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China's Livestock Production: Decomposing Total Factor Productivity *

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Abstract

Studies of total factor productivity in livestock production are rare, but when available provide useful information especially in the context of developing countries such as China where livestock is becoming more important in the domestic agricultural economy. We use revised data to estimate total factor productivity (TFP) for four major livestock products in China employing a stochastic frontier production function, and decompose total factor productivity change into technical efficiency, technical change, and scale effect components. The results show that the TFP change and pattern of its components vary between the 1980s and the 1990s. While there is evidence of considerable technical innovation in China's livestock sector, technical efficiency has been relatively slow, especially for hog, milk and beef production.

Keywords: Stochastic frontier production function, total factor productivity, technical efficiency, China, livestock, data.

JEL Classification: D240, Q100, Q160.

Introduction

Given possible policy and resource constraints, achievement of the Chinese government's goal of food self-sufficiency may have to rely on continuing improvements in agricultural productivity. It follows that the measurement of agricultural productivity will become crucial for estimating the future supply of domestic agricultural commodities and in turn for predictions of future grain and meat trade balances.

While several studies have examined China's aggregate agricultural TFP (see Mead 2003 for a summary of many of them) to the best of our knowledge no comprehensive livestock TFP studies have been reported for China. We are aware only of Somwaru, Zhang and Tuan's (2003) analysis of hog technical efficiency in selected provinces of China, and the work of Jones and Arnade (2003), and Nin *et al.* (2003) that make TFP estimates for the aggregate crops and livestock sectors separately, for a number of countries including China. Studies that measure sector-wide productivity may neglect commodity-specific productivity growth. In fact, industry and government agencies often have little interest in what happens to the sector as a whole and given the diverse and highly specialized nature of modern agriculture, it would be much more useful to have forecasts of productivity growth for individual subsectors. Therefore one objective of this paper is to make TFP growth estimates for several sub-sectors of the Chinese livestock industry.

The estimation of China's past productivity growth has also been controversial due in part to considerable doubt over the reliability of the underlying agricultural statistics. Only recently have some researchers made efforts to adjust for discrepancies in existing data series or to access alternative data sources. We make

use of such data in this research, and compare our results with those that were obtained when certain traditional official data are used.

Even when TFP growth estimates are available, from a policy point of view it is useful to know whether growth in productivity has been due to technical progress (outward shifts of the production frontier) or improved technical efficiency (producers making more efficient use of available technologies – that is, ‘catching-up’). These two TFP components are analytically distinct, can change at different rates, and therefore might have quite different policy implications. For example, should policies be designed to encourage innovation, or the diffusion of existing technologies? Another of our objectives, therefore, is to decompose TFP change into its components.

In following sections we present a brief review of our methodology, followed by discussion of some problems with China’s official livestock production and cost data and the adjustments we made to those data. The stochastic frontier production function estimate and TFP decomposition are then presented for four livestock sub-sectors - hogs, eggs, milk and beef cattle¹, followed by our conclusions and implications.

Methodology

Since the stochastic frontier production function was independently proposed in Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), there has been considerable research to extend and apply the model (Battese and Coelli, 1995). The stochastic frontier production function postulates the existence of technical inefficiency of production of firms involved in producing a particular output, which reflects the fact that many firms do not operate on their frontiers but

somewhere below them. As a consequence, there are various theoretical and empirical studies on the modelling of technical inefficiency using a stochastic frontier production function (see Coelli, Rao and Battese 1998, and Kumbhakar and Lovell 2000 for such references).

As panel data permit a richer specification of technical change and obviously contains more information about a particular firm than does a cross-section of the data, recent development of techniques for measuring productive efficiency over time has focused on the use of panel data (Kumbhakar, Heshmati and Hjalmarsson, 1999; Henderson, 2003). Moreover, panel data allow the relaxation of some of the strong assumptions that are related to efficiency measurement in the cross-sectional framework (Schmidt and Sickles, 1984). Therefore, this paper uses a panel data approach to measure and decompose total factor productivity for China's livestock sub-sectors by estimating a stochastic frontier production function for major animal outputs.

