I am writing to require that it will not have this submission form of my accepted contributed paper "Gaofei Yang- Smartphone use and environmental efficiency of maize production in China: Correcting for selectivity bias" included or archived on the AgEcon Search repository at the University of Minnesota.

Smartphone use and environmental efficiency of maize production in China: Correcting for selectivity bias

Abstract

While there is a broad literature on the impact of information technologies (IT) on the economic performance of different industries, only a few studies have looked at the environmental effect of IT adoption in agricultural production from an economic perspective. This study aims to investigate the effect of smartphone use on environmental efficiency based on a cross-sectional dataset covering 449 maize farmers in Henan, Shandong, and Gansu Provinces, China, in 2017. The translog hyperbolic distance function with stochastic frontier (SF) model is employed to assess environmental efficiency. Greene's (2010) selectivity-bias-corrected SF approach is used to examine how smartphone usage affects environmental efficiency, accounting for the selectivity bias arising from unobservable factors. Our results show that greenhouse gas (GHG) emissions from maize production are, on average, 876.1 kg·Ce/mu, and the mean environmental efficiency of maize production is 0.83.

Keywords: Smartphone use; Environmental efficiency; Selectivity bias; Stochastic Frontier model; Translog hyperbolic distance function; Greenhouse gas emissions.

1 Introduction

There is a consensus that information and communicate technologies (ICT) adoption could help disseminate agricultural marketing information fast and at a low cost (H. Zheng et al. 2021; Michels et al. 2020; Aker and Ksoll 2016) . The widespread adoption of ICT in developing countries such as China can reduce the information asymmetry of agricultural markets. The number of rural Internet users in China has reached 225 million, and the Internet penetration rate increased from 32% in 2015 to 38% in 2018 (CNNIC 2019). More than 95% of Internet users in rural China access agricultural information through smartphone applications (Ma and Zheng 2021), such as weather reports, the comparison of the price and quality of agricultural inputs, and relevant news and videos about new sustainable agricultural technologies.

Our objective is to examine the effect of smartphone use on the environmental efficiency of maize production. Farmers and policymakers usually ignore the undesirable by-products in agricultural production because it is hardly marketed and priced. Therefore, a more appropriate tool for estimating environmental efficiency would be a composite index, which simultaneously allows the undesired outputs to be reduced and the desired outputs to be increased. We utilize the translog hyperbolic distance function (HDF) in the stochastic frontier (SF) framework to assess the environmental efficiency of maize production based on a sample of 449 farm households in the 3 main corn-producing provinces in China. We also apply Greene's (2010) SF approach with full information maximum likelihood estimation (FIMLE) to analyze the unbiased impact of smartphone use on environmental efficiency, accounting for the selectivity bias from unobserved factors.

Environmental efficiency is derived from distinguishing between desirable outputs and undesirable outputs based on distance functions, which can be further calculated by parametric (stochastic frontier analysis, SFA) or nonparametric (data envelopment analysis, DEA) approach (Adenuga et al. 2019; Färe et al. 2007; Färe & Grosskopf 2000; Reinhard et al. 2000; Cuesta et al. 2009; Picazo-Tadeo et al. 2012). For example, Cuesta et al. (2009) introduced the properties of the conventional output distance function and hyperbolic distance function within a parametric stochastic framework to calculate environmental efficiency with SO2 emissions by the U.S. electricity industry with the application of country-level panel data. Adenuga et al. (2019) applied the hyperbolic distance function with SF model in a dairy farm to analyze the environmental efficiency and consequently estimated the shadow price of N surplus using panel data from the island of Ireland.

Previous studies have also shown that ICT, such as the Internet and smartphone use, has direct effects on the environment. Especially in agricultural production, Internet use could help reduce the overuse of environmentally detrimental inputs, such as chemical fertilizers and pesticides, which could improve agricultural sustainability

(Ma and Zheng 2022; Pitt et al. 2011; Yuan et al.2021; Zhao et al. 2021; Kaila and Tarp 2019). They suggested that ICT adoption, such as Internet use or smartphone use, can improve agricultural sustainability via transaction cost reduction, easy access to market information, government services, and information about refraining from the usage of environmentally detrimental inputs and reduce the pollutants to alleviate the climate change (Deichmann et al. 2016; Li et al. 2022; Munyegera and Matsumoto 2018) . However, the environmental effect of ICT adoption on the environmental efficiency of agricultural production, from the economic perspective, has hardly been analyzed.

