribution around 0, i.e., { z_{kl} }= {-6, -3, 0, 3, 6}.[4] The bound of six is chosen because it is slightly larger than the maximum absolute value of the log of all the outputs. Using this set of $\{z_{kl}\}$, we can estimate the intercepts by maximizing (6). In the second stage, we calculate the expected value and the standard error of the intercepts for each of the three crops, and reset $\{z_{kl}\}=\{\bar{c}_k - 4\sigma_k$, $\bar{c}_k - 2\sigma_k, \bar{c}_k, \bar{c}_k + 2\sigma_k, \bar{c}_k + 4\sigma_k\}$, where $\bar{c}_k$ and σ_k are the estimated mean value and standard error for equation k from the first stage. Here, $\bar{c}_k$ is greater than 0, implying that the support space is not symmetric around 0, but around a positive number.

With the additional constraint (7) imposed, the production functions and input allocations for the seven regions can be solved using the GAMS/CONOPT2 software, which takes about 2.5 hours to run using a Pentium 400 computer.

The following pseduo-R^2 is defined to evaluate the fitness of estimations for the three equations in the seven regions.

$$R^2(k,r) = 1 - \frac{\sum_{i\in r} |\varepsilon_{ikt}|^2}{\sum_{i\in r} |y_{ikt} - \bar{y}_{kt}^{(r)}|^2} \quad , \tag{8}$$

where $\bar{y}_{kt}^{(r)}$ is the mean value of output k at time t in region r. Although there are ways to derive asymptotic covariance expressions for some GME estimators, the problem is much complicated by the joint estimation of the shares and the parameters in this case. Hence,

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[4] We also set the number of support as 3 and the results are similar. Adding more points to the support would decrease the variance of the associated point estimator (Golan, Judge and Miller, 1995) but would increase the burden of computation. As a compromise, we set s=5 here.

in this paper, the standard errors are not estimated, which may limit the confidence of the estimation results.

3. ESTIMATION RESULTS

The estimated input elasticities of the seven regions in the selected years of 1975, 1985, and 1996 and pseudo-R^2s are presented in Table 1. The high pseudo-R^2 in Table 1 indicates good fitness in the estimated production functions in the seven regions. The national input elasticities for grain crops, aggregated from those values in the seven regions using output values as weights, are graphed in Figure 1, and also presented in Table 2 for the year of 1985, along with other studies (see Appendix B for the derivation).

Several features are immediately apparent from Figure 1 and Tables 1 and 2. First, the production technologies among crops differ. From Tables 1 and 2, it is evident that grain crops have higher land elasticity and lower nonland input elasticities compared with cash crops and other activity, while cash crops have the highest labor elasticity and lowest land elasticity.

Table 1: Estimated input elasticities

Parameters	Northeast			North			Northwest			Central			East			South			Southwest		
	Grain	Cash	Other	Grain	Cash	Other	Grain	Cash	Other	Grain	Cash	Other	Grain	Cash	Other	Grain	Cash	Other	Grain	Cash	Other
1975																					
intercept	0.82	1.59	1.85	0.91	1.42	1.85	1.19	1.59	1.50	1.16	1.38	2.03	1.32	1.57	2.22	1.48	1.51	2.26	0.97	1.52	2.16
land	0.61	0.08	0.26	0.50	0.04	0.19	0.39	0.10	0.22	0.50	0.06	0.25	0.50	0.14	0.29	0.28	0.12	0.29	0.48	0.07	0.25
labor	0.14	0.25	0.29	0.12	0.24	1.85	0.17	0.26	0.23	0.13	0.24	0.24	0.15	0.23	0.26	0.19	0.25	0.26	0.15	0.25	0.24
fertilizer	0.04	0.17		0.10	0.23		0.05	0.16		0.08	0.18		0.11	0.21		0.14	0.17		0.06	0.16	
machinery	0.14	0.26	0.29	0.21	0.35	0.39	0.30	0.24	0.42	0.16	0.31	0.29	0.12	0.20	0.22	0.16	0.23	0.19	0.18	0.28	0.27
draft animal	0.07	0.24	0.17	0.06	0.15	0.15	0.10	0.24	0.13	0.12	0.21	0.22	0.13	0.22	0.24	0.23	0.23	0.27	0.14	0.25	0.24
1985																					
intercept	1.13	1.59	2.13	1.21	1.42	2.09	1.23	1.57	1.37	1.40	1.46	2.22	1.57	1.86	2.86	1.53	1.81	2.96	1.22	1.47	2.46
land	0.53	0.09	0.38	0.40	0.10	0.22	0.29	0.10	0.24	0.43	0.13	0.34	0.49	0.19	0.44	0.24	0.22	0.45	0.29	0.09	0.32
labor	0.12	0.23	0.19	0.18	0.27	0.29	0.22	0.25	0.29	0.15	0.22	0.21	0.15	0.23	0.21	0.20	0.20	0.17	0.21	0.27	0.24
fertilizer	0.07	0.18		0.12	0.19		0.08	0.14		0.11	0.18		0.12	0.20		0.15	0.16		0.11	0.15	
machinery	0.13	0.24	0.20	0.18	0.26	0.29	0.22	0.26	0.27	0.14	0.23	0.21	0.15	0.24	0.22	0.17	0.17	0.14	0.17	0.24	0.18
draft animal	0.15	0.27	0.23	0.13	0.18	0.21	0.19	0.24	0.20	0.17	0.24	0.24	0.09	0.15	0.12	0.24	0.25	0.24	0.22	0.25	0.26
1996																					
intercept	1.43	1.97	2.91	1.41	1.64	2.62	1.35	1.69	1.47	1.52	1.55	3.05	1.73	1.99	3.72	1.63	2.15	3.72	1.38	1.52	2.72
land	0.53	0.13	0.60	0.29	0.13	0.29	0.37	0.15	0.33	0.36	0.17	0.60	0.45	0.20	0.67	0.27	0.29	0.57	0.24	0.14	0.35
labor	0.04	0.08	0.04	0.11	0.13	0.09	0.14	0.15	0.19	0.13	0.18	0.09	0.12	0.16	0.07	0.14	0.08	0.04	0.20	0.24	0.19
fertilizer	0.10	0.24		0.11	0.11		0.09	0.16		0.13	0.17		0.17	0.23		0.21	0.14		0.13	0.14	
machinery	0.09	0.19	0.10	0.20	0.24	0.21	0.18	0.23	0.23	0.14	0.19	0.10	0.21	0.34	0.23	0.19	0.15	0.08	0.16	0.20	0.14
draft animal	0.24	0.36	0.27	0.30	0.39	0.41	0.21	0.29	0.25	0.24	0.29	0.20	0.05	0.06	0.03	0.19	0.34	0.31	0.27	0.28	0.32
R-Square	0.96	0.93	0.88	0.90	0.97	0.84	0.92	0.98	0.79	0.88	0.97	0.95	0.97	0.97	0.99	0.94	0.95	0.90	0.89	0.96	0.92

