

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search http://ageconsearch.umn.edu aesearch@umn.edu

Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.





Agrekon Agricultural Economics Research, Policy and Practice in Southern Africa

ISSN: 0303-1853 (Print) 2078-0400 (Online) Journal homepage: www.tandfonline.com/journals/ragr20

The Impact of Adoption of Recommended Tea Plucking Interval on Tea Yields in Kenya

Vincent Ngeno

To cite this article: Vincent Ngeno (2017) The Impact of Adoption of Recommended Tea Plucking Interval on Tea Yields in Kenya, Agrekon, 56:3, 290-295, DOI: 10.1080/03031853.2017.1335221

To link to this article: https://doi.org/10.1080/03031853.2017.1335221

4	1	(1
Е			
Е			
С			

Published online: 16 Jun 2017.



Submit your article to this journal 🗗





View related articles



View Crossmark data 🗹

	Citing articles: 1 View citing articles	
--	---	--



Check for updates

The Impact of Adoption of Recommended Tea Plucking Interval on Tea Yields in Kenya

Vincent Ngeno

Department of Agricultural Economics and Resource Management, Moi University, Eldoret 30100, Kenya

ABSTRACT

This study employs the endogenous switching regression model to examine the impact of the adoption of recommended tea plucking interval on tea yields among small-scale tea farmers in main tea-growing regions of Kenya. The study utilises cross-sectional farm household level data collected from a randomly selected sample of 413 households. Results support the notion that self-selection occurs and that estimates that do not consider selection-bias would be biased. Different determinants are found to be significant in explaining the tea yields for adopters and non-adopters. Thus, policy makers should consider these differing effects when designing development projects to increase tea yields.

KEYWORDS

Impact evaluation; endogenous switching regression; tea production; recommended tea plucking interval

1. INTRODUCTION

Kenya is the third largest producer of tea in the world. More than 90% of Kenyan tea is exported, making tea a top foreign exchange earner in Kenya (FAOSTAT, 2015; TBK, 2015). Around 65% of tea plantations are managed by small-scale producers spread throughout the tea growing region. The smallholder sector is managed by the Kenya Tea Development Agency (KTDA). The remaining 35% are large-scale farms owned by the large-scale companies. The large-scale producers are grouped around the Kenya Tea Growers Association (KTGA) (TBK, 2015).

Tea production in the smallholder sub-sector has been persistently low when compared with large-scale sub-sector. Lower yields remains a serious problem for farm households, since it often leads to severe income and food shortages and welfare losses. Low yields have therefore remained a major concern for policy makers, with several attempts made to address the problem through the promotion of Good Agricultural Practices (GAPs).

The adoption of GAPs that increase agricultural productivity remains crucial to achieving the goals of food security and poverty alleviation. Hence, understanding the determinants of technology adoption rates has clear implications for agricultural policy design (Lewis *et al.*, 2011). The Government, KTDA and international organisations have invested in developing and disseminating GAPs aimed at enhancing tea productivity. One such practice is the plucking interval; recommended plucking interval is 7–10 days. The Tea Research Institute (TRI) results from plucking frequency experiments show that short plucking rounds produce more leaf, which makes higher quality tea than long rounds, when standard plucking of two leaves and a bud is maintained. In order to maximise yield, the frequency of harvesting is necessary (Wijeratne, 2003).

Despite the efforts put in by the KTDA through extension agents using Farmer Field Schools (FFS) and rainforest alliance to encourage the adoption of this practice, the adoption rate is quite low. The low adoption rate probably indicates that while the practice is generally effective in improving yields,

constraints such as capital, labour and other factors may serve as barriers to adoption. This paper identifies the factors that affect farmers' decisions to adopt the recommended plucking interval and how this practice impacts on tea yields.

2. Data

The data employed in this study come from a recent household survey conducted in Bomet and Kericho county in Kericho Highlands; a main tea-growing region where a high proportion of Kenyan tea is produced. The survey sample in the two counties included small-scale tea farmers, a fact that is common in Kenya's tea-growing regions. A multistage sampling procedure with purposive selection of villages and random selection of households was employed to select 431 farmers for the survey. The two counties in which the survey was conducted were chosen to ensure representation of adopters and non-adopters of the GAP, as well as different landholdings and household types. The sample therefore adequately represents farm types found in the region. Information from the farmers was gathered through interviews. Enumerators who speak both the local language and English were hired to conduct the interviews. Farmers were asked to provide detailed information on specific farm activities. Additional information was obtained from the KTDA. The data covered information on production system, input use, costs, socioeconomic characteristics of farmers, as well as plot-level characteristics.