The rest of the paper is structured as follows. In Section 2, we present the theoretical framework and methods used in the research, and we also provide a detailed description of data and empirical specification models in Section 3. We explain and discuss the empirical results in Section 4. Section 5 concludes with consequent policy implications.

2 Theoretical Framework

We present the theoretical model for our study in this section, which allows us to assess the environmental efficiency of maize production by incorporating GHG emissions as an undesirable output into the translog hyperbolic distance function with parametric SF framework. We also describe the Greene's (2010) SF model, which allows us to evaluate the impact of smartphone use on environmental efficiency after correcting the potential self-selectivity bias.

2.1 Environmental efficiency (EE) estimation

We applied the translog hyperbolic distance function (D_H) to undesirable outputs to estimate the environmental efficiency of maize production, which can be expressed as:

$$D_H(x, y, w) = inf\left\{\lambda > 0 \mid \left(x, \frac{y}{\lambda}, \lambda w\right) \in P\right\} \qquad (1)$$

where $D_H(x, y, w)$, x is a vector of input quantities, y is a vector of output quantities, and P represents the output possibility set in Eq. (1). λ indicates the degree of the same proportional changes of the desirable and undesirable output in opposite directions. Thus, it returns a non-negative value smaller than one for inefficient sets of $D_H(x, y, w)$, or it returns a value of one for fully efficient sets of $D_H(x, y, w)$. The general form of the translog hyperbolic distance function can be expressed as presented in Eq. (2).

$$D_H(x, \lambda y, \lambda^{-1} w) = \lambda D_H(x, y, w), \lambda > 0 \qquad (2)$$

The almost homogeneity condition of the hyperbolic distance function implies that if the desirable outputs increase at a given proportion, the undesirable outputs will decrease, and the distance function will increase by the same proportion, given the constant level of all inputs. Furthermore, it is non-decreasing in desirable outputs, $D_H(x, \lambda y, w) \leq D_H(x, y, w)$, $\lambda \in [0,1]$; non-increasing in undesirable outputs $D_H(x, y, \lambda w) \leq D_H(x, y, w)$, $\lambda \geq 1$ and non-increasing in inputs $D_H(\lambda x, y, w) \leq D_H(x, y, w)$, $\lambda \geq 1$. Then, imposing the almost homogeneity condition by setting $\lambda = \frac{1}{y_m}$ (y_m, the Mth output), it can be transformed as given in Eq. (3).

$$D_H\left(x_i, \frac{y_i}{y_m}, w_i y_m\right) = \frac{1}{y_m} D_H(x_i, y_i, w_i) \qquad (3)$$

After taking log in Eq. (3),

$$\frac{lnD_H(x_i,y_i,w_i)}{lny_m} = lnD_H\left(x_i,\frac{y_i}{y_m},w_iy_m\right) \tag{4}$$

The stochastic frontier analysis (SFA) framework enable us to estimate the frontier of best production practices, which assumes that there is an inefficiency term and a standard error term. Following Cuesta et al. (2009) and Adenuga et al. (2019), we get the specification of the translog hyperbolic distance function in Eq. (5).

$$\begin{aligned}\frac{lnD_H(x_i,y_i,w_i)}{y_{moi}} &= \alpha_0 + \sum_{j=1}^{J}\alpha_j lnx_{ji} + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J}\alpha_{jj'}lnx_{ji}lnx_{j'i} + \sum_{m=1}^{M-1}\beta_m lny_{mi}^{*} \\ &+ \frac{1}{2}\sum_{m=1}^{M-1}\sum_{m'=1}^{M-1}\beta_{mm'}lny_{mi}^{*}lny_{m'i}^{*} + \sum_{k=1}^{K}\gamma_k lnw_{ki}^{*} + \frac{1}{2}\sum_{k=1}^{K}\sum_{k'=1}^{K}\gamma_{kk'}lnw_{ki}^{*}lnw_{k'i}^{*} \\ &+ \sum_{j=1}^{J}\sum_{m=1}^{M-1}\delta_{jm}lnx_{ji}lny_{mi}^{*} + \sum_{j=1}^{J}\sum_{k=1}^{K}\psi_{jk}lnx_{ji}lnw_{ki}^{*} + \sum_{m=1}^{M-1}\sum_{k=1}^{K}\mu_{mk}lny_{mi}^{*}lnw_{ki}^{*} + v_i\end{aligned} \tag{5}$$