Table 2: Comparison of input elasticities among different studies

Authors	Land	Labor	Fertilizer	Machinery	Draft animal	Dependent variable	Study period	Comments
Fan (1991)	0.10	0.20	0.30	0.27		GVAO	1965-85	aggegate inputs
Fan & Pardey (1997)	0.15	0.11	0.21	0.15		GVAO	1965-93	aggegate inputs
Huang & Rozelle (1995)		0.29	0.10			rice yield	1975-90	aggegate inputs
Lin (1992)	0.67	0.13	0.19	0.07		total values of crops	1979-87	adjusted based on shares&values
Wu & Meng (1995)	0.52	0.04	0.14	0.04	0.01	grain output	1993-94	aggegate inputs
Zhang & Carter (1997)	0.44	0.23	0.20	0.03		grain output	1980-90	derived from cost survey
This study								
Grain crops	0.40	0.17	0.11	0.16	0.16	total values of grain	1975-96	adjusted inputs
Cash crops	0.13	0.24	0.18	0.24	0.21	total values of cash crop	1975-97	adjusted inputs
Other activity	0.34	0.23		0.22	0.22	total values of other activity	1975-98	adjusted inputs

Note:

1. The total input elasticities in this study are calculated by aggregating the individual elasticities in the seven regions in 1985 using output values as weights.
2. Fan's elasticities are evaluated in 1985; the elasticities in Fan and Pardey are taken from the second specifications of five different sets of results in their paper.
3. Labor in Wu and Meng refers to male agricultural labor; labor in Wu and Meng refers to male agricultural labor. Since the input variables used in alternative studies are not exactly same, we only report the estimations for the inputs that are comparable to those used in our study. As a consequence, the sum of the parameters may appear less than 1 due to the exclusion of some inputs.

