Documents de travail

« Measuring the Effect of Agricultural Extension on Technical Efficiency in Crop Farming:Meta-Regression Analysis»

Auteurs

Nicolas Lampach, Phu Nguyen-Van, Nguyen To-The

Document de Travail n° 2018 – 48

Novembre 2018

Bureau d'Économie Théorique et Appliquée BETA

www.beta-umr7522.fr

@beta_economics

Contact :
jaoulgrammare@beta-cnrs.unistra.fr

Measuring the Effect of Agricultural Extension on Technical Efficiency in Crop Farming: Meta-Regression Analysis[§]

Nicolas Lampach[a*] Phu Nguyen-Van[b]

Nguyen To-The[c]

[a] *Centre for Legal Theory and Empirical Jurisprudence, KU Leuven (Belgium)*

[b] *BETA, CNRS & University of Strasbourg (France)*

[c] *Vietnam National University of Agriculture (Vietnam)*

Agricultural extension services have been dominated by development programs to improve the productivity of crops and to increase farmers' income. The virtues and limitations of these programs ignite a debate among scholars from distinct strands of research. How effective are agricultural extension services in improving the productivity level of the agricultural output? We examine the key determinants driving systematic variations in the obtained technical efficiency estimates from all relevant crop farming studies. A weighted least square meta-regression analysis is conducted by using 193 observations from 96 farm level studies to evaluate the estimates of technical efficiency in crop farming and to review the relationship between agricultural extension services and farm performance. Evidence for the absence of a publication bias in the farm studies used in the meta-analysis is identified. The empirical results manifest that there is a positive and significant effect of extension services on technical efficiency estimates. Farm productivity is significantly influenced by country level characteristics, sample size of farm studies and type of crops. Our empirical findings are robust when replacing missing observations with imputed values applying the multiple imputation method.

Keywords: Agricultural extension; Crop farming; Meta-analysis; Multiple Imputation; Publication bias; Technical efficiency; Weighted Least Square Estimation
JEL Classification: Q16, O18, C14, C29

[§] We gratefully acknowledge the financial support from the Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 502.01-2018.13. All remaining errors are our own.

[*] *Corresponding author*: Nicolas Lampach. Address: Centre for Legal Theory and Empirical Jurisprudence, International House, 45 Tiensestraat, 3000 Leuven, Belgium; Tel: +32 16 37 76 08; E-mail: `nicolas.lampach@kuleuven.be`.

Measuring the Effect of Agricultural Extension on Technical Efficiency in Crop Farming: Meta-Regression Analysis

Abstract

Agricultural extension services have been dominated by development programs to improve the productivity of crops and to increase farmers' income. The virtues and limitations of these programs ignite a debate among scholars from distinct strands of research. How effective are agricultural extension services in improving the productivity level of the agricultural output? We examine the key determinants driving systematic variations in the obtained technical efficiency estimates from all relevant crop farming studies. A weighted least square meta-regression analysis is conducted by using 193 observations from 96 farm level studies to evaluate the estimates of technical efficiency in crop farming and to review the relationship between agricultural extension services and farm performance. Evidence for the absence of a publication bias in the farm studies used in the meta-analysis is identified. The empirical results manifest that there is a positive and significant effect of extension services on technical efficiency estimates. Farm productivity is significantly influenced by country level characteristics, sample size of farm studies and type of crops. Our empirical findings are robust when replacing missing observations with imputed values applying the multiple imputation method.

Keywords: Agricultural extension; Crop farming; Meta-analysis; Multiple Imputation; Publication bias; Technical efficiency; Weighted Least Square Estimation

JEL Classification: Q16, O18, C14, C29

1 Introduction

The importance of agriculture for the economic development of a given country and for human welfare has been recognized for years. The agricultural sector facing challenges with the stability of rising food prices, the sustainable use of natural resources and the adaptation to climate change have significant implications on the technical efficiency and farm productivity growth. The main sources of growth in plant production stem from the expansion of land area, increasing cropping frequency through water irrigation and boosting yields. Since the potential of land expansion and availability of water supply appear to be reaching its limit at a global view, a more efficient use of natural resources through modern technology will continue to play a substantial role in the future (FAO, 2015).

Investments in extension services may contribute to improve agricultural productivity and create incentives for farmers to adopt new modern technologies (Anderson and Feder, 2004). In the last decades, extension programs have been introduced in many developing and developed countries with the objective to spur farm productivity by disseminating information to farmers on improved agricultural technologies. Extension agents interact with farmers to give advices on more effective management options, optimal input use and more efficient methods of production (Alene and Hassan, 2003; Dinar et al., 2007).

Cereals (e.g. wheat, maize, barley, rice and millet) account as the most prevalent group of crops across the world and its cultivation exceeds 20% of global land surface.[1] Part of minor crops group are vegetables, fruits, root/tuber, nuts and other fibbers in which each take up less than 2% of the worlds crop surface. Crop diversification is of vital importance for food security owing to larger crop diversity mitigates farmers' vulnerability and climate risks. On global scale, a large amount of regions (e.g Midwestern United States, Brazil,

[1] i.e 61% of the total cultivated area.

Mexico, Japan, most of Russia, Middle East and most of southern Asia and Indochina) are heavily cultivated with low crop diversity (Leff et al., 2004).

Scholars have used a large set of available metrics to analyze the efficiency and productivity growth in agriculture. We focuse on technical efficiency defined as a state when a farm is able to realize the maximum achievable output given a fixed level of inputs and available technology (Farrell, 1957).

$$- - -\Big[\text{Figure 1 here}\Big] - - -$$

Plotted in Figure 1 are the number of scientific articles[2] reporting the technical efficiency in the field of agriculture over the last decades. Given the rapid surge in articles on the topic, systematic reviews and meta analysis are crucial tools to design effective decision making. Meta-analysis also provides a common basis to clarify a specific research question and to explore puzzling and contradictory findings from large number of studies within a certain research field.

Meta-analysis has become an increasing popular and widely applied method in a broad range of disciplines (Gurevitch et al., 2018). The main idea behind the methodology is to combine the results and findings from independent studies. It uses the empirical estimates from available scientific resources – in our case the technical efficiency estimates – and seeks to explain the variation of these estimates based on fundamental divergences across studies in a regression model. Stanley et al. (2013) reports that no less than 200 meta studies are conducted per year on economic topics.[3]

[2]Google Scholar free services is of great help to discover quickly scientific resources. One main drawback is that Google Scholar is lacking information on the actual size and coverage of the scientific collections (Jacsó, 2005, 2008, Mayr and Walter, 2007). The retrieved hits should not be taken as a measure of scholarly production or impact, but rather as an macroscopic view of the content indexed by Google Scholar.

[3]Interested reader may find further information on meta-analysis in the field of economics in Alston et al. (2000); Bravo-Ureta et al. (2007); Card and Krueger (1995); Dalhuisen et al. (2003); Espey et al. (1997); Jiang and Sharp (2015); Moreira and Bravo-Ureta (2010); Thiam et al. (2001) and among others.

Scholars reviewed the large literature on technical efficiency in the field of agriculture and put substantial effort into understanding the main drivers for systematic disparities in the efficiency estimates (Bravo-Ureta et al., 2007, Iliyasu et al., 2014, Jiang and Sharp, 2014, Thiam et al., 2001). Most notably, the study by Bravo-Ureta et al. (2007) applies a meta-regression analysis on the technical efficiency in farming and reveals that the average efficiency estimate is higher for animal production compared to crop farming. Despite their careful investigation, the operationalization of the data is limited. We argue that a more fine grained review on farm performance by analysing separately animal and crop production classification would not only expand our understandings on the technical feasibility within each system, but also allows to provide distinct policy implications for both groups. Due to the high effort of data collection, we restrict our analysis merely to crop farming studies.

Meta-analysis studies have neglected so far to explore the relationship between agricultural extension services and technical efficiency. Although, systematic reviews by Birkhaeuser et al. (1991), Evenson (1997), Maredia et al. (2000) and Purcell and Anderson (1997) indicate convincing evidence that extension efforts can have a significant effect on output, it is hard to establish empirically a direct causal relationship. The effectiveness of extension programs on farm productivity depends on how services are delivered and on specific circumstances of the recipients. Anderson and Feder (2004) stress that evaluating the impact of extension measures on farm performance is difficult due to measurement errors (i.e weak accountability) or the mutual influence of other systematic and random effects (e.g. crop prices, credit constraints, climate). For this reason, a rigorous and careful examination of econometric and quasi-experimental methods represent a necessary condition to draw robust policy implications from the empirical results.

Findings of studies examining the effect of extension services on technical efficiency in crop farming are puzzling and therefore our understanding about the effectiveness of extension programs appears to be fragile and fragmented. While Asres et al. (2014), Alene and Hassan (2003), Bravo-Ureta and Evenson (1994) found no significant differences in the technical efficiency between both groups agricultural extension participants and non-participants, others manifest that there is a positive and significant relationship between the contact with extension agents and farm performance (Binam et al., 2004; Cerdán-Infantes et al., 2008; Dinar et al., 2007; Ho et al., 2014; Owens et al., 2003; Nguyen-Van and To-The, 2016). In general, the literature distinguishes between two approaches in which the extension policy measure is included either as a separate input factor in the production function or as a determinant to explain variations of technical inefficiency associated with the production function, whereas the latter represents the most common approach in crop farming studies.

We investigate which determinants are systematically explaining differences in the efficiency estimates in crop farming studies and we review the link between extension services and technical efficiency. Our contribution is therefore to provide empirically evidence on the effect of agricultural extension on farm productivity in crop framing. In light of the increased interest in agricultural extension programs in developed and developing countries, knowing whether extension policy is an effective strategy to improve farm productivity, can provide a key insight to both policymakers willing to invest in agricultural extension and private research firms delivering extension services.

A sample of 193 observations of 96 farm level studies on plant production is collected to estimate the technical efficiency by the means of meta-regression analysis. The majority of the studies report only the mean and the range of technical efficiency, however the variance (or standard deviation) is needed for the meta-analysis. Following Hozo et al. (2005), we estimate the variance using the mean, the low and high range, and the sample size. Additional complication arises from missing sample variance for studies reporting solely the mean technical efficiency. To deal with missing observations in our meta analysis, we draw on multiple imputation method to replace missing observations with imputed values (Chowdhry et al., 2016).

Applying visual and numerical assessment tools, the absence of a publication bias is detected for both complete case and imputed data. Our setup gives clean indication of the evaluation of extension services, as it turns out, studies focusing on extension have found greater level of farm productivity than those who do not. Our findings contribute to the applied agricultural economics literature by empirically validating the technical efficiency in crop farming studies and the development literature by reviewing the effect of extension policies on farm performance.

The remaining of this paper is organized as follows. Section 2 presents the concept of meta analysis followed by the specification of the meta-regression. Section 3 explores potential publication bias in studies used in our meta analysis. Section 4 reports the estimation results and discusses our findings. Section 5 concludes the study and provides policy implications within the agricultural extension literature.