As in Kumbhakar (2000), the generic form of stochastic frontier production function for panel data can be expressed as:

$$(1) \quad y_{it} = f(x_{it}, t) \exp(v_{it} - u_{it})$$

where y_{it} is the output of the i th firm ($i = 1, 2, \dots, N$) in period t ($t = 1, 2, \dots, T$); $f(\cdot)$ is the production technology; x is a vector of J inputs; t is the time trend variable; v_{it} is assumed to be an iid $N(0, \sigma_v^2)$ random variable, independently distributed of the u_{it} ; and u_{it} is a non-negative random variable and output-oriented technical inefficiency term. There are several specifications that make the technical inefficiency term u_{it} time-varying, but most of them have not explicitly formulated a model for these technical inefficiency effects in terms of appropriate explanatory

variables (see Kumbhakar and Lovell (2000, chapter 7), and Cuesta (2000), for a complete review of recent approaches to the incorporation of exogenous influences on technical inefficiency). Battese and Coelli (1995) proposed a specification for the technical inefficiency effect in the stochastic frontier production function as:

$$(2) \quad u_{it} = z_{it}\delta + w_{it}$$

where the random variable w_{it} is defined by the truncation of the normal distribution with zero mean and variance σ^2 , such that the point of truncation is $-z_{it}\delta$, i.e., $w_{it} \geq -z_{it}\delta$. As a result, u_{it} is obtained by truncation at zero of the normal distribution with mean $z_{it}\delta$ and variance σ^2 . The normal assumption that the u_{it} s and v_{it} s are independently distributed for all $i = 1, 2, \dots, N$ and $t = 1, 2, \dots, T$ is obviously a simplifying but restrictive condition. However, equations (1) and (2) are required to account for possible correlated structures of the technical inefficiency effects and the random errors in the frontier (Battese and Coelli, 1995).

Technical inefficiency, u_{it} , is actually used to measure the proportion by which actual output, y_{it} , falls short of maximum possible output, which is normally labelled as frontier output $f(x, t)$. Therefore technical efficiency can be defined by:

$$(3) \quad TE_{it} = y_{it} / f(x_{it}, t) = \exp(-u_{it})$$

Time is included as a regressor in the frontier production function and used to capture trends in productivity change – popularly known as exogenous technical change and is measured by the log derivative of the stochastic frontier production function with respect to time (Kumbhakar, 2000). That is, technical change (TC) is defined as:

$$(4) \quad TC_{it} = \frac{\partial \ln f(x_{it}, t)}{\partial t}$$

Since technical inefficiency is time-varying the overall productivity change, given input quantities, is not only effected by technical change but also by change in technical efficiency (TE_{it}). That is:

$$(5) \quad \frac{\partial \ln y_{it}}{\partial t} = TC_{it} + TEC_{it}$$

where $TEC_{it} = -\frac{\partial u_{it}}{\partial t} = \frac{\partial \ln TE_{it}}{\partial t}$. TC_{it} is positive if the exogenous technical change shifts the production frontier upward given the inputs. Similarly, TEC_{it} is negative if technical efficiency (TE_{it}) declines over time. That is, a positive value of TEC_{it} would indicate that a producer is moving closer to the production frontier (technical efficiency increasing over time, *ceteris paribus*).

When input quantities change, the productivity change can be measured by TFP change and is defined as:

$$(6) \quad TFP_{it} = \dot{y}_{it} - \sum_j S_{jit} \dot{x}_{jit}$$

where S_{jit} is the share of the j th input for i th firm at time t . Following Kumbhakar (2000), the overall technical efficiency change is decomposed into a pure technical efficiency change effect and a scale efficiency change effect by differentiating equation (1) totally and using the definition of TFP change in equation (6). We obtain:

$$(7) \quad TFP = (RTS - 1) \sum_j \lambda_j \dot{x}_j + TC + TEC + \sum_j (\lambda_j - S_j) \dot{x}_j$$

where $RST = \sum_j \frac{\partial \ln y}{\partial \ln x_j} \equiv \sum_j \varepsilon_j$ is the measurement of returns to scale and ε_j are input elasticities defined at the production frontier $f(x_{it}, t)$, and $\lambda_j = f_j x_j / \sum_k f_k x_k = \varepsilon_j / RTS$ when f_j is the marginal product of input x_j (assuming that inefficiency effects u_{it} are not functions of inputs). Thus, equation (7)

decomposes TFP change into four components. As shown from left to right in equation (7), the first term is the scale effect, the second term is pure technical change, the third term is technical efficiency change, and the last term is the input allocative effect.

Data Issues

An ongoing problem for the study of livestock productivity in China is obtaining relevant and accurate data. The majority of published studies of Chinese agricultural productivity have used data published in China's Statistical Yearbook. While this source disaggregates gross value of agricultural output into crops, animal husbandry, forestry, fishing and sideline activities, input use is not disaggregated by sector. A major improvement therefore is to utilise additional data that will allow the construction of time-series of input use by the livestock sector. A further problem with livestock data from the official statistical yearbooks is the apparent over-reporting of both livestock product output and livestock numbers (ERS, 1998; Fuller, Hayes and Smith, 2000). This problem also needs to be addressed if the possibility of biased livestock productivity estimates is to be avoided.