Figure 1: Input elasticities for grain crops

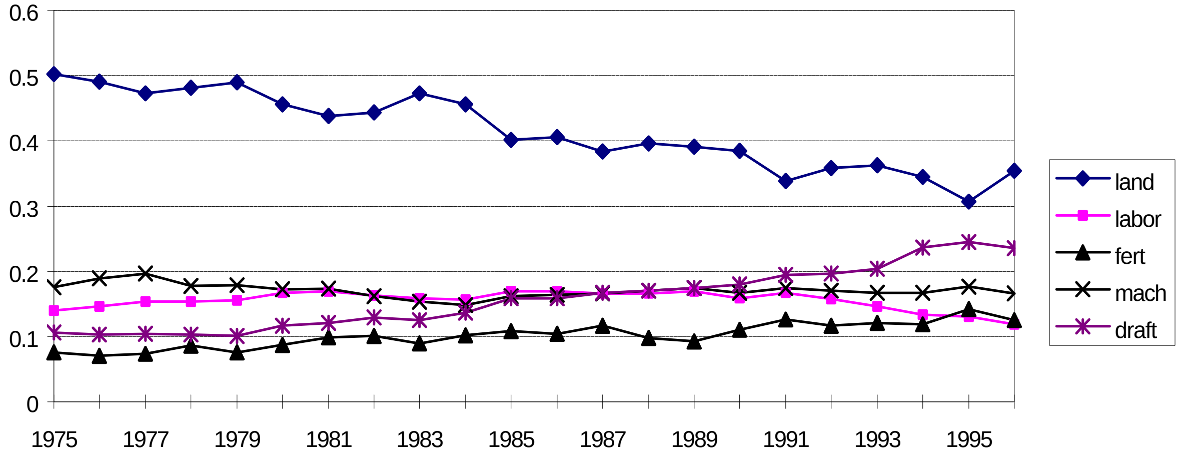


Figure 2a: Input shares for grain crops

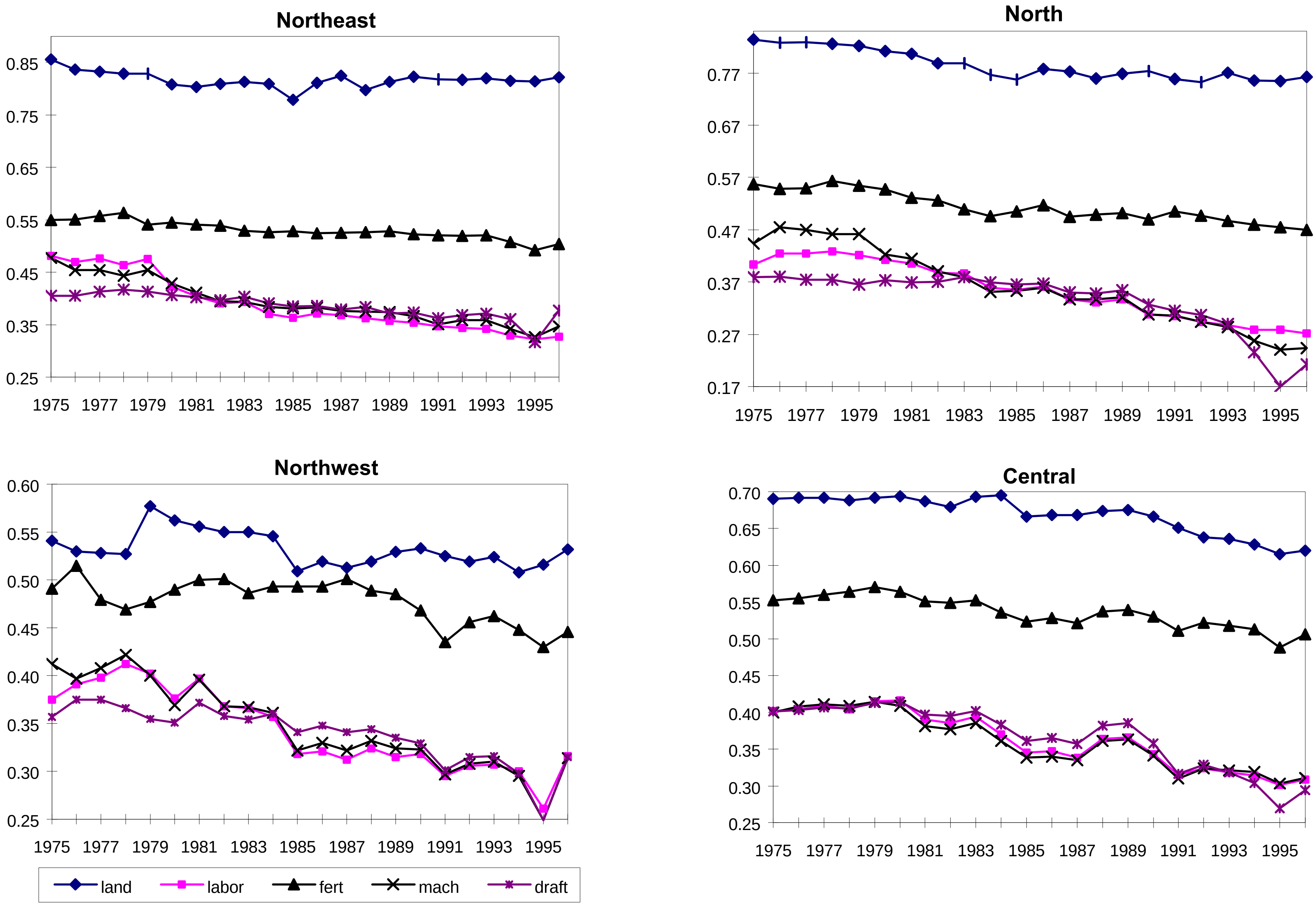
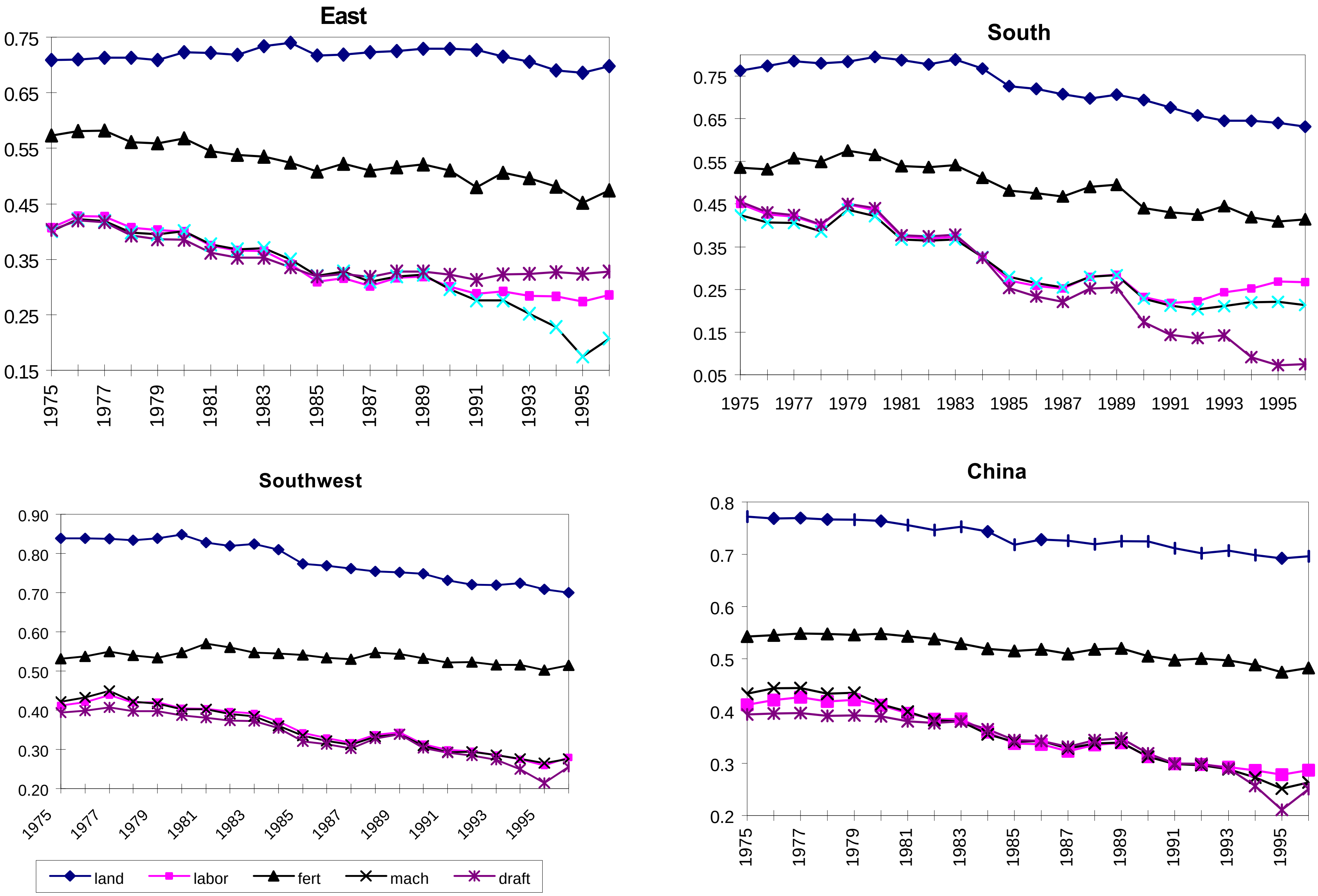