3. Empirical Model Specification

Following the work of (Abdulai & Huffman, 2000) farmers normally take into account outcomes such as potential yields when making decisions on the adoption on new practices. Thus, the practices employed by the farmers need to be taken into account when analysing outcomes such as yields. Failure to do so may result in selection bias. The bias arises because farmers who would obtain lower than average net returns from the new practice, given prices and fixed factors, choose not to adopt and as such truncate the observed technology profit distribution (Pitt, 1983). In particular, selection bias occurs if unobservable factors influence both error terms in the practice choice equation (ε) and the outcome equation (u), thus resulting in correlation of the error terms of outcome and choice equations, with corr(ε , u) = ρ .

As noted by Suri (2011), knowledge of unobservable factors can allow for targeted policy interventions to alleviate their constraints and as such enables them to adopt new practices to improve yields. When such unobservable factors are not measured by the researcher, then there would be a correlation between the regressors and the error term resulting in $\rho \neq 0$. In such cases, standard regression techniques such as ordinary least squares would yield biased results.

Given our interest in examining the determinants of adoption, as well as the impact of adoption, the endogenous switching regression model is employed to account for selection bias in estimation of the impact of adoption on farm yields. In the switching regression approach, the farmers are partitioned according to their classification as adopters and non-adopters in order to capture the differential responses of the two groups.

Given that farmers choose to either adopt the practice or not to adopt it, the observed net benefits take the following values:

Regime 0 (Non - adopters):
$$Y_{jN} = X'\beta_{jN} + u_{jN}$$
 if $D_j = 0$.
Regime 0 (Adopters): $Y_{jA} = X'\beta_{jA} + u_{jA}$ if $D_j = 1$. (1)

where Y_{jA} and Y_{jN} are the outcome variable for the adopters and non-adopters, respectively, X' is a vector of variable factor prices, fixed factors and farm-level and household characteristics. The vector $\boldsymbol{\beta}$ in (1) is the associated parameter to be estimated.

292 👄 V. NGENO

Self-selection into adopters or non-adopters categories may lead to nonzero covariance between the error terms and the outcome variable between the error terms and the outcome equation. The error terms ε , u_{A} , u_{N} are assumed to have trivariate normal distribution with mean vector zero and the following covariance matrix:

$$\operatorname{cov}(u_{A}, u_{N}, \varepsilon) = \sum = \begin{bmatrix} \sigma_{A}^{2} & \sigma_{AN} & \sigma_{A\varepsilon} \\ \sigma_{AN} & \sigma_{N}^{2} & \sigma_{N\varepsilon} \\ \sigma_{A\varepsilon} & \sigma_{N\varepsilon} & \sigma_{\varepsilon}^{2} \end{bmatrix}$$
(2)

Where $\operatorname{var}(u_A) = \sigma_{A,}^2$, $\operatorname{var}(u_N) = \sigma_{N,}^2$, $\operatorname{var}(\varepsilon) = \sigma_{\varepsilon}^2$, $\operatorname{cov}(u_A, u_N) = \sigma_{AN}$, $\operatorname{cov}(u_A, \varepsilon) = \sigma_{A\varepsilon}$, and $\operatorname{cov}(u_N, \varepsilon) = \sigma_{N\varepsilon}$. For this reason, the error terms in (1), conditional on the sample selection criterion, have nonzero expected values, and ordinary least squares estimates coefficient β_A and β_N suffer from sample selection bias (Lee, 1982).