We attempt this in two ways. First, we use the updated livestock data and methods of Ma, Huang and Rozelle (2004) to substitute for various data series in the official statistics. Second, we make use of China's Agricultural Commodity Cost and Return Survey. This provides data on input use by various crop and livestock enterprises. Surprisingly, it seems to have been used in only a small number of productivity studies (Tian and Wan, 2000; Jin et al., 2002; Carter et al., 2003). Detailed descriptions of the survey can be found in Tian and Wan and Jin et al.

We specify four inputs in the production functions - labour, feed, animal inventories and non-livestock capital. We describe below the construction of data series for these livestock production inputs, as well as our approach to overcoming the over-reporting of animal numbers and outputs.

Livestock Production Measurement

Concerns over the accuracy of official published livestock data include an increasing discrepancy over time between supply and consumption figures and a lack of consistency between livestock output data and that on feed availability. Fortunately, Ma, Huang and Rozelle (2004) have provided adjusted series for livestock slaughterings and production (and consumption) that are internally consistent by recognizing that the published data do contain valid information but introducing new information from other sources including the First National Agricultural Census of China of 1997.

From the Cost and Return Surveys we obtained annual provincial data on net liveweight gain for hogs and beef cattle, and milk and egg yields per animal. From the database of Ma, Huang and Rozelle (2004) we obtained their updated series on hog and beef cattle slaughter numbers, and inventories of layers. We used the same approach of Ma, Huang and Rozelle to generate updated series on dairy cow inventories, since these were not included in their study. Livestock production was then computed by multiplying these adjusted data series on slaughterings and animal inventories by the relevant yield per animal.

Labour, Feed and Non-livestock Capital Inputs

Annual provincial data for these production inputs were obtained directly from the Agricultural Commodity Cost and Return Survey. The survey provides detailed cost items on a 'per animal unit' basis for all major animal commodities, including those covered in this paper, at provincial and national level. These data included labour inputs (days) and feed consumption (kg. grain equivalent), animal purchases (including liveweight data for purchased piglets and calves) and fixed asset depreciation which we deflated by a fixed asset price index. We obtained aggregate labour, feed and non-livestock capital inputs by multiplying the inputs per animal by slaughtered numbers for hog and beef cattle and by inventory numbers for dairy cows and layers. It is clear that this procedure, necessitated by the available data, excludes some input usage, such as that by other animal categories within the livestock herds.

Livestock capital

Following Jarvis we recognize the inventory of breeding animals as a major capital input to livestock production. Thus opening inventories of sows, milking cows, laying hens, and female yellow cattle were used as the livestock capital inputs in the models for pork, milk, eggs and beef respectively. Inventory data for layers were taken from the databases of Ma, Huang and Rozelle (2004). Those for sows, milking cows and female yellow cattle were derived by us from official sources and adjusted for possible over-reporting using the methodology of Ma, Huang and Rozelle.

Additional problems existed with regard to poultry inventories. China's yearbooks and other statistical publications present poultry inventories aggregated over both layers and broilers, with none publishing separate data for layers. However Ma, Huang and Rozelle provided adjusted data on egg production, and the agricultural

production cost and return survey provided estimates of egg yields per hundred birds. Thus layer inventories, at both the national and provincial levels, were estimated by dividing output by yield.² A simple test showed that the sum across provinces of our provincial layer inventories was very close to our estimate of the national layer inventory in each year.

The Empirical Estimation and Results

We define the stochastic frontier production function in translog form:

$$(8) \ln y_{it} = \alpha_0 + \sum_j \beta_j \ln x_{jit} + \beta_1 t + \frac{1}{2} \sum_j \sum_k \beta_{jk} \ln x_{jit} \ln x_{kit} + \frac{1}{2} \beta_{tt} t^2 + \sum_j \beta_{jt} \ln x_{jit} t - u_{it} + v_{it}$$

where \ln denotes the natural logarithm, $i = 1, 2, \dots, N$ indexes the provinces, $t = 1, 2, \dots, T$ indexes the annual observations over time; y_{it} is total output as defined previously; J indicates inputs; t is time trend; and others are defined in previous section. In this study, as in Koh, Rahman and Tan (2004), we simply set $u_{it} = (1, t)$ in the specification of u_{it} due to data limitations and following Kumbhakar (2000), the provincial effects u_i are fixed parameters to be estimated from the coefficients of provincial dummies so that no extra distributional assumption is made on technical inefficiency. As a result, the technical inefficiency function u_{it} is defined as:

$$(9) u_{it} = \delta_0 + \delta_1 t + \sum \delta_{2i} D_i$$

where D are provincial dummies.