Figure 2b: Input shares for grain crops



Second, significant regional differences exist in terms of the magnitude of input elasticities.[5] For example, in 1975, the land elasticities for grain production range from 0.61 in the northeast to 0.28 in the south, while labor elasticities in these two regions are 0.14 and 0.19, respectively. Generally, land elasticities in northern and central China are greater than those in other regions, indicating that these two regions have higher marginal land productivity and therefore, greater potential for increased grain production.

Third, the changes in input elasticities in the seven regions over time share similar trends. With respect to grain crops, land elasticities have declined, while elasticities of chemical fertilizer and draft animals have increased. The elasticities of labor and machinery are relatively constant over time. Given the eventual limit on the area that can be sown, nonland input-intensive technologies such as use of more chemical fertilizer plays an increasingly important role in boosting grain production. This is consistent with the prediction by the induced innovation theory (Hayami and Ruttan, 1985). With population increasing, the land becomes scarcer, therefore, technology development will be induced to facilitate the substitution of increasingly more expensive factor-land, for less expensive factors, such as fertilizer. For cash crops, the input elasticities of land and draft animals show an increase, while labor input elasticity shows a decrease.

Fourth, the intercepts in all the equations have increased over time, which might be attributed to technological change, however, one should be aware of the impact of

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[5] Assuming all the provinces sharing a common production technology, and using the same procedure mentioned above, we could not find a feasible solution for the estimation. Perhaps this is because of regional heterogeneity inherent in Chinese agricultural production.

possible measurement errors of output values which are measured at constant prices on the intercepts.[6]

Figure 2 graphs the evolutions of the five input shares for grain production over time in the seven regions, and in China as a whole. Despite some slight fluctuations, the share of grain in total input use has declined however the magnitude differs across regions. The decline is more dramatic in the south and the east, where general economies have grown more rapidly than elsewhere. For instance, the draft-animal use for the grain crops in the south falls from over 40 percent to less than ten percent over the 22 year period, compared with a mere three percent decline in the northeast. These differences across regions and over time support our argument that if total inputs for agricultural production are used, the estimated grain production function may be biased, even after both regional and time effects have been taken into account.

In terms of the aggregate input use in agricultural production, machinery and chemical fertilizer use increases much faster than other inputs. From 1975 to 1996, the aggregate use of machinery, chemical fertilizer, draft animals, labor, and land increases by 420, 139, 73, 23, and three percent, respectively. Taking both the shifts in nonland input allocations and land use into account, we can derive the nonland input uses per unit of land for different agricultural activities, especially for grain crops. Figure 3 plots the trends of input use per unit of land for grain production in various regions. For most regions, the use of chemical fertilizer and machinery a representation of modern technology becomes increasingly intensive. In contrast, the changes in traditional inputs,

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[6] Fan (1997) has shown that if constant prices are used to aggregate total output growth, the annual growth of total output is overestimated by more than one percent

such as labor and draft animals, have been flat. This phenomenon is more evident in the east and south where the use of labor and draft animals actually declined during this period.

With the estimated input elasticities and input uses for all seven regions and China as a whole, we are in a position to compare the input elasticities for grain crops among different studies. The comparisons are presented in Table 2. The two studies by Fan (1991) and Fan and Pardey (1997), using the gross value of agricultural output (GVAO) as a dependent variable, provide lower land elasticities compared with other studies. This is consistent with our findings that the land production elasticity for grain crops is larger than that of other crops, since grain production typically uses more land and grain is just a part of total agricultural production. Huang and Rozelle (1995), who estimated a rice yield function by using total agricultural labor and fertilizer inputs as explanatory variables, reported a labor elasticity of 0.29. As a yield function is different from a production function, their labor and fertilizer elasticities are not comparable to other studies. However, as labor shares have changed over time and are different across regions, using total labor input would lead to biased results in their estimation. In the study by Wu and Meng (1995), the grain production function is estimated using household survey data in which total inputs are again used instead of those for grain. With the exception of fertilizer, most of their nonland input elasticities, are lower than those in this study. Although total nonland inputs have increased considerably over the

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compared with a more appropriate Törnqvist-Theil index.