2 Material and methods

The application of meta-analysis framework needs important consideration by following a clear and rigorous procedure to review the literature.[4] Original studies were identified through keyword searches (e.g., "Technical Efficiency", "Technical Progress", "Crop", "Crop Farming", "Extension Policy", "Extension Services", "Agricultural Extension Measures"

[4]Note that Meta Analysis of Economics Research (MAER) network provides helpful guidelines and recommendations on how meta analyses in the field of economics should comply with reporting protocols requirements (Stanley et al., 2013).

"Meta Analysis"). Published and non-published studies in English between January 1991 and December 2016 were searched through ISI Web of Knowledge, Google Scholar, Scopus, and AgEcon Search. In the present paper a thorough review was made in the following peer-reviewed journals: American J. of Ag. Econ.; World development; Australian J. of Ag. Econ.; Canadian J. of Ag. Econ.; European J. of Operational Research; Eur Rev. Ag. Econ.; J. of Ag. and Applied Econ; J. of Ag. Econ.; Ecological Econ.; J. of Prod. Analysis., Food Policy and other journals.[5]

Given that many of the papers report several technical efficiency coefficients for similar or different crop plant types, the data under analysis include a total of 193 observations. Since each study may contain multiple observations, the data has a nested hierarchical structure. The key future of nested data is that observations within a study are more similar than observations from other studies (Galbraith et al., 2010). Our data collection differs from Thiam et al. (2001) and Bravo-Ureta et al. (2007) who considered the average technical efficiency as a summary measure referring to the entire sample for any particular study. We provide an overview of all studies used in this evaluation by summarizing most important information, such as the first author, the year of publication, the country and crop type analyzed, the number of observations and the technical efficiency coefficient in Supplementary Materials.

Scholars discussed a large set of factors, ranging from econometric techniques, choice of functional form, type of data, mathematical programming techniques to number of observations, potentially affecting the estimated technical efficiency (Bravo-Ureta et al., 2007; Thiam et al., 2001). Nevertheless, a key determinant largely ignored by previous meta-analysis research is the effect of extension measures on technical efficiency. Governments

[5] Non peer-reviewed journals related to agriculture, economics, agricultural economics, productivity analysis and general review studies.

may support farmers by offering extension services encompassing a wide range of communication and learning activities organized by educators for farmers. Extension agents provide trainings to farmers on harvesting and conservation techniques, application of fertilizers and pesticides, technical instruction of plant production or agricultural marketing.

Two distinct approaches have been applied in the agricultural economics literature to measure the effect of extension services on technical efficiency (Dinar et al., 2007; Gebrehiwot, 2017). On the one hand, extension services serve as a separate input factor in the production function and its impact on technical efficiency is evaluated through it's direct effect on the output. On the other hand, it has been included as a determinant in the inefficiency effect function to explain variation in technical efficiency among farmers. In this way, the effect of extension services is assessed indirectly through the potential output gain. From a methodology perspective, each approach is informative by itself but it is limited since the effect of extension services is measured directly and indirectly on the performance of the farm. Under some conditions, these approaches are equivalent. For example, in the Cobb-Douglas production function, $y = AK^{\alpha}L^{\beta}E^{\gamma}$ where E represents extension services which are considered as an additional input besides capital K and labor L, we can assume the new productivity term $B = AE^{\gamma}$ to recover the production function $Y = BK^{\alpha}L^{\beta}$ where extension services are now included in the productivity (or technical efficiency) term B. As our sample comprises a low number of studies using extension measures as input factor in the production function, we do not distinguish between these two approaches in our meta-regression analysis. For this reason, we can only review the causal relationship between the indirect effect of extension activities on farm performance.

The meta analysis offers the possibility to link the information on the technical efficiency to a large set of characteristics from all relevant studies. Our primary aim is to examine the effects of extension services on the technical efficiency estimates when controlling for different crop plant types, model specification, methodologies and study-specific characteristics. With this is mind, our hypothesis to be investigated in this study can be summarized as following:

- Hypothesis: *Extension services have a positive effect on the technical efficiency in crop farming studies*

The lack of information on the variance as well as the low and high range of the estimated technical efficiency in our sample complicates the meta-regression analysis. A first solution to this problem is to estimate the variance of farm performance for those studies reporting the mean, low and high range, and the sample size. However, the amount of missing observations in our dataset still accounts for 21.24% after the variance estimation which might potentially lead to inaccurate estimates. Deleting missing cases would only be preferable if those are missing completely at random (Rubin, 1976). We provide further information on the percentage and the occurrence of missing cases in Supplementary Materials. A frequently used strategy to mitigate the impact of missingness and the bias of estimates in meta-regression analysis is multiple imputation method (Burgess et al., 2013; Higgins et al., 2008). Under the key assumption that observations are not missing completely at random, the imputation model replaces missing observations with imputed values (Rubin, 1976). To verify the underlying assumption of the imputation application, we perform Little (1988) test. We can reject the hypothesis that missing observations are missing completely at random ($p_{\text{value}} < 0.001$) and thus we perform within-study imputation using predictive mean matching. This approach imputes actual observed values from a pool of $k \geq 0$ values (i.e donor pool) with the most closest distance to the predicted value for the missing case.[6]

$$- - - \Big[\text{Figure 2 here}\Big] - - -$$

[6]An illustration and detailed explanation about the implementation of predictive mean matching in agricultural research can be found in Lampach et al. (2017).

We run a total number of $m = 100$ imputed dataset and analyse in section 4 each separately and combine the multiply imputed estimates according to Rubin's rule. It has been shown that predictive mean matching preserves effectively the original distribution of the empirical data (Kleinke, 2017). Plotted in Figure 2 is the original and imputed distribution for covariates including missing cases. It can be seen that the imputed distributions (i.e dashed line) largely overlap with the original distribution (i.e solid line) establishing a sufficient degree of confidence in the effectiveness of the multiple imputation method.

To assess our hypothesis, we estimate weighted least square meta-regression with weights equal to the inverse standard error of the technical efficiency estimates for both complete case analysis and imputed dataset. Alternatively, we run a model with weights equal to the inverse range of technical efficiency estimates. Weighted regression method corrects for heteroscedasticity by assigning larger weights to studies with relatively small standard errors and smaller weights to studies with large standard errors in technical efficiency estimates. To explain the heterogeneity among the reported estimates, we control for within-study specific characteristics, regional disparities, data characteristics and model specification differences.

The specification for the model is:

$$TE_i = \alpha_1 + \beta_1 EXT_i + \sum_{k=1}^{K} \gamma_k Z_{ik} + \epsilon_i \tag{1}$$

where the dependent variable TE is the technical efficiency as reported in the crop farming studies. Estimating equation 1 using weights which equals to the inverse standard errors of technical efficiency estimates ($SE(TE_i)$) assumes that the error term ϵ_i is independently distributed with mean zero and variance $\frac{1}{SE(TE_i)^2}$. In the same way, weights corresponding to the inverse range of technical efficiency estimates ($R(TE_i)$) implies that ϵ_i is independently distributed with mean zero and variance $\frac{1}{R(TE_i)^2}$. While the intercept α_1 measures the mean effect size of the technical efficiency, our variable of interest is EXT referring to the inclusion of extension policy and takes the value one if a study accounts for an agricultural extension measure and zero otherwise. Z_{ik} denotes the control variables and ϵ_i is the error term in equation (1). Z_{ik} comprises the economic development from the studied country (LIE, $LMIE$, MIE, $UMIE$, HI), type of crop plants ($Crops1$, $Crops2$, $Crops3$, $Crops4$, $Crops5$, $Crops6$, $Crops7$, $Crops8$, $Crops9$), cross-sectional data ($Type$), number of observations (Obs), model specification based on Data Envelopment Analysis (DEA) and specification of the production function ($Other$, CD, TL).

The economic development variables are dichotomous based on World Bank (2016) country classification by income level. We use a set of five dummy variables, low income ecomomy (LIE), low-middle-income economy ($LMIE$), middle-income economy (MIE), upper middle-income economy ($UMIE$) and high-income economy (HIE). The proportion for each country category is illustrated in Supplementary Materials (Figure 4). With the largest proportion of studies in our sample coming from low-middle income economy ($LMIE$), we choose this category as the reference in the meta-regression.

According to FAO (2012), we use the crop classification to categorize the plant production types of the relevant crop farming studies. We use nine dummy variables where the former represents the largest share among the type of crops in our sample: cereals crops ($Crops1$), vegetables and melons ($Crops2$), fruit and nuts ($Crops3$), oil seed crops ($Crops4$), root and tuber $Crops5$, beverage and species ($Crops6$), leguminous crops ($Crops7$), sugar crops ($Crops8$) and non-food crops ($Crops9$). The proportion of the crop types are displayed in Supplementary Materials (Figure 5). We merge three categories (Crops3, Crops7 and Crops8) due to the low number of frequencies and we create a new dummy category denoted as $Miscellaneous$ (Crops3, Crops7, Crops8).

The specification of the production function is measured by three dummy variables where TL denotes the translog, CD represents the cobb-douglas function (CD) and *Other* stands for other functional forms (served as the reference category). Prior to performing the weighted least square meta-regression model, we verify graphically and numerically whether a publication bias is apparent in the crop farming studies used in the meta-analysis.

3 Publication bias

There is a large degree of consent that the presence of biases in systematic reviews might influence the precision and accuracy of the treatment effects. The fact that studies reporting relatively larger effect sizes are more likely to be published in academic journals than those reporting smaller effects and therefore have higher odds to end up in meta-analysis is widely known as publication bias. Identifying the existence of the publication bias is crucial to draw accurate conclusions from systematic reviews (Hang et al., 2017, Lin and Chu, 2018, Sutton et al., 2000).

Funnel plots are helpful graphical tools to spot an unbiased sample. A symmetric-inverted funnel plot indicates that the deviations of the mean technical efficiency decline with increasing precision in their estimates. Figure 3 displays the relationship between the study size and the technical efficiency estimates to identify the presence and magnitude of publication bias in the studies included in the meta analysis.

$$- - - \Big[\text{Figure 3 here}\Big] - - -$$

According to Sterne and Egger (2001), we use the standard error (rather than sample size or variance) on the vertical axis and log odds ratio on the horizontal axis. Detecting asymmetries in funnel plot may indicate publication bias in the studies included in the meta analysis. The precision in the estimation of the technical efficiency will be more accurate as the size of the relevant crop farming studies increases. The results from small studies will therefore scatter more widely while larger studies spread narrower around zero (i.e center).

Panel 3a and 3b point to the absence of publication bias. This result can be confirmed by regression tests for funnel plot asymmetries in meta analysis. The Egger test performs a linear regression of the technical efficiency estimates on their standard errors. We can not reject the null hypothesis that small studies have an effect in the meta-analysis ($p_{\text{value}} = 0.155$ and $p_{\text{value}} = 0.178$, respectively for both complete case and multiple imputation). We can conclude from the graphical and numerical assessment that there is no evidence for a publication bias in the reported estimates.