where $y_{mi}^{*} = \frac{y_{mi}}{y_{moi}}$ and $w_{ki}^{*} = w_{ki} * y_{moi}$. α, β, γ, δ, ψ, and μ are parameters to be estimated. Assuming that $u \equiv - lnD_H(x_i,y_i,w_i) \geq 0$ follows a half-normal or truncated normal distribution (i.e., $u \sim N^{+}(\mu,\sigma_u^2)$) and another disturbance term v follows a normal distribution (i.e., $v \sim N(0,\sigma_v^2)$). The stochastic translog hyperbolic distance function model can be specified as given in Eq. (6).

$$\begin{aligned}-\ln y_{moi} &= \alpha_0 + \sum_{j=1}^{J}\alpha_j lnx_{ji} + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J}\alpha_{jj'}lnx_{ji}lnx_{j'i} + \sum_{m=1}^{M-1}\beta_m lny_{mi}^{*} \\ &+ \frac{1}{2}\sum_{m=1}^{M-1}\sum_{m'=1}^{M-1}\beta_{mm'}lny_{mi}^{*}lny_{m'i}^{*} + \sum_{k=1}^{K}\gamma_k lnw_{ki}^{*} + \frac{1}{2}\sum_{k=1}^{K}\sum_{k'=1}^{K}\gamma_{kk'}lnw_{ki}^{*}lnw_{k'i}^{*} \\ &+ \sum_{j=1}^{J}\sum_{m=1}^{M-1}\delta_{jm}lnx_{ji}lny_{mi}^{*} + \sum_{j=1}^{J}\sum_{k=1}^{K}\psi_{jk}lnx_{ji}lnw_{ki}^{*} + \sum_{m=1}^{M-1}\sum_{k=1}^{K}\mu_{mk}lny_{mi}^{*}lnw_{ki}^{*} \\ &+(v_i - u_i)\end{aligned} \tag{6}$$

u and v in Equation (6) should be conditionally independent; the inefficiency term and a disturbance term account for statistical noise. Environmental efficiency can be calculated by $\mathrm{u} =-\ln D_H$ and expressed by $\mathrm{E}[\exp(-\mathrm{u})]$.

2.2 Sample selection correction model

The original SF model with the composed error term can be written as follows (Aigner et al. 1977; Meeusen et al. 1977):

$$y_i = \beta x_i + v_i - u_i$$
$$u_i = \sigma_u |U_i|, u_i \sim N(0,1)$$
$$\upsilon_i \sim \mathrm{N}(0, \sigma_v^2) \quad (7)$$

where y_i is the logarithmic output quantity of each farm i; x_i is the vector of input quantities in logarithmic form; β denotes the vector of parameters to be estimated; v_i denotes the statistical noise (random variations) with variance σ_v^2; u_i represents the inefficiency term with scale parameter σ_u; and $N(.)$ indicates normal distribution.

To correct the sample selection bias, the SF model can be conducted using various techniques. For example, Greene (2010) utilized the maximum simulated likelihood (MSL) approach. However, we use the full information maximum likelihood (FIMLE) (Dakpo et al., 2021), which is more appropriate than MSL, considering undesirable outputs with the hyperbolic distance function.