Since there are serious econometric problems with two-stage formulation estimation (Kumbhakar and Lovell, 2000, pp264), this study employs simultaneous

estimation of the parameters of the stochastic frontier function (8) and the model for the technical inefficiency effects (9). The likelihood function of the model is presented in the appendix of Battese and Coelli (1993). The likelihood function is expressed in terms of the variance parameters $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma \equiv \sigma_u^2 / \sigma^2$, γ is the unknown parameter to be estimated. The stochastic frontier function may not be significantly different from the deterministic model if γ is close to 1 (Coelli, Rao and Battese, 1998, p.215). On the other hand, if the null hypothesis $\gamma = 0$ is accepted, this would indicate that σ_u^2 is zero and thus the term u_{it} should be removed from the model, leaving a specification with parameters that can be consistently estimated by ordinary least squares. We use the FRONTIER 4.1 computer program developed by Coelli (1996) to estimate the stochastic frontier function and technical inefficiency models simultaneously and this program also permits the use of unbalanced panel data.

To test the appropriateness of our model specification, we conducted some hypothesis tests before the final stochastic frontier function was chosen. The hypothesis tests show that the translog stochastic frontier production function is an appropriate functional form and that livestock production demonstrates significant technological change and factor input biases (appendix 1).

While the stochastic frontier production functions and technical inefficiency models were estimated from provincial data, we report only national aggregate results of TFP, calculated as weighted averages of provincial results using provincial outputs as weights. To save space, we do not report the stochastic frontier production function parameter estimates.³

The Decomposition of TFP Changes and Technical Efficiency at National Level

The TFP change was decomposed into technical efficiency, technical change and returns to scale effects.⁴ The results (means over province) by products are reported in table 1. It can be seen that during the entire study period (1981-2001), hog production TFP growth is 1.67 percent per annum, which is mostly due to technical change (1.17 percent per annum, accounting for more than 70 percent of total TFP change during the last two decades). However, splitting the last two decades into two sub-periods, we found that the structure of TFP components apparently changes between the 1980s and the 1990s. For example in the 1980s, the TFP change is 2.26 percent per annum, of which about 50 percent is caused by technical efficiency improvement (1.11 percent per annum), while in the 1990s, the rate of the TFP change halves to 1.13 percent, of which technical change accounts for a substantial proportion. It can be seen that associated with the deterioration in technical efficiency, technological change has been very fast, doubling from 0.73 percent per annum in the 1980s to 1.56 percent per annum in the 1990s. The returns to scale effect tends to remain static throughout the whole study period for hog production.

Turning to egg production, we found that during the period 1983-2001, TFP growth is very rapid, at a rate of 9.57 percent per annum, of which nearly 90 percent is due to improvement in technical efficiency (8.46 percent per annum). Similar to the pattern we found in the case of hogs, after splitting the study period into two sub-periods, we found that the TFP change in the first sub-period (1983-1990) is 10.14 percent per annum and technical efficiency improvement accounts for all of it after compensating the deterioration of technical change (-4.42 percent per annum) and returns to scale (-3.28 percent per annum). However, we found that in the second sub-period (1991-2001) the TFP change is 9.16 percent per annum and in contrast, almost all of it is due to technical change (8.26 percent per annum).

Data for the milk and beef models covered only the 1990s, during which time TFP growth differed considerably between milk (1.93 percent per annum) and beef (7.64 percent per annum). Furthermore, the patterns of the TFP components also vary substantially. Both technical change and returns to scale are negative for milk production, while both are positive for in the case of beef. Technical efficiency improvement is the only engine for TFP growth in milk production. Of the beef production TFP change, however, technical efficiency improvement accounts for two thirds and returns to scale accounts for other one third.

The fastest TFP change overall was found for egg production at almost 10 percent per annum, followed by beef production at a rate of 7.64 percent per annum. The lowest TFP change can be observed for hog production. For both hog and egg production, the TFP change during the 1980s is driven mainly by improvement in technical efficiency, while in the 1990s technical change is relatively more dominant.