According to Johnson and Kotz (1970), the expected values of the truncated error terms ($u_A | D = 1$) and ($u_N | D = 0$) are then given as

$$E(u_N|D=0) = E(u_N|\varepsilon \le -Z'\gamma) = \sigma_{N\varepsilon} \frac{-\phi(Z'\gamma/\sigma)}{1 - \varphi(Z'\gamma/\sigma)} \equiv \sigma_{N\varepsilon}\lambda_N$$
(3)

And

$$E(u_{A}|D=1) = E(u_{A}|\varepsilon > -Z'\gamma) = \sigma_{A\varepsilon} \frac{\phi(Z'\gamma/\sigma)}{\varphi(Z'\gamma/\sigma)} \equiv \sigma_{A\varepsilon}\lambda_{A},$$
(4)

where ϕ and φ are the probability density and cumulative distribution function of the standard normal distribution, respectively. The ratio of ϕ and φ evaluated at $Z'\gamma$ is referred to as the inverse mills ratio, λ_A , λ_N (selectivity terms). The selectivity terms are incorporated into equation (1) to account for selection bias.

The model is estimated using the full information maximum likelihood method suggested by Lokshin and Sajaia (2004). It simultaneous estimates the adoption and outcome equations. Of particular interest are the signs and significance levels of the correlation coefficients (ρ) from the estimates. As indicated previously, these are the correlations of the error terms of the outcome and choice equations (corr(ε , u) = ρ). specifically, there is endogenous switching, if either $\rho_{A\varepsilon}(\sigma_{A\varepsilon}/\sigma_{A}\sigma_{\varepsilon})$ or $\rho_{N\varepsilon}(\sigma_{N\varepsilon}/\sigma_{A}\sigma_{\varepsilon})$ is significantly different from zero, which would result in selection bias. If $\rho > 0$, this would imply negative selection bias, indicating that farmers with below average yields are more likely to adopt the technology. On the other hand, $\rho < 0$ implies positive selection bias, suggesting that farmers with above average yields are more likely to adopt the technology.

4. Empirical Results

Results for the selection equation (technology adoption equation) are shown in the first column of Table 1, interpreted as normal probit coefficients. It important to note that the aim of the selection equation is not to perfectly explain adoption, but to account for unobserved heterogeneity that could bias the yield impacts derived from the outcome equations (Kabunga *et al.*, 2012). For proper identification, the selection equation needs to include one or more valid instruments. Group membership was used as the instrument. Group membership is uncorrelated with yield and on the other hand it is highly significant in the selection equation, so the instrument is valid. Pearson correlation analysis also reveals that the group membership is significantly correlated with the adoption of recommended plucking interval, but uncorrelated with yield variable. This finding confirms the validity of the group membership as an instrument.

The selectivity term is found to be significant and negative for adopters. This finding indicates selfselection occurred in the adoption of the recommended plucking cycle. Hence, adoption of the recommended plucking cycle may not have the same effect on the non-adopters, if they would adopt, as

	Technology adoption equation		Tea yields			
Variable			Adopters		Non-adopters	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z–value
Constant	0.662***	3.10	0.019***	4.14	0.399**	2.13
Education	0.053***	3.17	0.136***	5.10	5.34***	4.11
Age	0.384	0.33	0.608	0.54	0.092	0.89
Access to credit	0.333**	1.97	0.222**	2.26	0.082***	5.44
Illness	-0.299**	-2.18	-0.711***	-3.03	-0.333**	-2.03
Gender	0.264	1.23	0.215	1.11	0.003	0.19
Loam soil	0.151*	1.69	0.068***	4.56	0.078***	7.02
Slope	-0.501***	-6.09	-0.088**	-2.18	-0.329***	-3.12
Land holding	0.008	0.34	0.021	1.39	-0.002	-1.09
Non-farm	0.478***	3.13	0.217***	3.16	0.161	0.45
Livestock holding	-0.584	-1.27	0.12	0.47	-0.013	-0.40
Extension	0.006	0.59	0.027**	2.57	0.011	0.54
Road distance	0.037	0.23	-0.006	-0.05	-0.021	-1.54
Memberships	0.019***	4.26				
Selectivity term			-0.391**	-0.278	0.354	0.289
Number of observatio	ns 431					
Log pseudo-Likeliho	od –817.4567					
Likelihood ratio test	for independent e	quations 29.56***				

Table 1. Endogenous switching regression results for impact of adoption on tea yields

Notes: ****, **, and * denotes statically significance at the 1%, 5% and 10% level, respectively. Z-values are estimated based on robust standard errors.

it has on adopters. Covariance estimates for non-adopters, that are not significantly different from zero, imply that prior to adoption there were no significant differences in the average behaviour of the two groups due to unobserved factors (Fuglie & Bosch, 1995). The significance of the selectivity term in this analysis suggests that sample selection bias would result if the outcome equations were estimated without considering the adoption decision. The signs of covariance between the disturbance term of the selection equation and the outcome equation reveal whether observations are positively or negatively selected into adoption (Winship & Mare, 1992).