Following the FIMLE of Dakpo et al. (2021), the conditional density (on U_i) of the two-sided error disturbance v_i is:

$$f(y_i|x_i, |U_i|) = \frac{1}{\sigma_v} \phi \left(\frac{y_i - \beta x_i + \sigma_u |U_i|}{\sigma_v} \right) \quad (8)$$

where ϕ is the density function of the standard normal distribution, and $|U_i| \in [0, \infty)$. The log-likelihood function can be obtained by integrating the density in Equation (13) over the range of $|U_i|$. Thus:

$$log f(y_i|x_i) = log \int_{U_i} \frac{1}{\sigma_v} \phi \left(\frac{y_i - \beta x_i + \sigma_{ui} |U_i|}{\sigma_v} p(|U_i|) d|U_i| \right) \quad (9)$$

where $p(|U_i|) = 2\phi(U_i)$. The canonical form of Heckman's (1979) two-step model for the correction of sample selection bias is:

$$y_i = \beta x_i + v_i$$
$$D_i^* = \gamma z_i + w_i \quad (10)$$

where D_i^* denotes a latent (unobserved) variable; z_i denotes a vector of explanatory variables; γ represents parameters to be estimated; and w_i is an error term accounting for statistical noise. The second one in Eq. (10) is the selection equation model using a probit model to estimate, where $[\mathrm{D}_i = 1(\mathrm{D}_i^* > 0) \wedge \mathrm{D}_i = 0(\mathrm{D}_i^* \leq 0)]$ based on the utility maximum theory.

More importantly, values of y and x are only observed when $\mathrm{D}_i = 1$, and where N_2

is the bivariate normal distribution. Since Heckman's two-step approach is inappropriate for nonlinear models, such as the translog production function (Greene, 2010) , we use FIMLE (Maddala, 1983) to estimate environmental efficiency for correcting its sample selection bias:

$$y_i = \beta x_i + v_i - u_i$$
$$D_i^* = \gamma z_i + w_i$$

$$(\mathrm{v}, \mathrm{w}) \sim N_2 \left[\begin{matrix} 0 \\ 0' \end{matrix} \begin{pmatrix} \sigma_v^2 & \rho\sigma_v \\ \rho\sigma_v & \sigma_w^2 = 1 \end{pmatrix} \right] \quad (11)$$

where ρ indicates the correlation between w_i and v_i capturing the sample selection bias. The full information likelihood is built up from Prob(selection) × density|selection for selected observations and Prob(non − selection) for non-selected observations. Thus, the conditional (on u_i) density can be written as:

$$\mathrm{L_i} = \mathrm{d_i} \{ \mathrm{f}(\mathrm{y_i}\,\mathrm{x_i}, |\mathrm{U_i}|, \mathrm{w_i} > -\gamma' \mathrm{z_i}) \mathrm{P}(\mathrm{w_i} >- \gamma' \mathrm{z_i}) \} + (1 - \mathrm{d_i}) \mathrm{P}(\mathrm{w_i} \leq - \gamma \mathrm{z_i}) \quad (12)$$

$$\mathrm{f}(\mathrm{y_i}\,\mathrm{x_i}, |\mathrm{U_i}|, \mathrm{w_i} > -\gamma' \mathrm{z_i}) \mathrm{P}(\mathrm{w_i} >- \gamma' \mathrm{z_i}) = \int_{-\gamma' z_i}^{\infty} f(v_i, w_i) dw_i$$

$$\int_{-\gamma' z_i}^{\infty} f(v_i, w_i) dw_i = \phi(v_i) \Phi \left[\frac{\frac{\rho}{\sigma_v} v_i + \gamma' z_i}{\sqrt{1-\rho^2}} \right] \quad (13)$$

where Φ is the cumulative distribution of the standard normal distribution. The log-likelihood function of the model specified in (12) is obtained by integrating the density in (13) over the range of |Ui|, where $v_i = y_i - \beta' x_i + \sigma_u |U_i|$. Thus, we have:

$$\mathrm{f}(\mathrm{y_i}\,\mathrm{x_i}, |\mathrm{U_i}|, \mathrm{w_i} > -\gamma' \mathrm{z_i}) = \phi(y_i - \beta' x_i + \sigma_u |U_i|) \Phi \left(\frac{\frac{\rho}{\sigma_v}(y_i - \beta' x_i + \sigma_u |U_i|) + \gamma' z_i}{\sqrt{1-\rho^2}} \right) \quad (14)$$

