Doubts on input quality: The effect of inaccurate fertilizer content on the estimation of production functions and technical efficiency

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Abstract

Household survey responses regarding levels of input use are sometimes affected by bias of which even the households themselves are not aware. Some examples include poor quality seed with a mixture of the fertile and infertile types, and pesticide content that has been substituted with less effective chemicals. We analyze in our paper the effect of low quality fertilizer, which contains less nitrogen than is advertised on the packaging. We show that this could lead to bias in the estimation of marginal effect and technical efficiency. Using panel data from the Hebei province of China, we calculate the magnitude of the bias across different levels of fertilizer quality. We find that the bias could be between -2% and -7% for marginal effect of fertilizer at mean input levels, and between 1% and 4% for technical efficiency.

JEL Classification: Q12, Q18

Keywords: Low quality fertilizer; Estimation bias; Production function

1. Introduction

Rising food prices push farmers to increase agricultural output, and one of the adopted solutions is to apply more farm inputs. A question that follows is whether this increase in input use is actually beneficial. An example is the overuse of chemical fertilizer that leads to problems such as a rise in the deposition of atmospheric nitrogen that degrades both the land and water ecosystems (He et al., 2007; Zhang et al., 2008), and nitrate leaching into groundwater (Chen et al., 2005; Wan et al., 2009) that pollutes the main water sources of many different uses including drinking water, which might cause gastric cancer (Fraser et al., 1980; Hu et al., 2005).

The primary focuses of socioeconomic studies of fertilizer use are on its application level and determining factors (Denbaly and Vroomen, 1993; Babcock and Hennessy, 1996; Lamb, 2003), the marginal productivity of fertilizer (Wang et al., 1996b; Chen et al., 2003), its efficiency (Reinhard et al., 1999; Fernandez et al., 2002), and its effects on changing production risks (SriRamaratnam et al., 1987; Kumbhakar, 1993; Battese et al., 1997). Babcock (1992) examines how the uncertainty of weather and soil fertility affects optimal fertilizer use. The focus of our article will be on the uncertainty of the fertilizer itself and how its inaccurate content affects the estimation of production functions and technical efficiency.

There have been recent reports of low quality or fake fertilizer in developing countries such as Bangladesh (Zahur, 2010), Vietnam (Viet Nam News, 2010), Nigeria (Liverpool-Tasie et al., 2010), China (Wang, 2011), and Cambodia (Hamaguchi, 2011). We incorporate fertilizer content into the estimation of production functions, and show that the estimates will be biased if we ignore the quality effect, for example when the real fertilizer content is less than the labeled content on the package. We then derive a measurement for the bias and use panel data to illustrate its magnitude. We focus our attention on fertilizer, but the analysis can be used for other purchased inputs as well, especially when the input is of a lower quality than what the households assume, which leads to inaccuracy in the responses of household surveys.

Section 2 of this paper briefly discusses the structural model. Section 3 then shows how the technical efficiency estimation method first developed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977) can be applied to include below expectation input quality. The section then goes on to describe the data and variables that we use in the regression to calculate the magnitude of bias, the results of which are shown in Section 4. Finally, Section 5 concludes.

2. Model

We start with a stochastic production function with only two inputs. The basic model is modified from Zellner et al. (1966):

$$Y = AF^a X^b e^{\epsilon}, \tag{1}$$

with Y as output, A as total factor productivity, F as fertilizer, X as another input, a and b as elasticities, and ϵ as the production error term. Following Aigner et al. (1977), the error term consists of two components:

$$\epsilon = u + v, \tag{2}$$

where v is the stochastic component with a normal $N(0, \sigma_v^2)$ distribution and u is the efficiency component, which is made up of the non-positive portion of a normal $N(0, \sigma_u^2)$ distribution. The two error components are assumed to be independent of each other.

A term, e^z, is added to the production function to capture the real fertilizer content:

$$Y = A(e^z F)^a X^b e^{\epsilon}. \tag{3}$$

We restrict the e^z term to be between 0 and 1, as we are trying to account for the fertilizer manufacturer deliberately reducing the content of their products to save costs. It means that the effective fertilizer quantity the farmers use is less than the actual amount labeled on the product package. This leads to inaccurate responses in household surveys, as the amount captured by the data is the amount that the farmers think they have used and not the amount that is actually in the package.