Figure 3a: The input use per unit of land for grain crops

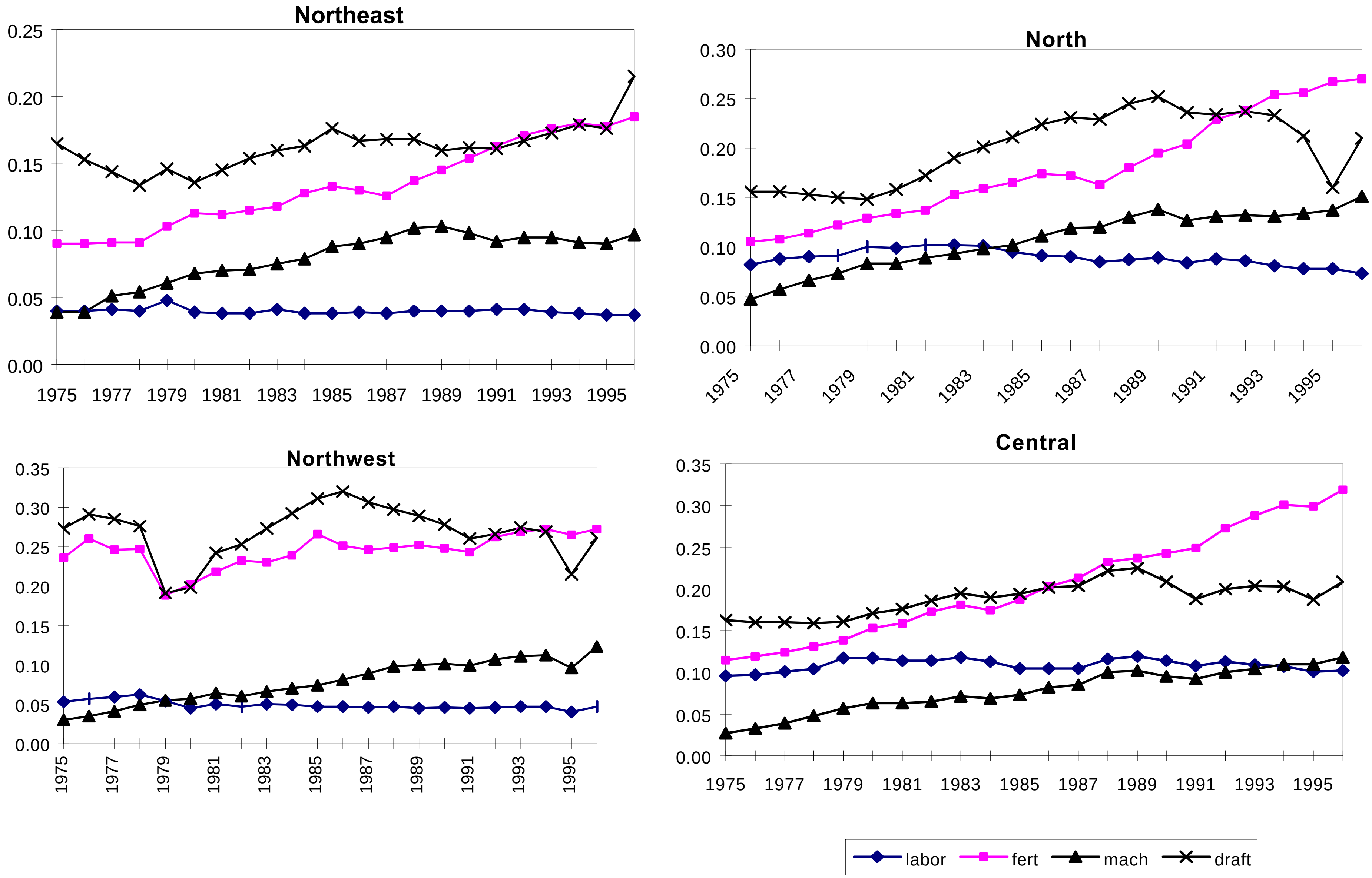
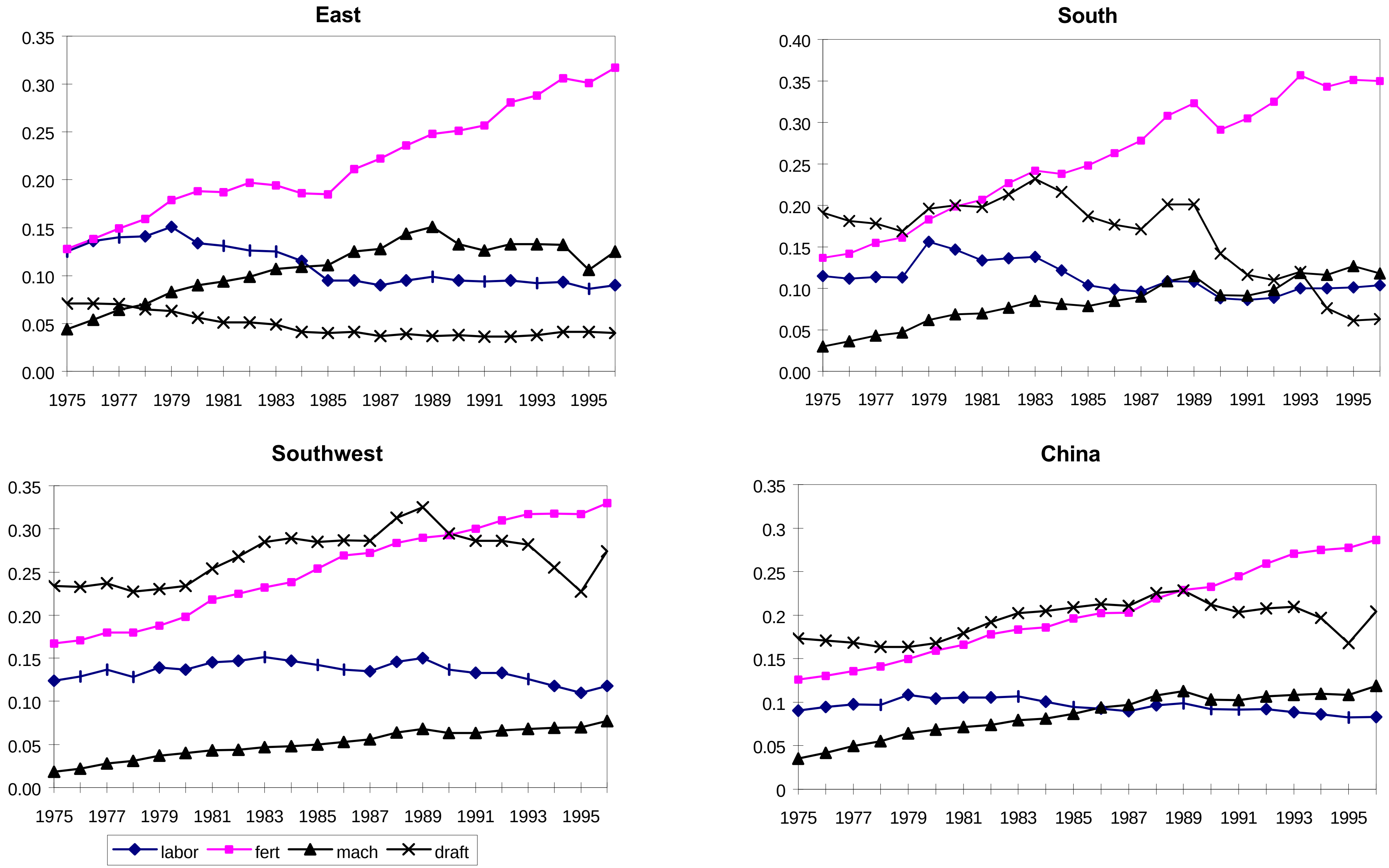