To maximize the log-likelihood function (14) based on a hybrid two-step limited information maximum likelihood (LIML) estimation, the log-likelihood function to be maximized is simplified as follows (with $|U_i| \in [0, \infty)$):

$$\mathrm{logf}(y_i x_i) = log \left[\int_{|U_i|} \phi(y_i - \beta' x_i + \sigma_u |U_i|) \Phi \left(\frac{\frac{\rho}{\sigma_v}(y_i - \beta' x_i + \sigma_u |U_i|) + a_i}{\sqrt{1-\rho^2}} \right) d|U_i| \right] \quad (15)$$

where the observations for non-adopted ($D_i = 0$) do not contribute information about the parameters, so that $(1 - D_i)\Phi(a_i) = 0$, and $a_i = \widehat{\gamma'} z_i$. To account for sample selection, the estimation of environmental efficiency follows Greene (2010), then

$$P(u_i\varepsilon_i) = \frac{P(u_i,\varepsilon_i)}{P(\varepsilon_I)} = \frac{P(u_i\varepsilon_i)P(u_i)}{\int_{u_i} P(u_i\varepsilon_i)P(u_i)du_i}$$

$$E[u_i|\varepsilon_i] = \frac{\int_{u_i} u_i P(\varepsilon_i u_i)P(u_i)du_i}{\int_{u_i} P(\varepsilon_i u_i)P(u_i)du_i} \quad (16)$$

where $P(u_i\varepsilon_i)$ denotes the probability and $\varepsilon_i = v_i - u_i$ and $u_i = \sigma_u|U_i|$. Therefore, $|U_i| \in [0, \infty)$. The denominator of formula (16) is obtained as the predicted value of f $(y_i x_i)$ in Equation (15). The numerator's integral is solved with the parameters obtained from maximizing Equation (16). Finally, environmental efficiency is computed as $\exp[-\hat{E}[u_i|\varepsilon_i]]$.

3 Data and Empirical Framework

Cross-sectional data collected by a farm household survey in three major maize-producing provinces in China in 2017 were used in this paper to estimate the effect of smartphone use on environmental efficiency. China is the second largest maize-producing country, producing 274 (million tons) in 2022, compared with the biggest maize-producing country, the United States, with 352.9 (million tons) in 2022[1]. Maize is mainly produced in Northern China, covering three provinces in Northeastern China (Heilongjiang, Jilin, Liaoning), Shandong, Henan, Hebei, Gansu, Ningxia, Shaanxi, Inner Mongolia, and Shanxi provinces.

The collected information on household demographics and assets, maize production and sale activities, and access to information (e.g., smartphone use) are used to answer our research question. Furthermore, well-trained enumerators recruited from local universities in each province conducted face-to-face interviews with a total of 499 farmers in the selected villages. After cleaning the missing values and extreme values of some observations, we finally used a total of 449 maize farmers, and the validity of this survey is 90%. Smartphone use is defined as a binary variable in this study, which is consistent with previous studies (smartphone papers). Of the 449 farm households interviewed in this survey, 292 are smartphone users, and the other 158 are nonusers and they self-selected themselves to be smartphone users or nonusers.

In order to estimate environmental efficiency, we have to identify and calculate the undesirable output first. The carbon footprint can be defined as a measure of the total amount of carbon dioxide emissions that are directly and indirectly caused by an activity or are accumulated over the life stages of a product (Wiedmann & Minx 2007) . While there are various specific definitions of carbon footprint in different industries at different scales (Pandey et al. 2011) , the carbon footprint from maize production is generally assessed by the total amount of GHG emissions which is accumulated over the life stages of maize production.

Due to limited data, the carbon footprint from maize production can be measured by the total amount of GHG emissions, including carbon dioxide (CO_2) and indirect nitrous dioxide (N_2O) emissions, induced by chemical fertilizer usage, diesel fuel usage, and openly burnt corn straw, which is accumulated over the life stages of maize production. The GHG emission calculation equations based on the carbon footprint method can be expressed as given in Eq. (17).