4 Estimation results

Table 1 presents the estimation results of the weighted least square meta-regression model. We report clustered standard errors at the level of studies (Espey et al., 1997, Thiam et al., 2001). Column (Ia and IIc) and (Ib and IId) present the estimates for the complete case analysis and imputed dataset, respectively. Most of the parameters of Model I and II are significant at 5% level.[7]

$$- - - \Big[\text{Table 1 here}\Big] - - -$$

Our empirical results manifest studies using extension measures as determinants in the technical inefficiency function significantly achieve lower levels of inefficiency in crop farming than those who do not. This result holds across all model specification and corroborates

[7]Computing bootstrap standard errors to provide a consistent inference in small sample using 10.000 iterations does not affect our results.

our hypothesis. Although, the effect of studies considering extension services is relatively small ranging from 2.8% to 4% lower technical inefficiency estimates compared to others, our empirical results demonstrate a positive relationship between farm extension activities and technical efficiency. This finding supports the argument that farmers could increase agricultural output from the contact of extension agents through a better use of available resources given the state of technology. Gains in output deduced from improvement in productivity are crucial to food security in many developing countries where resources are scanty and the opportunity of technology adoption is meager. In line with the literature, our finding suggests that extension services do not only accelerate the information dissemination process, but actually enhance farmers' managerial ability resulting in higher productivity (Alston et al., 2000; Asres et al., 2014; Birkhaeuser et al., 1991; Evenson, 1997; Feder et al., 1999; Umali-Deininger, 1997). The effectiveness of extension work may depend on farmer's access to information, education, larger farm holdings and better access to markets. Since information-intensive technologies require an increase demand in information diffusion systems, illiterate farmers located in regions with inadequate physical infrastructures face difficulties in adopting new agricultural technologies (Anderson and Feder, 2004; Asres et al., 2014).

Significant and negative effect is found for different crop types. Studies for vegetables and melons (Crops3), and beverage and species crops (Crops6), non-food crops (Crops9) produce lower estimates than those for cereals production across three or all model specifications. This finding indicates substantial disparities in the technical efficiency among distinct crop types. The group of cereals has the largest technical efficiency and represents the most dominant cultivation across the world. The low degree of diversification and the poor technical efficiency of other crops can have substantial consequences on farmers' livelihood. The efficiency in the use of resources might lead to reduced system diversity and thus endanger resilience. Higher degree of crop diversification would enhance the resilience, albeit farmers would end up with lower levels of productivity due to poor technical efficiency of other crops. This trade-off between efficiency in the use of resources and land-use diversity might indirectly influence farmers' cropping decision and consequently farm performance. Contrary to the findings of Thiam et al. (2001) and Bravo-Ureta et al. (2007), our empirical results reveal that studies in low income, middle income and high income countries achieve higher technical efficiency estimates than low middle income countries.

Diverging from Thiam et al. (2001), the positive sign and the significant effect for the number of observations (in log) indicates that studies with larger sample size produce lower technical efficiency estimates. The effect of the functional form on farm performance displays mixed results across all estimated models (the reference category for this group of dummies is other functional form). While the translog specification is only significant in the model with complete case analysis (Ia and IIc), and the Cobb-Douglas is significant in the model with imputed data (Ib and IId). Our findings converges with Ahmad and Bravo-Ureta (1996), Bravo-Ureta et al. (2007), Resti (2000) and Thiam et al. (2001) who found that studies using cobb-douglas function yield higher technical efficiency estimates compared to those applying other functional forms.

Inconsistent with the findings of Battese and Coelli (1995) and Thiam et al. (2001), the parameter of cross sectional data (Type) and the coefficient for data envelopment analysis (DEA) are not statistically significant.

5 Summary and conclusion

The empirically literature on the effect of extension activities on farm productivity, agricultural growth and technical efficiency is fragmented and suffers from methodological flaws in identifying the direct causal relationship. We apply a meta-regression analysis by using a sample of 196 observations from 96 farm level studies to evaluate the technical efficiency and review the link between extension services and the level of productivity in crop farming. The numerical and graphical assessment reveal no presence of publication bias of the studies included in the meta analysis. We show that extension activities have a significant and positive effect on technical efficiency. Studies using extension measures as determinant in the inefficiency effect function reduces the technical inefficiency gap. Significant differences were found among crop types suggesting that studies for cereals yield higher level of productivity compared to vegetables and melons, beverage and species, and non-food crops. Accounting for missing observations in our dataset through multiple imputation method confirms our empirical findings. While the methodology proposed in this paper can serve as a basis to review the impact of agricultural extension services on the technical efficiency, it is also flexible enough to be applied to distinct agricultural output measures and production systems.

These results have implications not only for evaluating farm productivity in crop farming, but also for designing effective agricultural extension programs to increase the efficiency in the use of available resources. Agricultural policies can rely on extension services to improve farm productivity by conveying information from local research to farmers. Our findings based on the meta-regression analysis of crop farming studies indicate that extension facilitate a shift to more efficient methods of production and reduces management gaps. Highest marginal returns of public investments in agricultural extension services are most likely to be generated for production systems with low level of technical efficiency in early stages. While the highest level of productivity was obtained by cereals production, it also represents the most prevalent group of crops occupying more than half of the world's cultivated surface. However, there is a trade-off between the efficiency in the use of resources and degree of crop diversification. On the one hand, cereals production yield high level of productivity but generates reduced land diversity which makes farmers more vulnerable to climate change, natural hazards, pests and diseases, on the other hand, higher degree of crops diversification enhance the resilience but might lead to higher level of technical inefficiency. Investing in extension services may help to overcome this problem by training farmers managerial ability to increase the technical efficiency in cultivating distinct crops. Policies aiming to enhance resilience by intensifying crop diversity may use extension services to foster the productivity of other crops.

The effectiveness of agricultural extension services can be limited by institutional factors and constraints at the supply side over which extension management has simply no leverage. Regions with high literacy rates, low level of education, poor physical infrastructure and unfavorable market conditions face greater difficulties in benefiting of extension services and adopting new technologies. Further research is needed to design and provide extension services to farmers in less favourable environments around the world.

Table 1: Weighted Least Square Meta-Regression

	Inverse Standard Errors				Inverse Range			
	Complete Case (Ia)		Imputation (Ib)		Complete Case (IIc)		Imputation (IId)	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Constant (α_1)	0.879**	0.024	0.825**	0.019	0.898**	0.037	0.852**	0.026
Extension Services (β_1)	-0.030**	0.008	-0.041**	0.006	-0.028*	0.012	-0.040*	0.010
Vegetables and Melon (Crops2)	-0.073**	0.012	-0.065**	0.010	-0.080**	0.016	-0.070**	0.014
Oil Seed (Crops4)	-0.042	0.031	0.017	0.013	-0.025	0.071	0.023	0.034
Root/Tuber (Crops5)	-0.076	0.030*	-0.070	0.029	-0.066	0.062	-0.060	0.058
Beverage and Species (Crops6)	-0.113*	0.013	-0.080*	0.013	-0.118*	0.022	-0.082	0.027
Non-Food (Crops9)	-0.130**	0.022	-0.129**	0.016	-0.135**	0.030	-0.135**	0.022
Miscellaneous (Crops3, Crops7, Crops8)	-0.033**	0.017	-0.040	0.015	-0.037	0.032	-0.043	0.041
Low Income Economy (LIE)	0.083**	0.016	0.094**	0.015	0.084**	0.022	0.096**	0.020
Middle Income Economy (MIE)	0.037**	0.008	0.035**	0.007	0.044**	0.012	0.041**	0.009
Upper Middle Income Economy (UMIE)	0.004	0.015	-0.011	0.009	0.000	0.017	-0.014	0.012
High Income Economy (HIE)	0.021	0.022	0.083**	0.009	0.031	0.025	0.087**	0.012
Data Envelopment Analysis (DEA)	-0.026	0.016	-0.011	0.009	-0.022	0.037	-0.016	0.020
Cross-Sectional Data (Type)	0.009	0.009	0.012	0.007	0.086	0.011	0.012	0.010
Number of Observations in Log (Obs)	-0.019**	0.004	-0.014**	0.003	-0.023**	0.006	-0.018**	0.004
Cobb-Douglas Function (CD)	-0.003	0.008	0.025*	0.007	0.001	0.012	0.022*	0.010
Trans-Log Function (TL)	-0.027**	0.009	-0.004	0.008	-0.022*	0.013	-0.009	0.011
Observations	152		193		152		193	
Weighted R^2	0.175		0.184		0.154		0.173	
AIC	149.63		228.48		141.91		217.75	
BIC	95.21		169.75		87.47		159.029	

[a] Note. **p<0.05; ***p<0.01*

[b] *Cluster robust standard errors are given in parentheses*

[c] *Reference category for country classification = Lower-Middle Income Economy (LMIE)*

[d] *Reference category for crop classification = Cereals (Crop1)*

[e] *Reference category for specification of production function = Other Functional Form (Other)*