The term z has to be non-positive, as e^z is bound between 0 and 1. The value of z will be more negative the more the manufacturer reduces its fertilizer content. If the manufacturer provides the same content as labeled on the product package, z would be 0 and the e^z term would become 1. The production function would then be the same as that in Eq. (1) without any reduction in fertilizer quality.

Since this is a stochastic production function, farmers choose the input level that maximizes their expected profits:

$$E(\pi) = p_y E(Y) - w_f E(e^z F) - w_x X. \tag{4}$$

The farmers do not know the actual content of the fertilizer when they buy the product. They can only base their decision on what the expected content is. So, the expected value of z, and not its actual value, is used in the expected profit function of Eq. (4). The first order conditions are

$$\frac{\partial E(\pi)}{\partial E(e^z F)} = 0 \text{ and } \frac{\partial E(\pi)}{\partial X} = 0. \tag{5}$$

Solving for the first order conditions in Eq. (5), we get the optimal input decisions:

$$\ln Y - \ln F = \ln \left(\frac{w_f}{p_y a} \right) - E(\epsilon) + (1 - a)E(z) + az + \epsilon + \gamma_f, \tag{6}$$

$$\ln Y - \ln X = \ln \left(\frac{w_x}{p_y b} \right) - E(\epsilon) + \epsilon + \gamma_x, \tag{7}$$

where γ_i is the stochastic error term in the use of input i, and the other variables are the same as previously defined. The model can also be generalized to include more inputs with similar results. Other than the additional efficiency term, u, and the fertilizer quality term, z, the conditions in Eqs. (6) and (7) are the same as the optimal input decisions derived by Zellner et al. (1966). After solving the profit maximization system of equations, they find that the function of optimal input use does not contain the stochastic error term of the production function, v. It shows that input use is exogenous and is not correlated with the error term. The reasoning behind this is that farmers make the input decision before the output is known. Due to the stochastic nature of the production function, the farmers decide on how much input to use based on the expected output, not the real output. The input decision, on the other hand, affects the real output, not the expected output. So, the input decision is contemporaneously exogenous in the estimation of a stochastic production function.

3. Methodology

A common method used in a production function estimation is the Maximum Likelihood (ML) approach, in which the efficiency term is part of the total error term, so we need the exogeneity of input use assumption and a distribution assumption for the efficiency term. These two assumptions are not needed if we have panel data and assume that the efficiency term is constant over time (Bravo-Ureta and Pinheiro, 1993). The constant efficiency assumption allows us to use the Fixed Effects (FE) approach, in which the fixed effects dummy for each household acts as the efficiency term of the individual household (Schmidt and Sickles, 1984). This takes the efficiency term, u, out of the total error term and the efficiency level is captured instead by the individual intercept of each household.

Technical efficiency can be estimated as part of a production function (Bravo-Ureta and Evenson, 1994), or a distance function (Bruemmer et al., 2002), which can be used for the analysis of multiple outputs. As we focus on only one output, we will use the production function approach with a translog functional form:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_j \ln(X_{jit}) + \frac{1}{2} \sum_{j=1}^{4} \sum_{k=1}^{4} \beta_{jk} \ln(X_{jit}) \ln(X_{kit}) + u_i + v_{it}. \tag{8}$$

Y_{it} and X_{it} are the output and input use, respectively, of household i in year t. The four inputs being included in the model are fertilizer, land, seed, and labor. u_i is the fixed effects dummy and captures the technical efficiency of each household. v_{it} is the stochastic error term of the production function. In the ML estimation, the $+u_i$ term becomes $-u_{it}$, where u_{it} is a non-negative term that reflects the inefficiency of each household.

3.1. Data

In a 2008 study by Boeber et al. (2009), the authors collect 14 samples of fertilizer from five villages in the southern part of China's Hebei Province. They find that 12 of the samples contain nitrogen levels that are different from what is labeled on the package, with four of those samples having less than 80% of the advertised nitrogen level.[1] The sample size of the study is too small to reach a conclusion on the severity of the problem, but it supports the claims of a few other news reports on this issue in the region (Han, 2009; Wang, 2011). So, we will concentrate on the Hebei province of China for our analysis. We will also focus on household farms because they are more likely to be affected by low quality fertilizer, as they have neither the buying power of big corporate farms nor the testing equipment in order to verify the fertilizer content.