[1] IndexMundi is a data portal that gathers facts and statistics from multiple sources and turns them into easy-to-use visuals.Our mission is to turn raw data from all over the world into useful information for a global audience. We capture statistics that are scattered or otherwise hidden and present them via user-friendly maps, charts, and tables which allow visitors to understand complex information at a glance.

$$CF_i = GHG_{fi} + GHG_N + GHG_{di} + GHG_{si}$$

$$GHG_{fi} = \sum_{m=1}^{M} F_{mi} EF_m + GHG_N$$

$$GHG_N = F_N * EF_N * \delta_N * \frac{44}{28} * 298$$

$$GHG_{di} = D_i * EF_d$$

$$GHG_{si} = Y_i \cdot R \cdot N \cdot CF \cdot EF \quad (17)$$

where CF_i refers to the total carbon footprint of corn production, GHG emissions with unit (kg·Ce/mu); CF_{fi} indicates the carbon dioxide emissions from all other fertilizer usage with unit (kg·Ce/mu) and CF_{N_2O} denotes the direct N_2O emission from nitrogen fertilizer usage with unit (kg·Ce/mu); CF_{di} is the carbon dioxide emissions from diesel fuel usage (kg·Ce/mu), and CF_{si} represents the carbon dioxide emissions from openly burning maize straw with unit (kg·Ce/mu).

The summary of total GHG emissions from maize production and the separate one induced by chemical fertilizers, diesel fuel, and openly burnt maize straw, respectively. GHG emissions from corn production (undesirable output) are around 876.1 kg · Ce/mu (GHG emissions with carbon equivalent), which is mainly caused by chemical fertilizer usage with 772.5 kg · Ce/mu (GHG emissions with carbon equivalent). The results suggest that it is important to take GHG emissions into account in the analysis of environmental efficiency with a parametric SF model.

4 Results and Discussion

We estimate the environmental efficiency utilizing the translog hyperbolic distance function with Greene's (2010) selectivity-bias-corrected SF model to establish the existence of any selection bias for farmers' decisions to use a smartphone. First, the factors affecting smartphone use are shown and discussed. Second, we present the translog hyperbolic distance function with stochastic frontier estimation results for the whole sample, sub-samples with selectivity bias correction, and without, respectively, to explain the environmental efficiency among maize farmers given to consider the potential self-selectivity for smartphone usage. Finally, environmental efficiency scores for sub-samples with and without sample selection correction are shown and discussed.

Environmental efficiency estimates using the conventional and selectivity-bias-corrected HDF models are illustrated in Table 7, Figure 1 and Figure 2. The mean environmental efficiency of maize production for all of 449 maize farmers is 0.832, which is relatively high and ranges from 0.32 to 0.98. It suggests that maize farmers can improve their production performance by increasing maize yield by 12.02% and simultaneously contracting GHG emissions by 16.8%. The statistical description of environmental efficiency scores for the whole sample and subsamples with and without selection bias correction are presented in Table 7 as well. It also shows a disaggregation in the smartphone use situation. The mean environmental efficiency score among smartphone users (0.86) is significantly higher than that among nonusers (0.82), implying that smartphone users can increase environmental efficiency by 4.89% (0.86-0.82)/0.82=0.489). This is in accordance with our hypothesis that smartphone use can help improve the environmental efficiency of maize production.

5 Conclusions

This study analyzed the role of smartphone use in enhancing environmental technical efficiency, using cross-sectional data covering 449 farmers from three main maize-producing provinces in China. We utilized a translog hyperbolic distance function (HDF) with greenhouse gas (GHG) emission and the stochastic frontier (SF) model to assess the environmental efficiency of maize production. We also used the combination of Greene’s (2010) sample selection correction SF model and Dakpo’s (2021) FIMLE to account for potential selectivity bias associated with unobserved attributes. These approaches allowed us to estimate the unbiased and consistent impact of smartphone use on environmental efficiency.

The empirical results revealed that smartphone use tends to enhance the environmental efficiency (EE) of maize production in China. In particular, for both conventional and sample selection SF model estimations, the results show that smartphone users are more environmentally efficient than nonusers. Moreover, relatively lower EE scores for smartphone nonusers and unchanged EE scores for smartphone users are associated with the use of the sample selection SF model, suggesting that there is no selectivity bias for users based on our available dataset. This also means that in non-randomized studies, it is important to account for selection bias because the significant result of the ρ parameter for users.

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