Given the assumption that not all firms operate on their frontiers, we calculated actual technical efficiency levels across animal products in order to observe “catching up” in China’s livestock sector. Table 2 presents the actual average technical efficiency levels and their growth rates for the period of 1992-2001. It can be seen that the highest average technical efficiency was more than 90 percent for egg production, while the technical efficiencies are almost at the same levels for hog, milk and beef cattle production (ranging between 70-75 percent). Although average technical efficiency levels are in the latter range for milk and beef, the improvement in technical efficiency has been relatively rapid in these cases with growth rates in excess of 3.5 percent per annum. Therefore technical efficiencies in these sectors reached more than 84 percent in recent years. On the other hand, average technical efficiency declined for hog production.

Comparison with TFP Decomposition Using Official Data

Having made considerable efforts to adjust the official data on animal numbers, to what extent does this influence our results? Ma, Huang and Rozelle have already shown significant differences between the adjusted production data series and the official production statistics in feed demand, and here we draw attention to differences in TFP and its decomposition. To do this we recalculated all of our data series using the official animal numbers (slaughterings and inventories) in place of our adjusted animal numbers. Note that this also changed our feedgrains, labour and non-livestock capital input series since these were computed as the products of inputs per animal and total slaughterings or opening inventories. Table 3 gives us the new estimates of TFP changes and their components. These results may be compared with those in tables 1 and 2 over comparable time periods. The period since 1990 is of particular interest, since our adjustments to official animal numbers were made from the late 1980s onwards. We found that there are substantial differences in the TFP growth rates and components.

The estimated results suggest that over-reporting animal numbers does not necessarily lead to over-estimation of TFP growth, since such over-reporting would have the effect of increasing both our production and input levels data. Using official hog slaughterings and inventories doubles TFP growth (1.13 percent using adjusted data and 2.61 percent using official data) and such a difference is even greater for beef production. However, TFP growth for eggs and milk appears less sensitive to the choice of livestock data. Considerable differences were found in the case of some components of TFP growth, such as technical efficiency for hogs, returns to scale for eggs and all TFP components in the case of beef production. For example, using

(over-reported) official hog numbers substantially over-estimated technical efficiency (it is nearly 95 percent when official statistics are used compared with 73 percent using the adjusted data. In other words, national hog production appears to have almost reached its frontier when official hog livestock data are used.

Conclusions

In this paper we estimated a stochastic frontier production function for each of four animal products. Considerable effort was made to adjust the official livestock data, widely recognised to have been over-reported. We compared results using both adjusted and official animal numbers. We found that TFP growth and its decomposition varies over animal products, and that failure to adjust for data over-reporting can also substantially influence results.

The driving forces of TFP change have shifted over the last two decades. Livestock TFP growth was driven primarily by improvements in technical efficiency during the 1980s, while technical change appears to have been the main driver over the 1990s for some major animal products (e.g., hog and eggs).

We found evidence of substantial differences in technical efficiency over animal products. Egg production has almost approached its frontier, while other products are still far below their frontiers. There appears to exist potential for a further 15-20 percent of improvement in technical efficiency in China's hog, milk and beef production.

Why have the determinants of TFP growth shifted over the last two decades? The reason may be straightforward in the case of egg production since efficiency growth over the 1980s allowed producers to reach the frontier, following which scope for further productivity growth would depend on technical change. However, it is

more difficult to explain why in the case of hog production there has been a shift from improving technical efficiency over the 1980s to investing in new technologies during the 1990s when technical efficiency was still relatively low. We observe that the improvement in technical efficiency for hog production was very slow for both sub-periods (and negative in the 1990s) compared with that of other livestock products. It is plausible that due to apparent difficulties in improving technical efficiency, the alternative approach may have been to invest in new technologies in order to improve TFP growth. Further evidence needs to be found to explain the determinants of technical efficiency developments in China's hog production before definitive conclusions can be reached.

Scale effects have played a role in determining the TFP changes, especially in beef production. Therefore, measured TFP changes may be biased if scale effects are neglected, particularly when the scale effect is not neutral. In other words, when scale effect is positive the TFP change would be underestimated, while when scale effect is negative the TFP change would be over-estimated.

Finally, our results suggest that a cautionary approach should be adopted to the interpretation of productivity studies that rely on official published animal numbers.