The education variable is positive and statistically significant in both specifications, suggesting that more-educated farmers are more likely to adopt the recommended tea plucking interval. This implies that good knowledge and firm understanding of recommended tea plucking interval may increase the benefits of tea production in terms of yields. This finding is consistent with the notion that education is important in helping farmers in their decisions on adopting good agricultural practices.

Access to credit tends to have a positive effect on yields for non-adopting farmers, though it is not significant for adopters. This suggests that adopters may be less financially constrained such that credits may be simply displaced by another source of financing such as savings. The positive and significant relationships between access to credit and yield is consistent with the work of Abdulai and Huffman (2000) and Abdulai and Binder (2006). The number of days spent sick by family members and not working tends to reduce yields, suggesting that illness distracts farmers from adopting the recommended tea plucking interval, probably because it is labour intensive.

Soil characteristics such as texture and slope also tend to influence crop yield. Soil texture generally exerts a positive influence on yields. On the other hand, slope exerts a negative influence, suggesting that fertility losses occurring through erosion processes at steeper slopes are probably not compensated through fertiliser use. In the long run, this might lead to soil degradation and further decrease the yield. Indeed such a trend has already been observed for some regions, where agricultural activities have been carried out for many years (Burpee & Turcios, 1997). The significant influence of soil variables on yields suggest that biases in the estimations of yields are likely to occur, if environmental variables are omitted. This finding is in line with the argument put forward by Sherlund, Barrett, and Adesina (2002). Participation in non-farm activities tends to have a significant and positive effect on productivity for non-adopters, but no impact for adopters. To the extent that non-adopters are more credit constraint compared with adopters, the significant impact on non-adopters may be due to the fact that income accruing from these activities is used to purchase productivity-enhancing inputs like labour and fertiliser to increase yields. Non-farm income helps in easing liquidity constraints needed to invest in plucking-improving inputs.

Contact with extension agents exerts a positive and significant impact on tea yields of adopters of recommended tea plucking interval. Agricultural extension is the system of learning and building the human capital of farmers by giving information and exposing them to farm technologies which can increase agricultural productivity, and, in turn, consumption expenditure and welfare (Asfaw *et al.*, 2012). Farmers who are frequently visited by government and KTDA extension agents tend to be more progressive and experiment with recommended tea plucking interval. A study by Olagunju and Adesiji (2011) indicates that the greater the frequency of farmer's contact with extension workers, the more productive the farmer is. This means that the more advice, information, and knowledge received by a farmer, the greater is his productivity, suggesting that extension has been contributing effectively in terms of advisory service and education of farmers with regard to tea production in Kenya.

5. Conclusions and Implications

This paper evaluates the potential impact of adoption of recommended tea plucking interval on tea yields in Kenya. The study utilises cross-sectional farm household level data collected from a randomly selected sample of 413 household. The causal impact of adoption of recommended tea plucking interval is estimated by utilising endogenous switching regression. Results support the notion that self-selection occurs and estimates that do not consider selection-bias would be biased. Results also suggest adoption decision and tea yields are influenced by different factors. Furthermore, different determinants are found to be significant in explaining the tea yields for adopters and non-adopters.

The findings indicate a positive and significant influence of education on yields; a higher education level appears to contribute to higher yields among adopters, suggesting that learning effects may be an important issue for adopters. This confirms the importance of provision of schools in rural areas. Access to credit tends to have a positive effect on yields, underlying the importance of alleviating financial constraints especially for non-adopting farmers. This suggests that streamlining the acquisitions of credit among farmers may contribute to improving productivity.