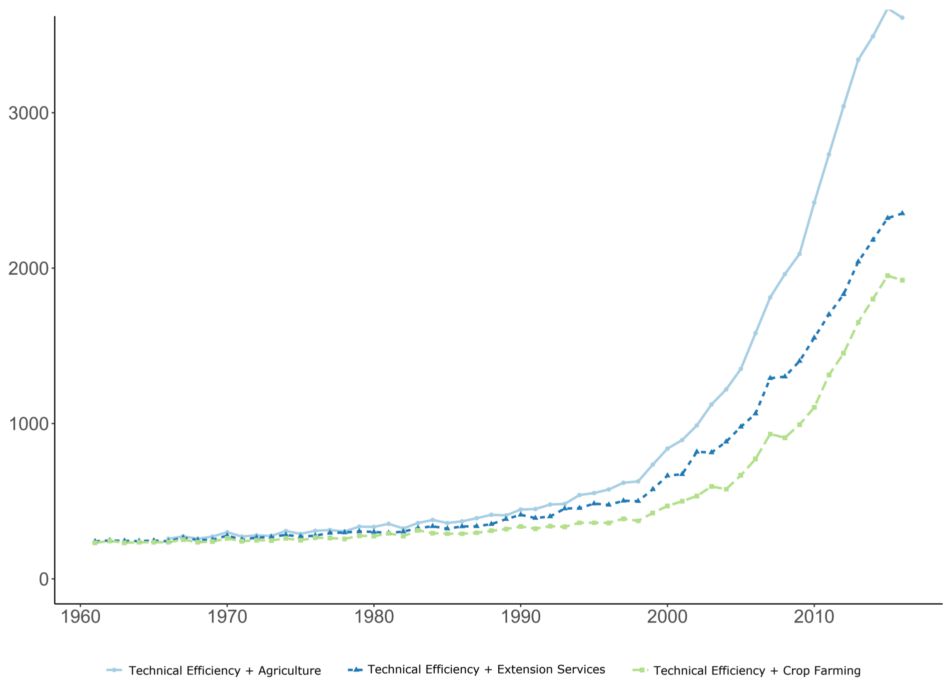
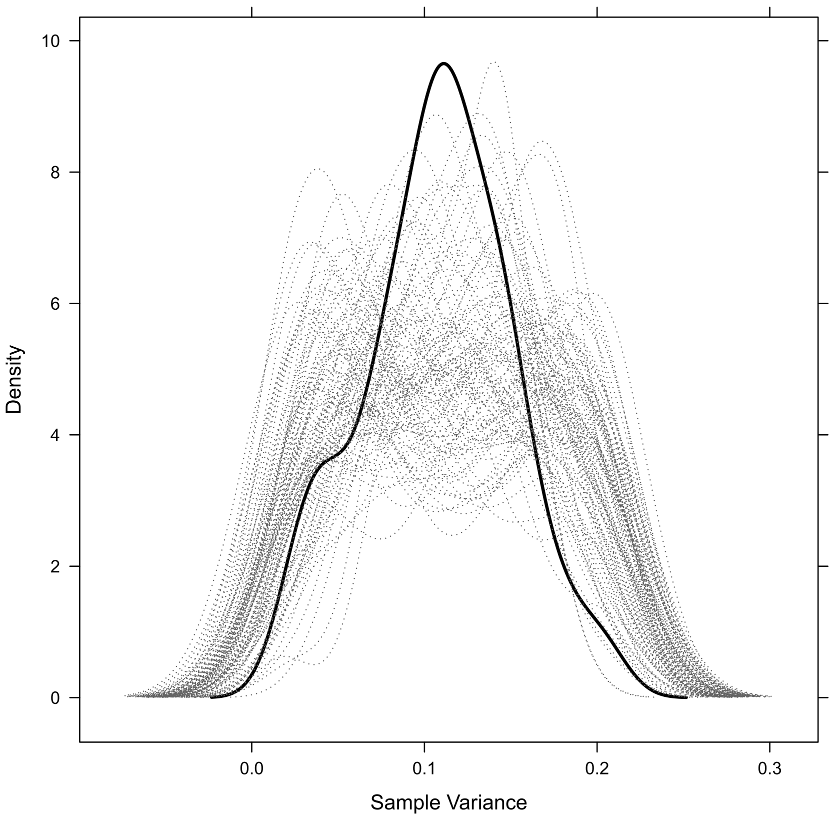
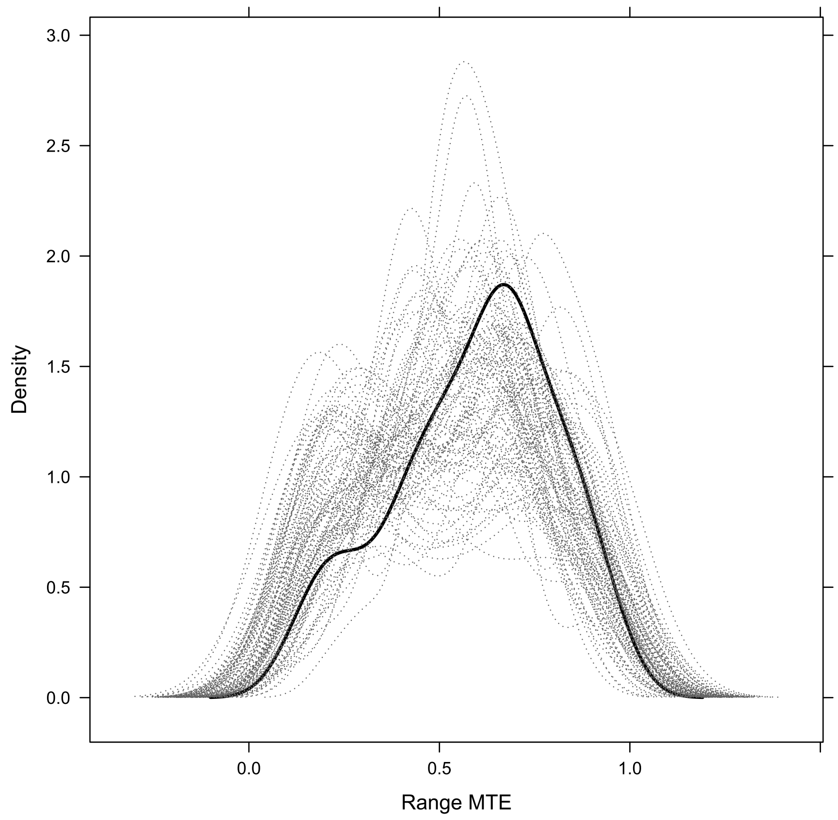


Figure 1: Search Hits in Google Scholar Articles



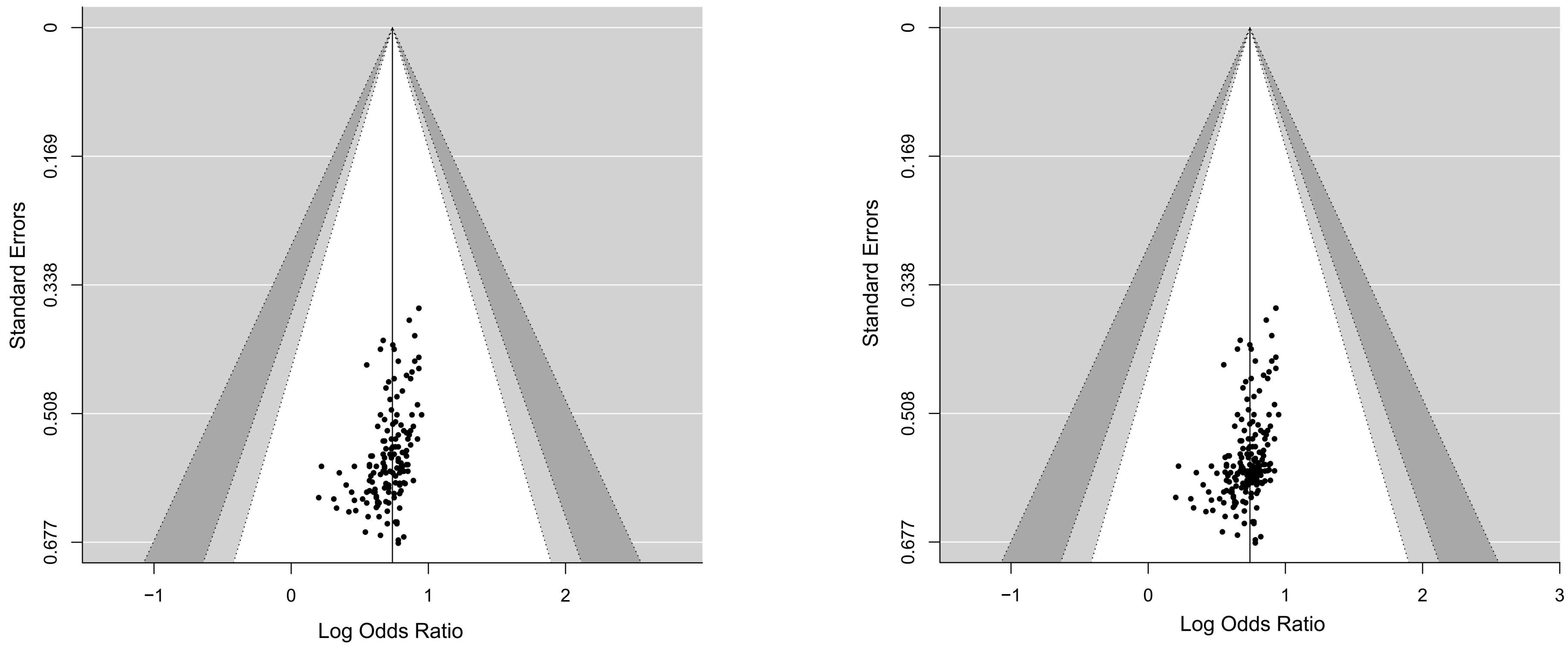
(a) Variance



(b) Range

Figure 2: Distribution of Original and Imputed Values using Predictive Mean Matching

Note. Dotted and dashed line denote the original and imputed distribution, respectively



(a) Complete Case

(b) Multiple Imputation

Figure 3: Funnel Plot with Confidence Intervals

Note. Dots represents the observed effect sizes. The solid vertical line denotes the overall mean effect of the technical efficiency applying fixed effects weighted regression. From inside to outside, the dashed lines limit the 90%, 95%, and 99% confidence intervals.

References

Adzawla, W., J. Fuseini, and S. A. Donkoh (2013): "Estimating technical efficiency of cotton production in Yendi Municipality, Northern Ghana," *Journal of Agriculture and Sustainability*, 4, 58–65.

Ahmad, M. and B. E. Bravo-Ureta (1996): "Technical efficiency measures for dairy farms using panel data: A comparison of alternative model specifications," *Journal of Productivity Analysis*, 7, 399–415.

Ahmad, M., G. M. Chaudhry, M. Iqbal, and D. A. Khan (2002): "Wheat productivity, efficiency, and sustainability: A stochastic production frontier analysis," *The Pakistan Development Review*, 41, 643–663.

Ajao, A. O., L. T. Ogunniyi, and A. A. Adepoju (2012): "Economic efficiency of soybean production in Ogo-Oluwa local government area of Oyo state, Nigeria," *American Journal of Experimental Agriculture*, 2, 667–679.

Alam, M. J., G. Van Huylenbroeck, J. Buysse, I. A. Begum, and S. Rahman (2011): "Technical efficiency changes at the farm-level: A panel data analysis of rice farms in Bangladesh," *African Journal of Business Management*, 5, 5559–5566.

Alemdar, T. and M. N. Oren (2006): "Determinants of technical efficiency of wheat farming in Southeastern Anatolia, Turkey: A nonparametric technical efficiency analysis," *Applied Sciences*, 6, 827–830.

Alene, A. D. and R. M. Hassan (2003): "Measuring the impact of Ethiopia's new extension program on the productive efficiency of farmers," in *Proceedings of the 25th International Conference of Agricultural Economists (IAAE)*, vol. 16, 22.

Alston, J. M., C. Chan-Kang, M. C. Marra, P. G. Pardey, and T. J. Wyatt (2000): *A meta-analysis of rates of return to agricultural R&D: Ex pede Herculem?*, vol. 113, Intl Food Policy Res Inst.

Anderson, J. R. and G. Feder (2004): "Agricultural extension: Good intentions and hard realities," *The World Bank Research Observer*, 19, 41–60.

Asante, B. O., M. K. Osei, A. A. Dankyi, J. N. Berchie, M. B. Mochiah, J. N. L. Lamptey, J. Haleegoah, K. Osei, and G. Bolfrey-Arku (2013): "Producer characteristics and determinants of technical efficiency of tomato based production systems in Ghana," *Journal of Development and Agricultural Economics*, 5, 92–103.

Asres, E., I. Akira, Y. Kumi, and A. Arega (2014): "The effect of agricultural extension service on the technical efficiency of teff (eragrostistef) producers in Ethiopia," *American Journal of Applied Sciences*, 11, 223–239.

Baten, A., A. A. Kamil, and M. A. Haque (2010): "Productive efficiency of tea industry: A stochastic frontier approach," *African Journal of Biotechnology*, 9, 3808–3816.

Battese, G. E. and T. J. Coelli (1992): "Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India," *Journal of Productivity Analysis*, 3, 153–169.