The data we use is a household panel dataset from the Hebei province collected by the Research Center for Rural Economy (RCRE) of China. The Center uses the stratified random sampling method for the survey. Counties in the province are separated into three groups based on their income level: high, middle, and low. Villages are then selected from each group of counties to ensure that all three groups are well represented in the survey. Finally, 40 to 120 households are randomly selected from each village. Selected households are asked to keep a diary recording their incomes and expenses. Designated villagers then collect the diaries once a month from the households (Benjamin et al., 2005). Table 1 shows a list of variables we use in our regression, and their respective descriptions.

The RCRE survey started in 1986, and its questionnaire has undergone significant changes over the years. The most recent data that we receive, which all comes from the same version of questionnaire, is from the period 2004 to 2008. This is the group of data that we use in our analysis. Due to attrition, the panel is unbalanced, with a total of 4218 observations from 894 households in five years. Although the dataset contains data for a few different crops, we choose to focus on maize, as it is a common crop in that region, and it has the most complete data of the crops covered by the survey. All the output and input variables, except labor, are for the production of maize. We do not have the data on labor input for maize, so we use the total household on-farm labor input as a proxy.

According to the China Agriculture Yearbook, the annual net income per capita in 2003 is 2,853 yuan for Hebei. This ranks Hebei at seventh out of the 27 provinces and

[1] In our paper, we use nitrogen content to represent fertilizer quality.

Table 1
Descriptions of variables

Variables	Descriptions
$lnoutput\_m$	ln {Total output for maize (kg)}
$lnfer\_m$	ln {Quantity of chemical fertilizer for maize (kg)}
$lnland\_m$	ln {Area of planted land for maize (mu)}
$lnseed\_m$	ln {Quantity of seed for maize (kg)}
$lnfwork\_total$	ln {On-farm work for whole household (day)}
$lnfer2\_m$	$\frac{1}{2} \times lnfer\_m \times lnfer\_m$
$lnland2\_m$	$\frac{1}{2} \times lnland\_m \times lnland\_m$
$lnseed2\_m$	$\frac{1}{2} \times lnseed\_m \times lnseed\_m$
$lnfwork2\_total$	$\frac{1}{2} \times lnfwork\_total \times lnfwork\_total$
$lnferland\_m$	$lnfer\_m \times lnland\_m$
$lnferseed\_m$	$lnfer\_m \times lnseed\_m$
$lnferfwork\_total$	$lnfer\_m \times lnfwork\_total$
$lnlandseed\_m$	$lnland\_m \times lnseed\_m$
$lnlandfwork\_total$	$lnland\_m \times lnfwork\_total$
$lnseedfwork\_total$	$lnseed\_m \times lnfwork\_total$

autonomous regions in Mainland China (Ministry of Agriculture, 2004). At the end of our study period in 2008, the annual net income per capita is 4,293 yuan for Hebei, which remains at the seventh spot on the list. Maize is the main grain crop grown in the province, closely followed by wheat. The total planted area for maize in Hebei is 2,577.4 million hectare, making it the second largest maize growing province in China. On the intensity of chemical fertilizer usage, the average at the country level is 0.281 tonne per hectare, with Hebei having a higher usage intensity at 0.312 tonne per hectare (State Statistical Bureau, 2003).

3.2. Literature

Stochastic Frontier Analysis has been a widely used method to examine the technical efficiency of farmers in various parts of the world. Fan (1991) is one of the first to use the stochastic approach to estimate the efficiency of agriculture in China. His analysis is based on the provincial level panel data that cover 29 provinces and municipalities between 1965 and 1985. The data are mainly taken from the various editions of the country's statistical yearbooks published by the State Statistical Bureau (SSB). The author examines the technical efficiency at the provincial level and also the regional level. There are seven regions in total based on his own grouping. He includes the interaction terms between each input variable and the year to examine the changing trend in the importance of the inputs. Fan (1991) finds that labor and land have a decreasing influence on output over time, while chemical fertilizer has an increasing influence. He also separates the production growth into three components and examines which component has the strongest influence on growth. The three components are change in input use, change in technology, and change in institution. Their contributions to production growth between 1965 and 1985 are 57.7%, 15.7%, and 26.6%, respectively. Studies on increasing agricultural input use, especially chemical fertilizer, and its impact can be found in Huang and Rozelle (1995), Wang et al. (1996b), and Zhen et al. (2006). More details on the change in agricultural institutions in China are available in Lin (1987), Lin (1992), and Young (2000).