Figure 3b: The input use per unit of land for grain crops



study period, the increase of these inputs in grain production is relatively slow, especially after the mid-1980s. Therefore, not surprisingly, regressing total input use on the grain output will result in lower nonland input elasticities. In estimating a crop-production function, Lin (1992) derived the labor use for crop production based on the shares of crop output values. As we have demonstrated, crop and noncrop production do differ in technologies, so adjusting input on the basis of output shares will also result in biased estimation. By deriving the input uses from the Provincial Production and Cost Survey, Zhang and Carter (1997) found a similar land input elasticity for grain production to this study. One striking difference of this study from others is that the input elasticities of machinery and draft animals are higher. The higher machinery elasticities for the three production activities justify the observation of a tremendous increase in total machinery use over the last two decades. Since the fertilizer used in this study refers only to chemical fertilizer, the high draft animal elasticity might be due to the dual roles of draft animals in providing both power and manurial fertilizer.

4. CONCLUSIONS AND POLICY IMPLICATIONS

The GME approach is used for the first time in this study to empirically estimate multi-output production functions and input allocations in Chinese agriculture. Several conclusions can be drawn. First, production technologies of various crops do differ from each other, implying that simply adjusting nonland input uses with the shares of output values is problematic because its underlying equal input elasticity assumption is unrealistic. By properly estimating the multi-input and multi-output production functions, we find that the land elasticity for grain crops in this study is lower, while the nonland input elasticities are generally higher. The increasing trend of chemical fertilizer elasticities and the relatively large machinery elasticity suggest that the rate of adoption of modern technologies may be higher than previously thought.

Second, input shares for crops do change over time, suggesting that a bias exists in estimating grain production function using total nonland inputs as proxies for a specific crop. The input shares for grain crops generally decreased over time. Even in terms of absolute values, labor and draft animal inputs in grain production have been stagnant. For China as a whole, farmers are increasingly relying on modern inputs such as chemical fertilizers and machinery.

Third, differences in the estimated parameters among regions indicate that regional differences have to be taken into account when modeling China’s grain production. Our results suggest high grain production potentials in the northern and central parts of China, especially in the northeast region. In the more developed eastern and southern regions, farmers have shifted their resources towards more profitable cash crops and other agricultural production activities. Higher nonland input elasticities for grain production imply that China may continue to increase nonland inputs to promote future grain production. China has abundant labor and nonland inputs, but limited land resources, therefore the potential for more grain production may have been underestimated.

As the real contention over China’s trade position on grain in the future is focused on the potential of grain production, it is crucial to identify grain production technology correctly. By properly dealing with input allocations and regional heterogeneity, this study provides a better and richer set of parameters for modeling China’s food balance in the next century.