——— (1995): "A model for technical inefficiency effects in a stochastic frontier production function for panel data," *Empirical Economics*, 20, 325–332.

Battese, G. E., S. J. Malik, and M. A. Gill (1996): "An investigation of technical inefficiencies of production of wheat farmers in four districts of Pakistan," *Journal of Agricultural Economics*, 47, 37–49.

Binam, J. N., J. Tonye, G. Nyambi, M. Akoa, et al. (2004): "Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon," *Food policy*, 29, 531–545.

Birkhaeuser, D., R. E. Evenson, and G. Feder (1991): "The economic impact of agricultural extension: A review," *Economic Development and Cultural Change*, 39, 607–650.

Bozoğlu, M. and V. Ceyhan (2007): "Measuring the technical efficiency and exploring the inefficiency determinants of vegetable farms in Samsun province, Turkey," *Agricultural Systems*, 94, 649–656.

Bravo-Ureta, B. E. and R. E. Evenson (1994): "Efficiency in agricultural production: The case of peasant farmers in eastern Paraguay," *Agricultural Economics*, 10, 27–37.

Bravo-Ureta, B. E., D. Solís, V. H. M. López, J. F. Maripani, A. Thiam, and T. Rivas (2007): "Technical efficiency in farming: A meta-regression analysis," *Journal of Productivity Analysis*, 27, 57–72.

Burgess, S., I. R. White, M. Resche-Rigon, and A. M. Wood (2013): "Combining multiple imputation and meta-analysis with individual participant data," *Statistics in medicine*, 32, 4499–4514.

Card, D. and A. B. Krueger (1995): "Time-series minimum-wage studies: A meta-analysis," *American Economic Review*, 85, 238–243.

Cerdán-Infantes, P., A. Maffioli, and D. Ubfal (2008): "The impact of agricultural extension services: The case of grape production in Argentina," Tech. rep.

Chakraborty, K., S. Misra, and P. Johnson (2002): "Cotton farmers' technical efficiency: Stochastic and nonstochastic production function approaches," *Agricultural and Resource Economics Review*, 31, 211–220.

Chepng'etich, E., E. K. Bett, S. O. Nyamwaro, and K. Kizito (2014): "Analysis of technical efficiency of sorghum production in lower Eastern Kenya: A data envelopment analysis approach," *Journal of Economics and Sustainable Development*, 5, 58–65.

Chowdhry, A. K., R. H. Dworkin, and M. P. McDermott (2016): "Meta-analysis with missing study-level sample variance data," *Statistics in medicine*, 35, 3021–3032.

Dalhuisen, J. M., R. J. G. M. Florax, H. L. F. De Groot, and P. Nijkamp (2003): "Price and income elasticities of residential water demand: A meta-analysis," *Land Economics*, 79, 292–308.

Dhungana, B. R., P. L. Nuthall, and G. V. Nartea (2004): "Measuring the economic inefficiency of Nepalese rice farms using data envelopment analysis," *Australian Journal of Agricultural and Resource Economics*, 48, 347–369.

Dinar, A., G. Karagiannis, and V. Tzouvelekas (2007): "Evaluating the impact of agricultural extension on farms' performance in Crete: A nonneutral stochastic frontier approach," *Agricultural Economics*, 36, 135–146.

Dlamini, S. I., M. B. Masuku, and J. I. Rugambisa (2012): "Technical efficiency of maize production in Swaziland: A stochastic frontier approach," *African Journal of Agricultural Research*, 7, 5628–5636.

Ebers, A., T. T. Nguyen, and U. Grote (2016): "Production efficiency of rice farms in Thailand and Cambodia: a comparative analysis of Ubon Ratchathani and Stung Treng provinces," *Paddy and Water Environment*, 1–14.

Espey, M., J. Espey, and W. D. Shaw (1997): "Price elasticity of residential demand for water: A meta-analysis," *Water Resources Research*, 33, 1369–1374.

Evenson, R. (1997): "The economic contributions of agricultural extension to agricultural and rural development. Improving agricultural extension: a reference manual." Tech. rep., FAO, Roma (Italia).

FAO (2012): *Statistical Yearbook 2011: World Food and Agriculture*, Food and Agriculture Organziation of the United Nations, Rome, Italy.

——— (2015): *World Tea Production and Trade. Current and Future Development*, Food and Agriculture Organziation of the United Nations.

Farrell, M. J. (1957): "The measurement of productive efficiency," *Journal of the Royal Statistical Society*, 120, 253–290.

Feder, G., A. Willett, and W. Zijp (1999): *Agricultural extension: Generic challenges and some ingredients for solutions*, The World Bank.

Fleming, E., T. Coelli, et al. (2004): "Assessing the performance of a nucleus estate and smallholder scheme for oil palm production in West Sumatra: A stochastic frontier analysis," *Agricultural Systems*, 79, 17–30.

Galbraith, S., J. A. Daniel, and B. Vissel (2010): "A study of clustered data and approaches to its analysis," *Journal of Neuroscience*, 30, 10601–10608.

Gebrehiwot, K. G. (2017): "The impact of agricultural extension on farmers' technical efficiencies in Ethiopia: A stochastic production frontier approach," *South African Journal of Economic and Management Sciences*, 20, 1–8.

Giannakas, K., R. Schoney, V. Tzouvelekas, et al. (2001): "Technical efficiency, technological change and output growth of wheat farms in Saskatchewan," *Canadian Journal of Agricultural Economics*, 49, 135–152.

Guesmi, B., T. Serra, Z. Kallas, and J. M. G. Roig (2012): "The productive efficiency of organic farming: The case of grape sector in Catalonia," *Spanish Journal of Agricultural Research*, 10, 552–566.

Gul, M., B. Koc, E. Dagistan, M. G. Akpinar, O. Parlakay, et al. (2009): "Determination of technical efficiency in cotton growing farms in Turkey: A case study of Cukurova region," *African journal of Agricultural Research*, 4, 944–949.

Gurevitch, J., J. Koricheva, S. Nakagawa, and G. Stewart (2018): "Meta-analysis and the science of research synthesis," *Nature*, 555, 175.

Hadri, K., C. Guermat, and J. Whittaker (2003a): "Estimating farm efficiency in the presence of double heteroscedasticity using panel data," *Journal of Applied Economics*, 6, 255–268.

——— (2003b): "Estimation of technical inefficiency effects using panel data and doubly heteroscedastic stochastic production frontiers," *Empirical Economics*, 28, 203–222.

Hang, M., J. Geyer-Klingeberg, A. W. Rathgeber, and S. Stöckl (2017): "Measurement matters: A meta-study of the determinants of corporate capital structure," *The Quarterly Review of Economics and Finance*.

Hashmi, M. S., M. A. Kamran, K. Bakhsh, and M. A. Bashir (2015): "Technical efficiency and its determinants in wheat production: Evidence from the Southern Punjab, Pakistan," *Journal of Environmental and Agricultural Sciences*, 3, 48–55.

Heriqbaldi, U., R. Purwono, T. Haryanto, and M. R. Primanthi (2014): "An analysis of technical efficiency of rice production in Indonesia," *Asian Social Science*, 11, 91–102.

Higgins, J. P., I. R. White, and A. M. Wood (2008): "Imputation methods for missing outcome data in meta-analysis of clinical trials," *Clinical Trials*, 5, 225–239.

Ho, T. Q., J. F. Yanagida, and P. Illukpitiya (2014): "Factors affecting technical efficiency of smallholder coffee farming in the Krong Ana Watershed, Vietnam," *Asian Journal of Agricultural Extension, Economics and Sociology*, 3, 37–49.

Hozo, S. P., B. Djulbegovic, and I. Hozo (2005): "Estimating the mean and variance from the median, range, and the size of a sample," *BMC Medical Research Methodology*, 5, 13.

Huang, Y. and K. P. Kalirajan (1997): "Potential of China's grain production: Evidence from the household data," *Agricultural Economics*, 17, 191–199.

Idiong, I. C. (2007): "Estimation of farm level technical efficiency in smallscale swamp rice production in Cross River State of Nigeria: A stochastic frontier approach," *World Journal of Agricultural Sciences*, 3, 653–658.

Iliyasu, A., Z. A. Mohamed, M. M. Ismail, and A. M. Abdullah (2014): "A meta-analysis of technical efficiency in aquaculture," *Journal of Applied Aquaculture*, 26, 329–339.

Iraizoz, B., M. Rapun, and I. Zabaleta (2003): "Assessing the technical efficiency of horticultural production in Navarra, Spain," *Agricultural Systems*, 78, 387–403.

Jacsó, P. (2005): "Google Scholar: The pros and the cons," *Online Information Review*, 29, 208–214.

——— (2008): "Google scholar revisited," *Online Information Review*, 32, 102–114.

Javed, M. I., S. A. Adil, A. Ali, and M. A. Raza (2010): "Measurement of technical efficiency of rice wheat system in Punjab, Pakistan using DEA technique," *Journal of Agricultural Resources*, 48, 227–238.

Jiang, N. and B. Sharp (2014): "Cost efficiency of dairy farming in New Zealand: A stochastic frontier analysis," *Agricultural and Resource Economics Review*, 43.

——— (2015): "Technical efficiency and technological gap of New Zealand dairy farms: A stochastic meta-frontier model," *Journal of Productivity Analysis*, 44, 39–49.

Kalaitzandonakes, N. G. and E. G. Dunn (1995): "Technical efficiency, managerial ability and farmer education in Guatemalan corn production: A latent variable analysis," *Agricultural and Resource Economics Review*, 24, 36–46.

Kalirajan, K. P. (1991): "The importance of efficient use in the adoption of technology: A micro panel data analysis," *Journal of Productivity Analysis*, 2, 113–126.

Kalirajan, K. P. and R. T. Shand (2001): "Technology and farm performance: Paths of productive efficiencies over time," *Agricultural Economics*, 24, 297–306.

Karagiannis, G. and V. Tzouvelekas (2001): "Self-Dual stochastic production frontiers, and decomposition of output growth: The case of the olive growing farms in Greece," *Agricultural and Resource Economics Review*, 30, 168–178.

Karani-Gichimu, C., M. Mwangi, and I. Macharia (2013): "Assessment of passion fruit orchard management and farmers' technical efficiency in Central-Eastern and North-Rift Highlands, Kenya," *Journal of Economics and Sustainable Development*, 4, 183–190.

Khai, H. V. and M. Yabe (2011): "Technical efficiency analysis of rice production in Vietnam," *Journal of ISSAAS*, 17, 135–146.

Khai, H. V., M. Yabe, H. Yokogawa, and G. Sato (2008): "Analysis of productive efficiency of soybean production in the Mekong River Delta of Vietnam," *Journal of the Faculty of Agriculture, Kyushu University*, 53, 271–279.

Khan, H. and F. Ali (2013): "Measurement of productive efficiency of tomato growers in Peshawar, Pakistan," *Agricultural Economics*, 59, 381–388.

Kleinke, K. (2017): "Multiple imputation under violated distributional assumptions: A systematic evaluation of the assumed robustness of predictive mean matching," *Journal of Educational and Behavioral Statistics*, 42, 371–404.