Building on the more generic analysis offered by the provincial level data, Wang et al. (1996a) examine both the technical and allocative efficiency at the household level using the data from the National Rural Household Survey by SSB. The authors randomly select the data for 1,786 households from the year 1991 survey and estimate a stochastic profit function with two outputs: crop and livestock. They find that the average production efficiency is 62%, with individual values between 6% and 93%.

The two aforementioned papers on China look at the efficiency of the agricultural sector or grain production as a whole. Their focus is on the aggregate level of all grains, not on individual crops. Tian and Wan (2000) analyze the efficiency and its determinants for four separate crops: Indica rice, Japonica rice, wheat, and maize. They take their production data from the Farm Production Costs and Returns Survey between year 1983 and 1996, which are available at the household level. Their results show that fertilizer has a high impact on wheat and Japonica rice production, but the impact is low on maize, and there is fertilizer overuse in Indica rice production as shown by its negative elasticity.

Piotrowski (2009) also analyzes the production efficiency of individual crops. He estimates the production function and technical efficiency of both total agricultural production and wheat production. He collects the household data in 2005, which cover 337 households in three provinces: Hebei, Shandong, and Henan. His results show that nitrogen fertilizer has a significant impact on the level of total production, but not on the level of wheat production, implying that fertilizer is overused in wheat production, but not in the production of other crops.

3.3. Fertilizer quality

Having an inaccurate input data is similar to the measurement error problem that produces biased estimates if the measurement error is correlated with any of the input variables, as the fertilizer quality term, z, is present in both the fertilizer variable and the error term. The bias is an attenuation bias in a univariate setting but the direction is less clear in a multivariate case (Levi, 1973). This reduction in fertilizer quality can be captured, however, by the fixed effects dummy if it does not vary over the time period of our study. In this case, the use of FE would prevent the endogeneity problem between input use and error term that leads to biased estimates. We will run a Hausman test to determine whether FE or ML is the more appropriate choice. We calculate the test statistic (Hausman, 1978) using the formula $H = (b_1 - b_0)'[Var(b_0) - Var(b_1)]^{-1}(b_1 - b_0)$, where b_0 and b_1 are the vectors of estimated coefficients from FE and ML, respectively, with $Var(b_0)$ and $Var(b_1)$ being their corresponding variance-covariance matrices. The null hypothesis of the test is that the coefficients from the two estimation methods are the same. If this is the case, we will use ML, as it is more efficient. If we reject the null hypothesis, it means that the ML method produces estimates that are inconsistent, and FE is the preferred choice.

Similar to the use of validation data in analyzing measurement error bias (Bound et al., 2001), we include a constant fertilizer quality term, z, into the translog production function to get the unbiased estimates:

$$
\begin{aligned}
lnoutput\_m_{it} = {} & \alpha_0 + \alpha_1(lnfer\_m_{it} + z) + \alpha_2 lnland\_m_{it} + \alpha_3 lnseed\_m_{it} \\
& + \alpha_4 lnfwork\_total_{it} + \frac{1}{2}\alpha_{11}(lnfer\_m_{it} + z)(lnfer\_m_{it} + z) \\
& + \frac{1}{2}\alpha_{22} lnland2\_m_{it} + \frac{1}{2}\alpha_{33} lnseed2\_m_{it} + \frac{1}{2}\beta_{44} lnfwork2\_total_{it} \\
& + \alpha_{12}(lnfer\_m_{it} + z) lnland\_m_{it} + \alpha_{13}(lnfer\_m_{it} + z) lnseed\_m_{it} \\
& + \alpha_{14}(lnfer\_m_{it} + z) lnfwork\_total_{it} + \alpha_{23} lnlandseed\_m_{it} \\
& + \alpha_{24} lnlandfwork\_total_{it} + \alpha_{34} lnseedfwork\_total_{it} + u_i + v_{it}.
\end{aligned} \tag{9}
$$