APPENDIX A: DATA DESCRIPTION AND SOURCES

This dataset covers 25 provinces over the period of 1975-96. The three centrally administrated cities Beijing, Shanghai, and Tianjin are not included in this study because they represent relatively small shares of agricultural production. Tibet is excluded due to lack of data. The data in Hainan Province since 1988 are aggregated into Guangdong Provinces. Following Fan (1991), China is divided into seven regions that take into account the availability of agricultural data, the geographical features, and the current social and cultural conditions. The seven regions are: (1) *northeast,* including Heilongjiang, Liaoning, and Jilin Provinces; (2) *north*, made up of Hebei, Henan, Shandong, Shanxi, Shaaanxi, and Gansu Provinces provinces; (3) *northwest*, encompassing the autonomous regions of Nei Monggol, Ningxia, Qinghai, and Xinjiang; (4) *central*, including Anhui, Jiangxi, Hunan, and Hubei Provinces; (5) *east*, composed of Jiangsu and Zhejiang provinces; (6) *southwest*, made up of Guangxi, Sichuan, Guizhou, and Yunnan provinces; and (7) *south* including the coastal provinces of Fujian and Guangdong.

Agricultural activities are classified as grain crops, cash crops, and other production, based on data availability and our focus on grain production. Grain crops mainly include rice, wheat, corn, sorghum, millet, soybean, tubers, and other miscellaneous grains. Cash crops encompass cotton, hemp, rapeseed oil, peanut oil, sesame oil, sunflower oil, huma oil, tea nut oil, tung nut oil, silk cocoons, sugarcane, sugarbeets, apples, bananas, citrus, grapes, other fruits, tea, tobacco, and vegetables. All the noncrop agricultural activities such as pork, beef, mutton, poultry, cows' milk, goats' milk, eggs, wool, cattle hides, goat skins, sheep skins, pig castings, hog bristles, honey, and fish comprise other production.

OUTPUT VALUES

Agricultural output in the Chinese statistical reporting system is measured as gross values of agricultural output (GVAO) by summing the production values of all products in the sector. The GVAO and cropping values are taken from various issues of China's Rural Statistical Yearbook and Collections of Provincial Historical Statistical Materials, 1949-1989. The GVAOs, measured both in constant and current prices, are reported. The constant GVAO output values for the 1980s are expressed in 1980 prices, while the values in the 1990s are based on 1990 prices. Using the deflator derived from the current and constant values, expressed as 1980 prices, all the values in 1990s can be converted to comparable 1980 prices. Current grain output values for the period of 1981-96 are available from China's Rural Statistical Yearbook, while the values in 1980 are from Prosperous Chinese Agriculture. The grain values prior to 1980 are estimated based on each year's total grain output and grain output values in 1980. The grain output data for each province are from the Agricultural Statistics of the People's Republic of China, 1949-1990. Constant grain output values can be derived according to the same ratio of current and constant GVAO. The values of cash crop and other production are obtained by subtracting grain values from total crop output values, and total crop output values from GVAO, respectively.

LABOR

Labor is measured in stock terms as the number of persons engaged in agricultural production at the end of each year. Provincial labor data after 1980 are from various issues of China’s Rural Statistical Yearbook. Data in other years are from Collections of Provincial Historical Statistical Materials, 1949-1989. However, detailed labor allocations among agricultural activities are not known.

LAND

Land in agriculture is taken to be the sum of sown area, fishpond, and grassland. This measure was chosen for several reasons. First, it approximates a flow-type variable by capturing the over-time and, especially, cross-sectional variation in multiple cropping patterns. Second, it is a more broadly based estimate of the total land used in agriculture than alternative arable land measures (which are limited strictly to cropped areas) and, in the way it is constructed here, at least makes some attempt to account for differences in the quality of cropped, versus grazed, areas. Finally, the accuracy of official statistics on arable (i.e., cultivated) land have commonly been called into question (China's Statistical Yearbook 1991, 1992, p. 314). The data for grain and cash crop sown areas prior to 1979 are taken from National Agricultural Statistical Materials for 30 Years, 1949-1979. The data for sown area for later years were taken from various issues of China's Agricultural Yearbook, China's Statistical Yearbook, and China's Rural Statistical Yearbook. The area for other production is estimated as the sum of fish pond and grassland areas. Grassland areas are available from China’s Statistical Yearbook, and are converted into sown areas using a weight of 0.0124, which represents the relative production values of grazed to cropped areas (China's Statistical Yearbook 1985, 1986). Fishpond areas are available from China's Rural Statistical Yearbook and Prosperous Chinese Agriculture. Some missing values in the late 1970s are recovered based on fish production in these years and average yield in other years.

CHEMICAL FERTILIZER

Chemical fertilizer is measured in pure nutrient terms. The data for chemical fertilizer prior to 1979 are reported in National Agricultural Statistical Materials for 30 Years, 1949-1979. Missing observations were estimated using the national trend and provincial 1979 weights. The data after 1978 were taken from various issues of China's Agricultural Yearbook, China's Statistical Yearbook and China's Rural Statistical Yearbook.

MACHINERY

Machinery input is measured in total machinery horsepower. The data on machinery horsepower are reported in National Agricultural Statistical Materials for 30 years, 1949-1979, Agricultural Yearbook and China's Statistical Yearbook.

DRAFT ANIMALS

This category represents the number of draft animals used in agricultural production. Prior to 1980, the numbers are taken from National Agricultural Statistical Materials for 30 Years, 1949-1979, and those after 1979 are reported in various issues of

China's Agricultural Yearbook, China's Statistical Yearbook and China's Rural Statistical Yearbook.