Kumbhakar, S. C. (1994): "Efficiency estimation in a profit maximising model using flexible production function," *Agricultural Economics*, 10, 143–152.

Kwon, O. S. and H. Lee (2004): "Productivity improvement in Korean rice farming: Parametric and non-parametric analysis," *Australian Journal of Agricultural and Resource Economics*, 48, 323–346.

Lampach, N., N. V. Phu, and T.-T. Nguyen (2017): "Robustness Analysis of Organic Technology Adoption: Evidence from Northern Vietnamese Tea Production," .

Leff, B., N. Ramankutty, and J. A. Foley (2004): "Geographic distribution of major crops across the world," *Global Biogeochemical Cycles*, 18.

Lin, L. and H. Chu (2018): "Quantifying publication bias in meta analysis," *Biometrics*, 74, 785–794.

Lindara, L. M. J. K., F. H. Johnsen, and H. M. Gunatilake (2006): "Technical efficiency in the spice based agroforestry sector in Matale District, Sri Lanka," *Agroforestry Systems*, 68, 221–230.

Little, R. J. (1988): "A test of missing completely at random for multivariate data with missing values," *Journal of the American statistical Association*, 83, 1198–1202.

Madau, F. A. (2007): "Technical efficiency in organic and conventional farming: Evidence form Italian cereal farms," *Agricultural Economics Review*, 8, 5–21.

Maredia, M., D. Byerlee, and J. R. Anderson (2000): "Ex post evaluation of economic impacts of agricultural research programs: a tour of good practice," .

Mariano, M. J., R. Villano, and E. Fleming (2011): "Technical efficiency of rice farms in different agroclimatic zones in the Philippines: An application of a stochastic meta frontier model," *Asian Economic Journal*, 25, 245–269.

Mayr, P. and A.-K. Walter (2007): "An exploratory study of Google Scholar," *Online Information Review*, 31, 814–830.

Mignouna, D. B., V. M. Manyong, K. D. S. Mutabazi, E. M. Senkondo, and J. M. Oleke (2012): "Assessing the technical efficiency of maize producers with imazapyrresistent maize for striga control in Western Kenya," *Journal of Development and Agricultural Economics*, 4, 245–251.

Moreira, V. H. and B. E. Bravo-Ureta (2010): "Technical efficiency and metatechnology ratios for dairy farms in three southern cone countries: A stochastic meta-frontier model," *Journal of Productivity Analysis*, 33, 33–45.

Moreira, V. H., J. L. Troncoso, and B. E. Bravo-Ureta (2011): "Technical efficiency for a sample of Chilean wine grape producers: A stochastic production frontier analysis," *Ciencia e Investigacion Agraria*, 38, 321–9.

Narala, A. and Y. C. Zala (2010): "Technical efficiency of rice farms under irrigated conditions in Central Gujarat," *Agricultural Economics Research Review*, 23, 375–381.

Nguyen, T. T., V.-N. Hoang, and B. Seo (2012): "Cost and environmental efficiency of rice farms in South Korea," *Agricultural Economics*, 43, 369–378.

Nguyen-Van, P. and N. To-The (2016): "Technical efficiency and agricultural policy: Evidence from the tea production in Vietnam," *Review of Agricultural, Food and Environmental Studies*, 97, 173–184.

Nonthakot, P., R. Villano, et al. (2009): "Impact of labour migration on farm efficiency: A study of maize farming in northern Thailand," *Asia-Pacific Journal of Rural Development*, 19, 1–16.

Nyagaka, D. O., G. A. Obare, J. M. Omiti, and W. Nguyo (2010): "Technical efficiency in resource use: Evidence from smallholder Irish potato farmers in Nyandarua North district, Kenya," *African Journal of Agricultural Research*, 5, 1179–1186.

Ofori-Bah, A. and J. Asafu-Adjaye (2011): "Scope economies and technical efficiency of cocoa agroforesty systems in Ghana," *Ecological Economics*, 70, 1508–1518.

Ogundari, K. and O. O. Akinbogun (2010): "Modeling technical efficiency with production risk: A study of fish farms in Nigeria," *Marine Resource Economics*, 25, 295–308.

Oladeebo, J. O. and A. A. Fajuyigbe (2007): "Technical efficiency of men and women upland rice farmers in Osun State, Nigeria," *Journal of Human Ecology*, 22, 93–100.

Ouedraogo, S. (2015): "Technical and economic efficiency of rice production in the KOU valley (Burkina Faso): Stochastic frontier approach," *Asian Journal of Agriculture and Rural Development*, 5, 53–63.

Owens, T., J. Hoddinott, and B. Kinsey (2003): "The impact of agricultural extension on farm production in resettlement areas of Zimbabwe," *Economic Development and Cultural Change*, 51, 337–357.

Padilla-Fernandez, M. D., P. L. Nuthall, et al. (2009): "Technical efficiency in the production of sugarcane in Central Negros area, Philippines: An application of data envelopment analysis," *Journal of International Society for Southeast Asian Agricultural Sciences(Philippines)*, 15, 77–90.

Paul, C., R. Nehring, D. Banker, and A. Somwaru (2004): "Scale economies and efficiency in US agriculture: are traditional farms history?" *Journal of Productivity Analysis*, 22, 185–205.

Poungchompu, S. and S. Chantanop (2015): "Factor affecting technical efficiency of smallholder rubber farming in Northeast Thailand," *American Journal of Agricultural and Biological Sciences*, 10, 83–90.

Purcell, D. L. and J. R. Anderson (1997): *Agricultural extension and research: Achievements and problems in national systems*, The World Bank.

Rajendran, S. (2014): "Technical efficiency of fruit and vegetable producers in Tamil

Nadu, India: A stochastic frontier approach," *Asian Journal of Agriculture and Development*, 11, 77–92.

Raphael, I. O. (2008): "Technical efficiency of cassava farmers in South Eastern Nigeria: Stochastic frontier approach," *Agricultural Journal*, 3, 152–156.

Resti, A. (2000): "Efficiency measurement for multi-product industries: A comparison of classic and recent techniques based on simulated data," *European Journal of Operational Research*, 121, 559–578.

Rubin, D. B. (1976): "Inference and missing data," *Biometrika*, 63, 581–592.

Seyoum, E. T., G. E. Battese, and E. M. Fleming (1998): "Technical efficiency and productivity of maize producers in eastern Ethiopia: A study of farmers within and outside the Sasakawa-Global 2000 project," *Agricultural Economics*, 19, 341–348.

Shafiq, M. and T. Rehman (2000): "The extent of resource use inefficiencies in cotton production in Pakistan's Punjab: An application of data envelopment analysis," *Agricultural Economics*, 22, 321–330.

Sherlund, S. M., C. B. Barrett, and A. A. Adesina (2002): "Smallholder technical efficiency controlling for environmental production conditions," *Journal of Development Economics*, 69, 85–101.

Si, W. and X. Wang (2011): "Productivity growth, technical efficiency, and technical change in China's soybean production," *African Journal of Agricultural Research*, 6, 5606–5613.

Singbo, A. G., A. O. Lansink, and G. Emvalomatis (2014): "Estimating farmers' productive and marketing inefficiency: An application to vegetable producers in Benin," *Journal of Productivity Analysis*, 42, 157–169.

Son, T. V. H., T. Coelli, and E. Fleming (1993): "Analysis of the technical efficiency of state rubber farms in Vietnam," *Agricultural Economics*, 9, 183–201.

Squires, D. and S. Tabor (1991): "Technical efficiency and future production gains in Indonesian agriculture," *The Developing Economies*, 29, 258–270.

Stanley, T., H. Doucouliagos, M. Giles, J. H. Heckemeyer, R. J. Johnston, P. Laroche, J. P. Nelson, M. Paldam, J. Poot, G. Pugh, R. S. Rosenberger, and K. Rost (2013): "META-ANALYSIS OF ECONOMICS RESEARCH REPORTING GUIDELINES," *Journal of Economic Surveys*, 27, 390–394.

Sterne, J. A. and M. Egger (2001): "Funnel plots for detecting bias in meta-analysis: guidelines on choice of axis," *Journal of Clinical Epidemiology*, 54, 1046–1055.

Sutton, A. J., S. Duval, R. Tweedie, K. R. Abrams, and D. R. Jones (2000): "Empirical assessment of effect of publication bias on meta analyses," *British Medical Journal*, 320, 1574–1577.

Syed Asif Ali, N. and A. Muhammad (2013): "Technical efficiency analysis of hybrid maize production using translog model case study in Chiniot district, Pakistan," *Agricultural Sciences*, 4, 536–540.

Tadesse, B. and S. Krishnamoorthy (1997): "Technical efficiency in paddy farms of Tamil Nadu: An analysis based on farm size and ecological zone," *Agricultural Economics*, 16, 185–192.

Taraka, K., I. A. Latif, M. N. Shamsudin, and S. bin Ahmad Sidique (2012): "Estimation of technical efficiency for rice farms in Central Thailand using stochastic frontier approach," *Asian Journal of Agriculture and Development*, 9, 1–11.

Taru, V. B., H. Lawal, and I. Tizhe (2011): "Technical efficiency of sole cowpea production in Adamawa State, Nigeria: A Cobb-Douglas stochastic frontier function," *Journal of Economics and International Finance*, 3, 504–507.

Theriault, V. and R. Serra (2014): "Institutional environment and technical efficiency: A Stochastic frontier analysis of cotton producers in West Africa," *Journal of Agricultural Economics*, 65, 383–405.

Thiam, A., B. E. Bravo-Ureta, and T. E. Rivas (2001): "Technical efficiency in developing country agriculture: A meta-analysis," *Agricultural Economics*, 25, 235–243.

Trewin, R., L. Weiguo, S. Erwidodo, and S. Bahri (1995): "Analysis of the technical efficiency over time of west Javanese rice farms," *Australian Journal of Agricultural Economics*, 39, 143–163.

Tzouvelekas, V., C. J. Pantzios, and C. Fotopoulos (2001): "Economic efficiency in organic farming: Evidence from cotton farms in Viotia, Greece," *Journal of Agricultural and Applied Economics*, 33, 35–48.

Umali-Deininger, D. (1997): "Public and private agricultural extension: Partners or rivals?" *The World Bank Research Observer*, 12, 203–224.

Villano, R., B. Bravo-Ureta, D. Solís, and E. Fleming (2015): "Modern rice technologies and productivity in the Philippines: Disentangling technology from managerial gaps," *Journal of Agricultural Economics*, 66, 129–154.

Wadud, A. and B. White (2000): "Farm household efficiency in Bangladesh: A comparison of stochastic frontier and DEA methods," *Applied Economics*, 32, 1665–1673.

Wadud, M. et al. (2003): "Technical, allocative, and economic efficiency of farms in Bangladesh: A stochastic frontier and DEA approach," *Journal of Developing Areas*, 37, 109–126.

Wilson, C. and C. Tisdell (2001): "Why farmers continue to use pesticides despite environmental, health and sustainability costs," *Ecological Economics*, 39, 449–462.