Rearranging the terms, we rewrite Eq. (9) to show the bias in regression output if we ignore the z term:

$$
\begin{aligned}
lnoutput\_m_{it} = {} & \alpha_0 + (\alpha_1 + \alpha_{11} z) lnfer\_m_{it} + (\alpha_2 + \alpha_{12} z) lnland\_m_{it} \\
& + (\alpha_3 + \alpha_{13} z) lnseed\_m_{it} + (\alpha_4 + \alpha_{14} z) lnfwork\_total_{it} \\
& + \frac{1}{2}\alpha_{11} lnfer2\_m_{it} + \frac{1}{2}\alpha_{22} lnland2\_m_{it} + \frac{1}{2}\alpha_{33} lnseed2\_m_{it} \\
& + \frac{1}{2}\alpha_{44} lnfwork2\_total_{it} + \alpha_{12} lnferland\_m_{it} + \alpha_{13} lnferseed\_m_{it} \\
& + \alpha_{14} lnferfwork\_total_{it} + \alpha_{23} lnlandseed\_m_{it} \\
& + \alpha_{24} lnlandfwork\_total_{it} + \alpha_{34} lnseedfwork\_total_{it} \\
& + \alpha_1 z + \frac{1}{2}\alpha_{11} z^2 + u_i + v_{it}.
\end{aligned} \tag{10}
$$

In our regression, we first obtain the coefficients in Eq. (8), $\boldsymbol{\beta}$, from a production function estimation. By referring to Eq. (10), we then calculate the real coefficients, $\boldsymbol{\alpha}$, taking into consideration the true fertilizer content:

$$
\begin{aligned}
& \alpha_k = \beta_k - \beta_{1k} z, \text{and } \alpha_{jk} = \beta_{jk}, \\
& \forall j = \{2, 3, 4\}, k = \{1, 2, 3, 4\}, \text{ and } j \leq k.
\end{aligned} \tag{11}
$$

In terms of technical efficiency, we can see that the bias is $\beta_1 z - \frac{1}{2}\beta_{11} z^2$ from Eqs. (10) and (11).

4. Results

We estimate the translog production function using both FE and ML methods. Table 2 shows the results. The signs of most coefficients are consistent across both methods, even though there are some differences in the statistical significance. The only exception is the interaction term of fertilizer and land, where it is negative and significant in one method, while positive in another. We also run some specification tests on the estimated production function and we include the results in Table 3. Test (i) rejects the null hypothesis that the interaction terms have no effect, which means that using the translog functional form is an appropriate choice. Tests (ii) for FE and (iii) for ML[2] reject the null hypothesis that the households are fully efficient, as the efficiency component of the production function is statistically significant at 1%. In the Hausman test to compare the FE and ML regression outputs, the test statistic is 384.60, which is statistically significant.[3] Thus, we reject the null hypothesis that the estimated coefficients from the two methods are the same, and focus our analysis on the FE method.

As there are many interaction terms involved, direct interpretation of the results from the coefficients table does not provide much insight. Therefore, we calculate and show the results in Table 4 the marginal effect of each input at the mean input levels,

$$\frac{\partial Y}{\partial X_k} = \left[\alpha_k + \sum_{j=1}^{4} \alpha_{jk} \overline{\ln X_j}\right] \left[\frac{\overline{Y}}{\overline{X_k}}\right], \quad \forall k = \{1, 2, 3, 4\}, \tag{12}$$

with X_1 being the true amount of fertilizer. The marginal effects of fertilizer, land, and labor are all significantly positive at the 1% level. The marginal effect of seed is negative but it is not statistically significant.[4]

In Fig. 1 we plot the change in marginal effect across a range of fertilizer quality multiplier, e^z, from low to high. At unity, we see the marginal effect that we would get if we ignored the inaccuracy in fertilizer quality or if the fertilizer were correctly labeled. As

[2] The construction of $\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$ follows Battese and Coelli (1995) and the estimation is produced by the FRONTIER 4.1 software (Coelli, 1996), while the mixed χ^2 critical value is obtained from Kodde and Palm (1986).

[3] The critical value has a $\chi^2_{(14)}$ distribution, and is 29.14 at the 1% significance level.

[4] Unless otherwise mentioned, we measure statistical significance at the 5% level for the remainder of this paper.