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Table 1. Decomposition of TFP Changes for China's Major Livestock Sector Based on Stochastic Frontier Production Function Using Adjusted Data

Periods	TFP Change	Technological Efficiency	Technological Change	Return To Scale Effect
Hog Production:				
1981-2001	0.0167	0.0008	0.0117	0.0042
1981-1990	0.0226	0.0111	0.0073	0.0041
1991-2001	0.0113	-0.0085	0.0156	0.0042
Eggs Production:				
1983-2001	0.0957	0.0846	0.0292	-0.0181
1983-1990	0.1014	0.1784	-0.0442	-0.0328
1991-2001	0.0916	0.0164	0.0826	-0.0074
Milk Production:				
1993-2001	0.0193	0.0407	-0.0138	-0.0076
Beef Production:				
1991-2001	0.0764	0.0504	0.0030	0.0231

Note: Total observations at provincial level are 547 for hog production from 1980-2001, 211 for egg production from 1982-2001, 192 for milk production from 1992-2001 and 97 for beef cattle production from 1989 to 2001. The smaller number of observations for beef cattle and milk production are because the cost survey only provides data for 14 major beef cattle producing provinces and 19 major milk producing provinces.

Table 2. Technical Efficiency and Annual Growth Rates across Livestock Products Based on Stochastic Frontier Production Function Using Adjusted Data ^a

Year	Hogs	Eggs	Milk	Beef Cattle
Average 1992-2001	0.7484	0.9349	0.7363	0.7105
Annual Growth (%): 1992-2001	-1.03	1.20	3.77	3.50
Present Level 1999-2001	0.7290	0.9659	0.8490	0.8459

^a Technical efficiency was calculated based on equation 3 (actual output divided by the frontier output), and annual growth rates are calculated using semilog regression approach.

Table 3. Decomposition of TFP Changes for China's Major Livestock Sector Based on Stochastic Frontier Production Function Using Official Animal Numbers, 1991-2001

Periods	TFP Change	Technological Efficiency	Technological Change	Return To Scale Effect
Hog Production	0.0261	0.0081	0.0179	0.0002
Eggs Production	0.0758	0.0168	0.0958	-0.0368
Milk Production ^a	0.0238	0.0347	-0.0104	-0.0005
Beef Production	0.2932	0.0133	0.1270	0.1530

Note: see table 1 for a reference of sample size of each animal product.

^a Averages from 1993-2001 for milk production.

Table 4. Technical Efficiency and Annual Growth Rates across Livestock Products Based on Stochastic Frontier Production Function Using Official Animal Numbers ^a

Year	Hogs	Eggs	Milk	Beef Cattle
Average 1992-2001	0.9205	0.9108	0.7426	0.7313
Annual growth (%): 1992-2001	0.75	1.46	5.05	3.05
Present Level 1999-2001	0.9466	0.9473	0.8507	0.7866

^a Technical efficiency was calculated based on equation 3 (actual output divided by the frontier output), and annul growth rates are calculated using semilog regression approach.

Appendix 1. Maximum Likelihood Ratio Tests for Stochastic Frontier Production Function Using Adjusted Data

Restricted Function	Likelihood Function		χ^2 Statistics ^b
	Restricted	Unrestricted ^a	
Hog Production:			
1. C-D function	295.85	361.55	131.4***
2. No factor bias	339.32	361.55	44.5***
3. No technical change	292.08	361.55	138.9***
Eggs Production:			
1. C-D function	-5.64	59.16	129.60***
2. No factor bias	48.41	59.16	21.49***
3. No technical change	35.47	59.16	47.38***
Milk Production:			
1. C-D function	83.04	145.42	124.77***
2. No factor bias	132.35	145.42	26.13***
3. No technical change	131.72	145.42	27.39***
Beef Cattle Production:			
1. C-D function	-44.27	-10.17	84.66***
2. No factor bias	-16.24	-10.17	28.61***
3. No technical change	-52.53	-10.17	101.20***

^a The unrestricted function is the translog stochastic frontier production function.

^b The numbers of restrictions are 15, 6 and 4 and critical values at 1 percent significant level are 30.58, 16.81 and 13.28 for the hypothesis tests of C-D function, no technical change and no factor biases, respectively.

*** stands for 1 percent significant levels.

Footnotes

* Financial support from FRST grant IERX0301 is gratefully acknowledged.

¹ We did not include broilers in this study due to problems with missing data. For example, data on inventories of breeding broilers were available only from 1998, and we could not discover any way of deriving earlier data from the available poultry statistics.

² The cost and return survey did not contain egg yields for each province for each of the past 15 years. Provincial trend regressions were used to estimate yields in such cases.

³ They are available upon request to the authors.

⁴ The price effects (allocative inefficiency component) were not calculated because information on animal prices were not available.