Wollni, M. and B. Brümmer (2012): "Productive efficiency of specialty and conventional coffee farmers in Costa Rica: Accounting for technological heterogeneity and self-selection," *Food Policy*, 37, 67–76.

World Bank (2016): "New country classification," available at: http://data.worldbank.org/news/new-country-classifications-2015 assessed on 20 April 2018.

Wossink, A. and Z. S. Denaux (2006): "Environmental and cost efficiency of pesticide use in transgenic and conventional cotton production," *Agricultural Systems*, 90, 312–328.

Wu, S., S. Devadoss, and Y. Lu (2003): "Estimation and decomposition of technical efficiency for sugarbeet farms," *Applied Economics*, 35, 471–484.

Xu, X. and S. R. Jeffrey (1998): "Efficiency and technical progress in traditional and modern agriculture: Evidence from rice production in China," *Agricultural Economics*, 18, 157–165.

Yao, R. T. and G. E. Shively (2007): "Technical change and productive efficiency: Irrigated rice in the Philippines," *Asian Economic Journal*, 21, 155–168.

Supplementary Materials

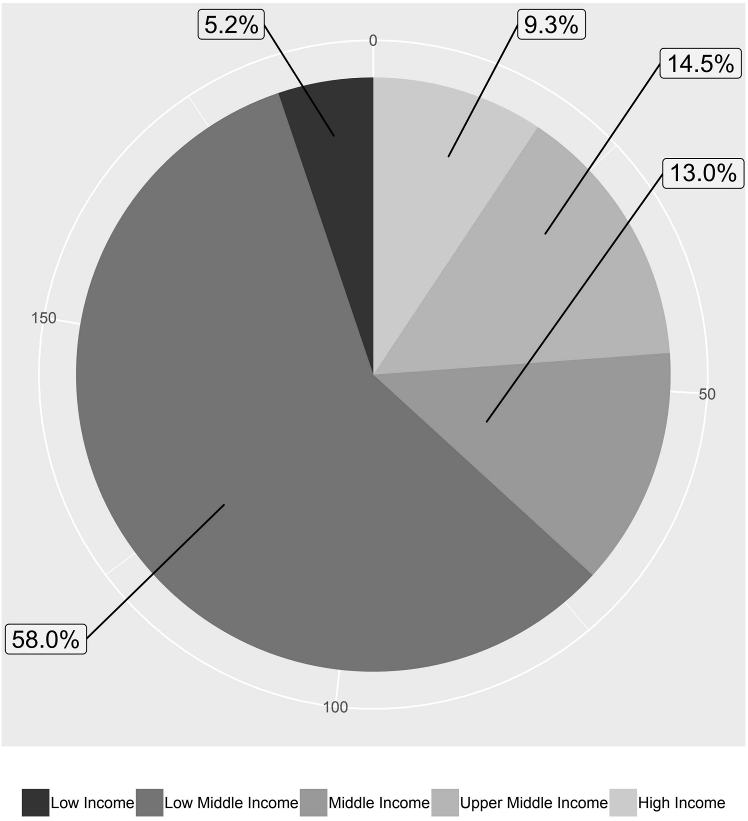


Figure 4: Proportion of Country Classification by Income

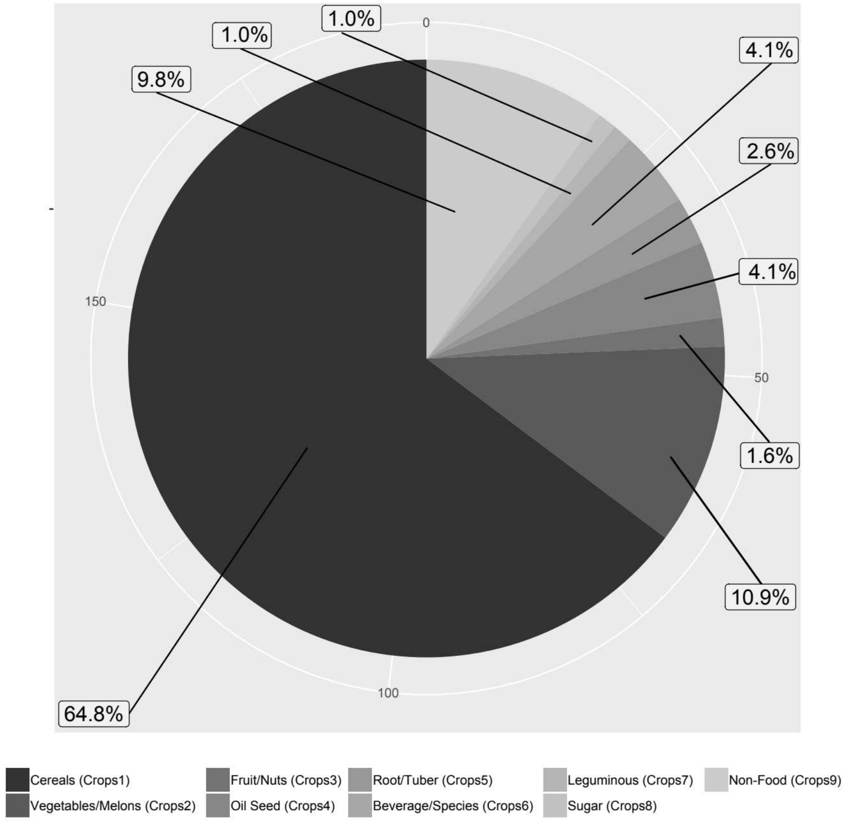


Figure 5: Proportion of Crop Types

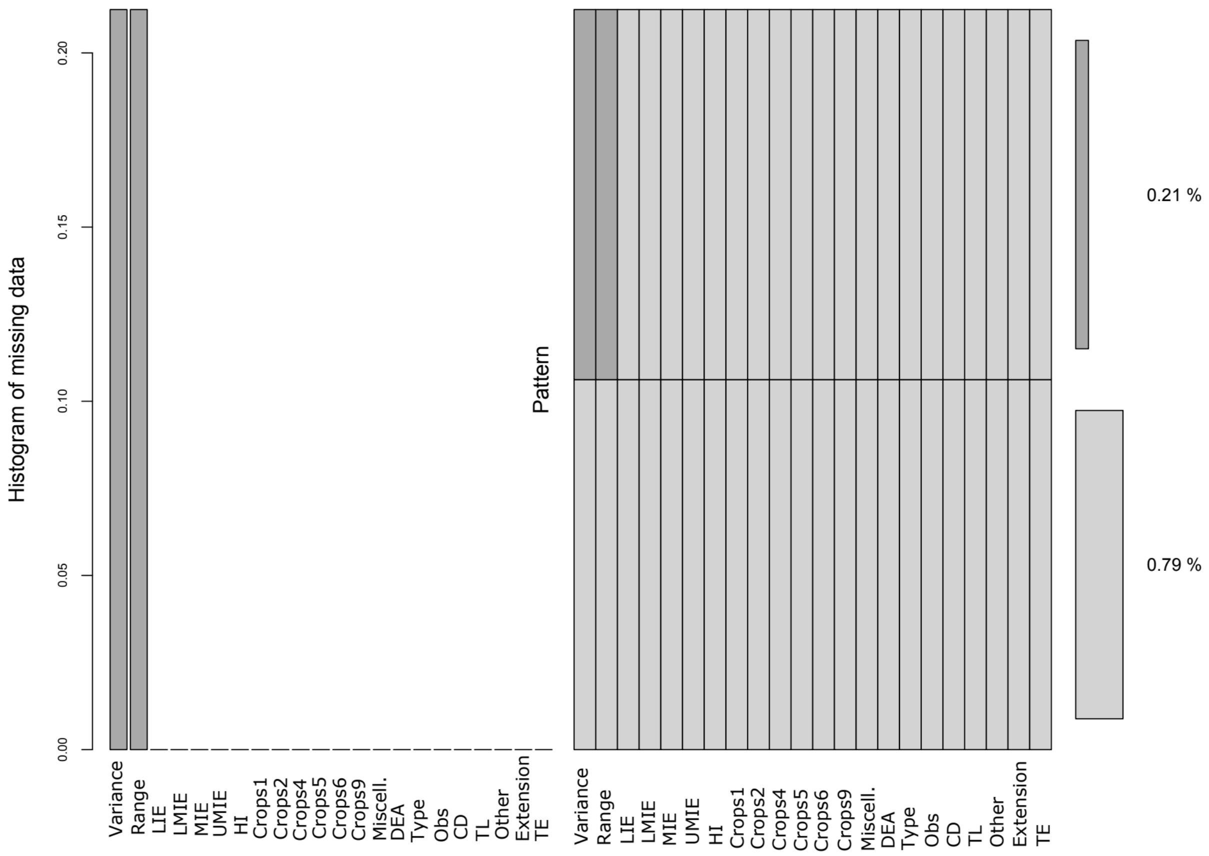


Figure 6: Missing Observations in the Meta Analysis

.1 Summary of Studies

Table A1: Definition of variables SPF

Authors	Years	Rank	Country	Production	Obs.	Mean TE
Adzawla et al. (2013)	2013	0	Ghana	Cotton	91	.88
Ahmad et al. (2002)	2002	0	Pakistan	Wheat	2368	.32
Alam et al. (2011)	2011	0	Bangladesh	Rice	219	.60
Asante et al. (2013)	2013	0	Ghana	Tomato	126	.85
Battese and Coelli (1992)	1992	1	India	Paddy	129	.82
Battese and Coelli (1992)	1992	1	India	Paddy	129	.94
Battese and Coelli (1995)	1995	1	India	Paddy	125	.80
Battese et al. (1996)	1996	1	Pakistan	Wheat	130	.79
Battese et al. (1996)	1996	1	Pakistan	Wheat	43	.59
Battese et al. (1996)	1996	1	Pakistan	Wheat	42	.57
Battese et al. (1996)	1996	1	Pakistan	Wheat	35	.77
Baten et al. (2010)	2010	0	Bangladesh	Tea	105	.59
Binam et al. (2004)	2004	1	Cameroon	Groundnut	150	.77
Binam et al. (2004)	2004	1	Cameroon	Maize	150	.73
Bozoğlu and Ceyhan (2007)	2007	0	Turkey	Vegetable	42	.81
Bozoğlu and Ceyhan (2007)	2007	0	Turkey	Vegetable	33	.80
Bravo-Ureta and Evenson (1994)	1994	1	Paraguay	Cotton	87	.58
Bravo-Ureta and Evenson (1994)	1994	1	Paraguay	Cassava	101	.58
Chakraborty et al. (2002)	2002	1	USA	Cotton	54	.80
Dlamini et al. (2012)	2012	0	Swaziland	Maize	127	.80
Ebers et al. (2016)	2016	0	Thailand	Rice	623	.72
Ebers et al. (2016)	2016	0	Cambodia	Rice	407	.64
Fleming et al. (2004)	2003	0	West Sumatra	Palm	70	.66
Giannakas et al. (2001)	2001	1	Canada	Wheat	800	.76
Guesmi et al. (2012)	2012	0	Spain	Grape	115	.64
Guesmi et al. (2012)	2012	0	Spain	Grape	26	.79
Hadri et al. (2003b)	2003	1	England	Cereal	606	.88
Hadri et al. (2003a)	2003	0	England	Cereal	606	.83
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	186	.82
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	274	.81
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	217	.86
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	238	.82
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	230	.69
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	345	.78
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	337	.81
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	339	.80