Table 2
FE and ML estimates of the translog production function

Variables	Inputs	FE	ML
lnfer_m	fertilizer	-0.697***	-0.104
		(0.208)	(0.174)
lnland_m	land	0.999***	0.438*
		(0.274)	(0.231)
lnseed_m	seed	-0.090	-0.133
		(0.188)	(0.157)
lnfwork_total	labor	0.537***	0.368***
		(0.123)	(0.095)
lnfer2_m	fertilizer × fertilizer	0.129***	0.026
		(0.034)	(0.030)
lnland2_m	land × land	-0.079	-0.094*
		(0.067)	(0.056)
lnseed2_m	seed × seed	0.021	0.016
		(0.028)	(0.024)
lnfwork2_total	labor × labor	0.008	0.019*
		(0.015)	(0.011)
lnferland_m	fertilizer × land	-0.081**	0.014
		(0.039)	(0.034)
lnferseed_m	fertilizer × seed	0.101***	0.080***
		(0.031)	(0.027)
lnferfwork_total	fertilizer × labor	-0.050**	-0.048***
		(0.022)	(0.017)
lnlandseed_m	land × seed	-0.067*	-0.031
		(0.038)	(0.032)
lnlandfwork_total	land × labor	0.109***	0.094***
		(0.030)	(0.021)
lnseedfwork_total	seed × labor	-0.089***	-0.060***
		(0.025)	(0.020)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3
Specification tests of the estimated translog production function

	H_0	Test statistics	
		FE	ML
(i)	$\beta_{jk} = 0$	8.95***	64.75***
(ii)	$\gamma = 0$		254.54***
(iii)	$u_i = 0$	2.32***	

$\forall j, k = \{1, 2, 3, 4\}; j \leq k$
*** p<0.01

Table 4
Marginal effect of all inputs at mean input levels

Inputs	$\frac{\partial Y}{\partial X}$
Fertilizer	0.074***
	(0.025)
Land	5.139***
	(0.196)
Seed	-0.016
	(0.032)
Labor	0.084***
	(0.028)

Standard errors in parentheses
*** p<0.01

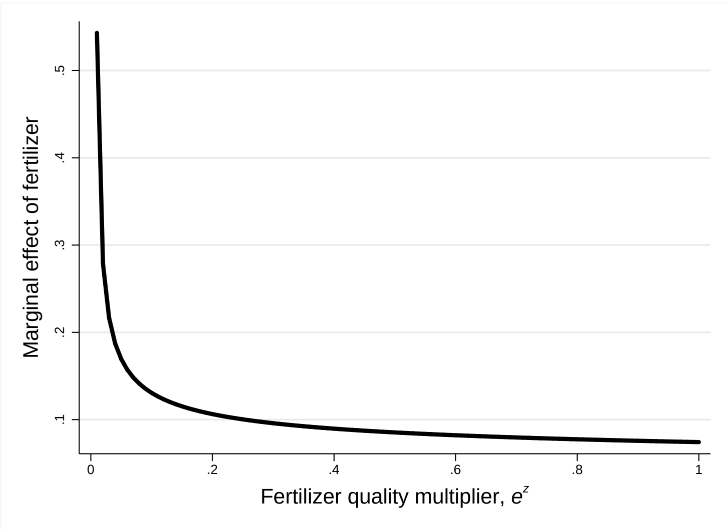

Fig. 1. Marginal effect of fertilizer at mean input levels across a range of fertilizer quality multiplier, e^z.

the fertilizer quality multiplier, e^z, decreases from unity, the marginal effect of fertilizer becomes higher. This is an expected outcome because a real fertilizer content that is less than the labeled content means that there is a lower actual fertilizer use while the output stays the same. So, the effect on output from a unit change in fertilizer is expected to be higher than before when the analysis is based on the labeled content of fertilizer. According to the study by Boeber et al. (2009), most of the fertilizer samples that they analyze do not have 100% of the labeled nitrogen content and only a few have less than 80%. So, at the realistic level of $0.7 \leq e^z \leq 0.9$, the marginal effect of fertilizer falls within the range of 0.0758 and 0.0796. For example, if we assume $e^z = 1.0$ instead of the more realistic $e^z = 0.8$, we would have underestimated the marginal effect of fertilizer by 4.18%.

We also use the input levels of each household in our analysis in addition to the mean input levels, and examine the percentage of households with negative marginal effect, the results of which are shown in Table 5. There are relatively few households with negative

Table 5
Percentage of households with negative marginal effect at individual input levels

Inputs	%
Fertilizer	16.93
Land	0
Seed	30.85
Labor	1.06

marginal effect in labor and none in land, but the percentage is quite high in fertilizer and seed, especially the latter. The negative effect could be due to the short planting distance between seeds that adversely affects the output (Keil, 2004, p. 106). This reasoning is supported by the highly positive partial elasticity of land, 0.78, implying that shortage of land is a problem faced by the households.