APPENDIX B: THE AGGREGATION OF INPUT ELASTICITIES OVER REGIONS

For simplicity, assume the production function in region i is $Y_i=f_i(L_i)$. Then the national aggregated production function is $y = \sum_i Y_i = \sum_i f_i(L_i)$. Let $L = \sum_i L_i$ represents total input. The national and regional input elasticities can be written as $e = \frac{L}{Y}\frac{dY}{dL}$ and $e_i = \frac{L_i}{Y_i}\frac{dY_i}{dL_i}$, respectively. We want to know the relationship between e_i and e. Let us assume the labor growth rates are equal among regions and there is no regional spatial correlation in terms of input use, i.e., $\frac{dL}{L} = \frac{dL_i}{L_i}$ for any i. Although the natural population growth rate in inland provinces is larger than in coastal provinces, labors tend to migrate from inland to coastal areas, albeit with many institutional restrictions (Kanbur and Zhang, 1999). Therefore, it may be reasonable to assume equal labor growth across regions. Given this assumption, we have $dL = \frac{L}{L_i}dL_i$. Using this identity, the national elasticity can be written as:

$$e = \frac{L}{Y}\frac{dY}{dL} = \frac{L}{Y}\frac{d(\sum_i Y_i)}{dL} = \frac{L}{Y}\frac{\sum_i dY_i}{dL} = \frac{L}{Y}\left(\sum_i \frac{dY_i}{dL}\right) = \frac{L}{Y}\left(\sum_i \frac{dY_i}{\frac{L}{L_i}dL_i}\right) = \sum_i \frac{Y_i}{Y}\frac{L_i}{Y_i}\frac{dY_i}{dL_i} = \sum_i s_i e_i$$

where s_i is the output share of region i relative to total output values.

REFERENCES

Carter, C.A. 1995*. Research on institutional reform and agricultural productivity growth in China*. Paper presented at the conference of Grain Market Reform in China and its Implications. East-West Center, Honolulu, September 16-19, 1995.

China Statistics Bureau (SSB). *China s rural statistical yearbooks* (in Chinese*)*. Beijing: China Statistical Press (various issues).

________. *China s statistical yearbook.* Beijing: China Statistical Press (various issues).

________. 1990. *Collections of provincial historical statistical materials, 1949-1989* (in Chinese*)*. Beijing: China Statistical Press.

________. 1982. *National agricultural statistical materials for 30 years, 1949-79* (in Chinese). Beijing: China Statistical Press.

________. 1985. *Prosperous Chinese agriculture* (in Chinese*)*. Beijing: China Statistical Press.

Colby, W.H., F.W. Crook, and S.H. Webb. 1992. *Agricultural statistics of the People s Republic of China, 1949-90.* Economic Research Service, U.S. Department of Agriculture. Statistical Bulletin No. 844, December.

Fan, S. 1991. Effects of technology change and institutional reform on production growth in China agriculture. *American Journal of Agricultural Economics* 73: 266-275.

Fan, S. and P. Pardey. 1997. Research, productivity, and output growth in Chinese agriculture. *Journal of Developmental Economics* 53: 115-137.

Fan, S. and M. Agcaoili-Sombilla. 1997. Why projections on China's future food supply and demand differ ? *Australian Journal of Agricultural and Resource Economics* 41: 169-90.

Golan, A., G. Judge, and D. Miller. 1996*. Maximum entropy econometrics: Robust estimation with limited data*. New York: John Wiley & Sons.

Hayami, Y. and V. Ruttan. 1985. *Agricultural development: An international perspective*. Baltimore: The John Hopkins University Press.

Huang, J. and S. Rozelle. 1995. Environmental stress and grain yields in China. *American Journal of Agricultural Economics* 77: 853-864.

Jaynes, E.T. 1957a. Information theory and statistics methods, I. *Physics Review* 106: 620-630.

________. 1957b. Information theory and statistics methods, II. *Physics Review* 108: 171-190.

Just, R., D. Zilberman, and E. Hochman. 1983. Estimation of multi-crop production functions. *American Journal of Agricultural Economics* 65: 770-780.

Just, R., D. Zilberman, E. Hochman, and Z. Bar-Shira. 1990. Input allocations in multi-crop system. *American Journal of Agricultural Economics* 72: 200-209.

Kanbur, R., and X. Zhang. 1999. Which regional inequality: The evolution of rural-urban and inland-coastal inequality in China, 1983-1995. *Journal of Comparative Economics,* forthcoming.

Lence, H.L., and D. Miller. 1998a. Recovering output-specific inputs from aggregate input data: A generalized cross-entropy approach. *American Journal of Agricultural Economics* 80: 852-867.

________. 1998b. Estimation of multi-output production functions with incomplete data: A generalized maximum entropy approach. *European Review of Agricultural Economics* 25: 188-209.

Lin, J.Y. 1992. Rural reform and agricultural growth in China. *American Economic Review* 82: 34-51.

Love, H.A. 1999. Conflicts between theory and practice in production economics. *American Journal of Agricultural Economics* 81: 696-702.

People’s Republic of China. *China s agricultural yearbook*. Beijing: China Agricultural Press (various issues).

Shannon, C. 1948. A mathematical theory of communications. *Bell Systems Technical Journal.* 27: 379-423.

Shumway, C.R. 1988. Estimation of multi-crop production functions: Comment. *American Journal of Agricultural Economics* 70: 729-732.

Shumway, C.R., R.D. Rope, and E.K. Nash. 1984. Allocable fixed inputs and jointness in agricultural production: Implications for economic modeling. *American Journal of Agricultural Economics* 66: 72-78.

Wu, H. X. and X. Meng. 1995. *Relocation of farm household labor and its implications on grain production in China*. Paper presented at the conference on Grain Market Reform in China and its Implication. East-West Center, Honolulu, September 16-19, 1995.

Zhang, B., and C.A. Carter. 1997. Reforms, the weather, and productivity growth in China’s grain sector. *American Journal of Agricultural Economics* 79: 1266-1277.