Table A2: Definition of variables SPF (continued)

Authors	Years	Rank	Country	Production	Obs.	Mean TE
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	216	.75
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	133	.79
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	185	.85
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	152	.32
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	199	.77
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	128	.88
Heriqbaldi et al. (2014)	2014	0	Indonesia	Rice	257	.82
Ho et al. (2014)	2014	0	Vietnam	Coffee	103	.74
Ho et al. (2014)	2014	0	Vietnam	Coffee	95	.68
Huang and Kalirajan (1997)	1997	1	China	Rice	1061	.68
Huang and Kalirajan (1997)	1997	1	China	Rice	770	.77
Huang and Kalirajan (1997)	1997	1	China	Rice	314	.73
Idiong (2007)	2007	0	Nigeria	Wheat	112	.77
Iraizoz et al. (2003)	2003	0	Spain	Asparagus	46	.80
Iraizoz et al. (2003)	2003	0	Spain	Tomato	46	.89
Karagiannis and Tzouvelekas (2001)	2001	1	Greece	Olive	110	.78
Kalirajan (1991)	1991	1	India	Rice	150	.69
Kalirajan and Shand (2001)	2001	1	India	Paddy	250	.75
Kalirajan and Shand (2001)	2001	1	India	Paddy	250	.66
Khai and Yabe (2011)	2011	1	Vietnam	Rice	4216	.81
Khai et al. (2008)	2008	1	Vietnam	Soybean	113	.73
Karani-Gichimu et al. (2013)	2013	0	Kenya	Fruit	22	.47
Karani-Gichimu et al. (2013)	2013	0	Kenya	Fruit	53	.65
Karani-Gichimu et al. (2013)	2013	0	Kenya	Fruit	48	.57
Khan and Ali (2013)	2013	0	Pakistan	Tomato	300	.66
Kumbhakar (1994)	1994	1	India	Paddy	227	.75
Kumbhakar (1994)	1994	1	India	Paddy	227	.75
Kumbhakar (1994)	1994	1	India	Paddy	227	.76
Kalaitzandonakes and Dunn (1995)	1995	1	Guatemalan	Maize	82	.74
Kwon and Lee (2004)	2004	1	Korean	Rice	148	.81
Kwon and Lee (2004)	2004	1	Korean	Rice	105	.65
Kwon and Lee (2004)	2004	1	Korean	Rice	120	.74
Kwon and Lee (2004)	2004	1	Korean	Rice	156	.80
Kwon and Lee (2004)	2004	1	Korean	Rice	138	.78
Kwon and Lee (2004)	2004	1	Korean	Rice	118	.70
Kwon and Lee (2004)	2004	1	Korean	Rice	124	.75
Kwon and Lee (2004)	2004	1	Korean	Rice	117	.76
Lindara et al. (2006)	2006	0	Sri Lanka	Spice	127	.84
Madau (2007)	2007	0	Italy	Cereal	93	.90
Madau (2007)	2007	0	Italy	Cereal	138	.78
Mariano et al. (2011)	2011	1	Philippines	Rice	3021	.64

Table A3: Definition of variables SPF (continued)

Authors	Years	Rank	Country	Production	Obs.	Mean TE
Mariano et al. (2011)	2011	1	Philippines	Rice	1285	.62
Mariano et al. (2011)	2011	1	Philippines	Rice	3160	.65
Mariano et al. (2011)	2011	1	Philippines	Rice	3611	.63
Mignouna et al. (2012)	2012	0	Kenya	Maize	573	.70
Moreira et al. (2011)	2011	0	Chile	Grape	38	.77
Moreira et al. (2011)	2011	0	Chile	Grape	38	.78
Moreira et al. (2011)	2011	0	Chile	Grape	38	.77
Moreira et al. (2011)	2011	0	Chile	Grape	38	.78
Narala and Zala (2010)	2010	0	India	Rice	240	.72
Nguyen et al. (2012)	2012	1	South Korea	Rice	480	.77
Nonthakot et al. (2009)	2009	0	Thailand	Maize	153	.86
Nguyen-Van and To-The (2016)	2016	0	Vietnam	Tea	241	.41
Nyagaka et al. (2010)	2010	0	Kenya	Potato	127	.66
Ofori-Bah and Asafu-Adjaye (2011)	2011	1	Ghana	Cocoa	340	.47
Ogundari and Akinbogun (2010)	2010	0	Nigeria	Rice	96	.66
Oladeebo and Fajuyigbe (2007)	2007	0	Nigeria	Rice	100	.89
Oladeebo and Fajuyigbe (2007)	2007	0	Nigeria	Rice	100	.90
Ouedraogo (2015)	2015	0	Burkina Faso	Rice	130	.80
Paul et al. (2004)	2004	1	USA	Soybean	386	.93
Poungchompu and Chantanop (2015)	2015	0	Thailand	Rubber	300	.57
Rajendran (2014)	2014	0	India	Vegetable	80	.56
Rajendran (2014)	2014	0	India	Vegetable	80	.61
Rajendran (2014)	2014	0	India	Banana	80	.63
Raphael (2008)	2008	0	Nigeria	Cassava	160	.77
Seyoum et al. (1998)	1998	1	Ethiopia	Maize	20	.93
Seyoum et al. (1998)	1998	1	Ethiopia	Maize	20	.79
Sherlund et al. (2002)	2002	1	Ivory Coast	Rice	464	.36
Sherlund et al. (2002)	2002	1	Ivory Coast	Rice	464	.76
Si and Wang (2011)	2011	0	China	Soybean	300	.81
Son et al. (1993)	1993	1	Vietnam	Rubber	33	.59
Squires and Tabor (1991)	1991	0	Indonesia	Rice	489	.69
Squires and Tabor (1991)	1991	0	Indonesia	Rice	323	.70
Squires and Tabor (1991)	1991	0	Indonesia	Cassava	161	.58
Squires and Tabor (1991)	1991	0	Indonesia	Peanuts	177	.69
Squires and Tabor (1991)	1991	0	Indonesia	Bean	69	.55
Syed Asif Ali and Muhammad (2013)	2013	0	Pakistan	Maize	120	.94
Tadesse and Krishnamoorthy (1997)	1997	1	India	Paddy	129	.83
Taraka et al. (2012)	2012	0	Thailand	Rice	323	.85
Taru et al. (2011)	2011	0	Nigeria	Cowpea	161	.89
Theriault and Serra (2014)	2014	1	Mali	Cotton	85	.72
Theriault and Serra (2014)	2014	1	Burkina Faso	Cotton	56	.84

Table A4: Definition of variables SPF (continued)

Authors	Years	Rank	Country	Production	Obs.	Mean TE
Theriault and Serra (2014)	2014	1	Benin	Cotton	81	.85
Trewin et al. (1995)	1995	0	Indonesia	Rice	171	.86
Tzouvelekas et al. (2001)	2001	0	Greece	Cotton	58	.71
Tzouvelekas et al. (2001)	2001	0	Greece	Cotton	58	.80
Villano et al. (2015)	2015	1	Philippines	Rice	2678	.68
Villano et al. (2015)	2015	1	Philippines	Rice	772	.70
Villano et al. (2015)	2015	1	Philippines	Rice	1906	.73
Wadud and White (2000)	2000	0	Bangladesh	Rice	150	.79
Wadud et al. (2003)	2003	0	Bangladesh	Rice	129	.86
Wilson and Tisdell (2001)	2001	1	England	Wheat	362	.87
Wollni and Brümmer (2012)	2012	1	Costa Rica	Coffee	258	.60
Wollni and Brümmer (2012)	2012	1	Costa Rica	Coffee	173	.68
Xu and Jeffrey (1998)	1998	1	China	Rice	100	.94
Xu and Jeffrey (1998)	1998	1	China	Rice	100	.91
Xu and Jeffrey (1998)	1998	1	China	Rice	100	.87
Xu and Jeffrey (1998)	1998	1	China	Rice	90	.85
Xu and Jeffrey (1998)	1998	1	China	Rice	90	.78
Xu and Jeffrey (1998)	1998	1	China	Rice	90	.74
Yao and Shively (2007)	2007	1	Philippines	Rice	747	72
Mean					**340**	**.73**

Table A5: Definition of variables DEA

Authors	Years	Rank	Country	Production	Obs.	Mean TE
Ajao et al. (2012)	2012	0	Nigeria	Soybean	80	.94
Alemdar and Oren (2006)	2006	0	Turkey	Wheat	112	.83
Chakraborty et al. (2002)	2002	1	USA	Cotton	23	.79
Chepng'etich et al. (2014)	2014	0	Kenya	Sorghum	71	.48
Chepng'etich et al. (2014)	2014	0	Kenya	Sorghum	72	.43
Dhungana et al. (2004)	2004	1	Nepal	Rice	76	.76
Gul et al. (2009)	2009	0	Turkey	Cotton	79	.79
Hashmi et al. (2015)	2015	0	Pakistan	Wheat	142	.73
Javed et al. (2010)	2010	0	Pakistan	Rice	200	.83
Kalaitzandonakes and Dunn (1995)	1995	1	Guatemalan	Maize	82	.93
Kwon and Lee (2004)	2004	1	Korean	Rice	148	.77
Kwon and Lee (2004)	2004	1	Korean	Rice	105	.64
Kwon and Lee (2004)	2004	1	Korean	Rice	120	.72
Kwon and Lee (2004)	2004	1	Korean	Rice	156	.86
Kwon and Lee (2004)	2004	1	Korean	Rice	138	.72
Kwon and Lee (2004)	2004	1	Korean	Rice	118	.65
Kwon and Lee (2004)	2004	1	Korean	Rice	124	.74
Kwon and Lee (2004)	2004	1	Korean	Rice	117	.73
Padilla-Fernandez et al. (2009)	2009	0	Philippines	Sugarcane	127	.74
Paul et al. (2004)	2004	1	USA	Maize	386	.89
Shafiq and Rehman (2000)	2000	1	Pakistan	Cotton	120	.60
Sherlund et al. (2002)	2002	1	Ivory Coast	Rice	464	.56
Sherlund et al. (2002)	2002	1	Ivory Coast	Rice	464	.90
Singbo et al. (2014)	2014	1	Benin	Vegetable	186	.13
Wadud and White (2000)	2000	1	Bangladesh	Rice	150	.79
Wadud et al. (2003)	2003	0	Bangladesh	Rice	150	.80
Wossink and Denaux (2006)	2006	0	USA	Cotton	49	.21
Wossink and Denaux (2006)	2006	0	USA	Cotton	79	.34
Wossink and Denaux (2006)	2006	0	USA	Cotton	74	.23
Wu et al. (2003)	2003	1	USA	Sugar beet	147	.88
Mean					**145**	**.68**