The fertilizer quality multiplier also affects the estimation of technical efficiency. Fig. 2 shows the change in technical efficiency of an average household[5] at different levels of e^z. As illustrated in the graph, technical efficiency decreases (i.e. the bias increases)

[5]In this case, average household refers to a household with mean technical efficiency.

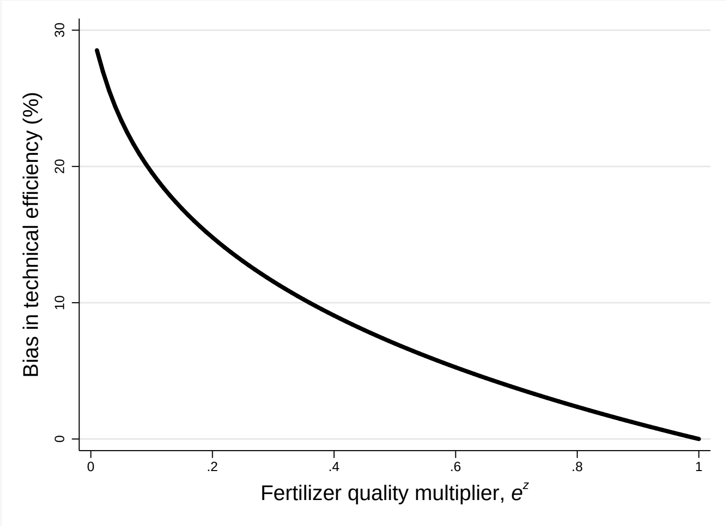

Fig. 2. Bias in technical efficiency of an average household across a range of fertilizer quality multiplier, e^z.

with a lower quality multiplier. This is a surprising result, as we would expect that if a household is able to produce the same amount of output using a lower amount of fertilizer, it is likely to be more technically efficient. However, the result shows otherwise, suggesting that uncertainty in fertilizer content could reduce technical efficiency. If we restrict the range of e^z to the more realistic values of between 0.7 and 0.9, we see that ignoring the real content of fertilizer results in overestimating the technical efficiency of an average household by about 1% to 4%.

5. Conclusion

Recent studies and news articles have reported the issue of questionable fertilizer quality in some developing countries, where the real fertilizer content might not be the same as the labeled content. The latter being what is reported by farmers in household surveys, our paper shows that ignoring this lower content could lead to bias in the estimates of both marginal effect and technical efficiency. We also show how to estimate the magnitude of the bias. Using panel data of household surveys from the Hebei province of China, we calculate the bias across a range of fertilizer content. If we focus on the realistic range of fertilizer quality multiplier, which is between 0.7 and 0.9 in the same province of China based on a previous study, we find that the marginal effect at mean input levels increases between 2% and 7% for fertilizer. As for technical efficiency, its magnitude for an average household decreases between 1% and 4%.

This paper focuses on fertilizer with lower than reported content, but the same method can also be applied to other purchased inputs, when the amount reported by households in surveys might not be the real amount of input use. Some examples include inaccuracy in seeds due to the mixture of fertile and infertile ovules, and inaccuracy in pesticide content due to the inclusion of cheaper and less effective chemicals.

Low quality fertilizer seems to be a problem in the study region as well as in other countries. Future studies and surveys could be carried out to examine how it affects household production decisions. In addition, testing of fertilizer content could also be incorporated into major household surveys to better understand the severity of the problem and its impact.

Poorly regulated fertilizer not only leads to bias in estimation, it also has food security implications. According to a study by Chavas and Holt (1996) on maize and soybean production in the U.S., most farmers are risk averse and show a decreasing absolute risk aversion with wealth, which is a finding supported by Bar-Shira et al. (1997). In addition, risk is found to have a negative effect on food supply (Just, 1974; Lin, 1977). Therefore, it is important to improve government supervision and regulation on fertilizer, or passing a legislation that gives a quality label to the products that meet the standards. It would also help to have independent testing facilities carry out regular examinations of fertilizer content in the market. Extension services can play a role as well in testing the fertilizer, in addition to raising the awareness of farm households on this issue and recommending better quality fertilizer to them.

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