The negative impact of poor health on yields underscores the importance of efforts by policy makers and non-governmental organisations to improve sanitation and health conditions in the rural areas via the provision of primary health care facilities such as clinics, and in some places hospitals. The analysis reveals that participation in non-farm work can contribute to higher household incomes and poverty reduction in rural areas. The findings are consistent with the evidence reported by Kousar and Abdulai (2014) and Abdulai and Huffman (2014). Improving the access of rural households to non-farm opportunities can have significant productivity effects. In particular, in rural areas with imperfect credit markets, where farm households find it difficult to obtain credit, improving non-farm work opportunities could provide a substitute for credit as a mechanism to facilitate investment in longer term plucking that improve measures that increase tea productivity.

The causal effect of positive and significant impact of the extension service on yields affirms the potential role of agricultural extension in raising farm productivity among tea farmers. The greater the frequency of farmer contact with extension workers, the more productive the farmer is. These findings confirm those of Birkhaeuser *et al.* (1991) and Evenson (2001). This confirms the greater role of the extension service in raising the tea yields through the provision of adequate and timely advice on improved tea management practices. To boost the effectiveness of extension services, efforts need to be directed at increasing the frequency of extension visits to farmers and more farmers need to be reached.

References

- Abdulai, A. and Binder, C.R. 2006. Slash-and-burn cultivation practice and agricultural input demand and output supply. *Environment and Development Economics* 11: 201–220.
- Abdulai, A. and Huffman, W. 2000. Structural adjustment and economic efficiency of rice farmers in northern Ghana. *Economic Development and Cultural Change* 48: 503–520.
- Abdulai, A. and Huffman, W. 2014. The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics* 90: 26–43.
- Asfaw, S., Shiferaw, B., Simtowe, F. and Lipper, L. 2012. Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food policy* 37: 283–295.
- Birkhaeuser, D., Evenson, R.E. and Feder, G. 1991. The economic impact of agricultural extension: A review. *Economic Development and Cultural Change* 39: 607–650.
- Burpee, C. and Turcios, W. 1997. Indicadores locales de la calidad del suelo: Resultados iniciales de Honduras. Tegucigalpa, Honduras: Centro Internacional de Agricultura Tropical (CIAT).

Evenson, R. E. 2001. Economic impacts of agricultural research and extension. *Handbook of Agricultural Economics* 1:573–628. FAOSTAT. 2015. http://www.fao.org/faostat/.

Fuglie, K. O. and Bosch, D. J. 1995. Economic and environmental implications of soil nitrogen testing: A switchingregression analysis. American Journal of Agricultural Economics 77: 891–900.

Johnson, N. and Kotz, S. 1970. Distribution in statistics, continuous univariate distributions. New York: Wiley.

Kabunga, N. S., Dubois, T. and Qaim, M. 2012. Yield effects of tissue culture bananas in Kenya: accounting for selection bias and the role of complementary inputs. *Journal of Agricultural Economics* 63: 444–464.

Kousar, R. and Abdulai, A. 2014. Impact of non-farm work and land tenancy contracts on soil conservation measures. Paper presented at the 88th Annual Conference, 9–11April 2014, AgroParisTech, Paris, France.

Lee, L.-F. 1982. Some approaches to the correction of selectivity bias. The Review of Economic Studies 49: 355–372.

- Lewis, D. J., Plantinga, A. J., Nelson, E. and Polasky, S. 2011. The efficiency of voluntary incentive policies for preventing biodiversity loss. *Resource and Energy Economics* 33: 192–211.
- Lokshin, M. and Sajaia, Z. 2004. Maximum likelihood estimation of endogenous switching regression models. *Stata Journal* 4: 282–289.
- Olagunju, F. and Adesiji, G. 2011. Impact of agricultural extension services on cocoyam production in Ogun State, Nigeria. Journal of Agricultural & Food Information 12: 294–303.
- Pitt, M. M. 1983. Farm-level fertilizer demand in Java: a meta-production function approach. American Journal of Agricultural Economics 65: 502–508.
- Sherlund, S. M., Barrett, C. B. and Adesina, A. A. 2002. Smallholder technical efficiency controlling for environmental production conditions. *Journal of Development Economics* 69: 85–101.
- Suri, T. 2011. Selection and comparative advantage in technology adoption. Econometrica 79: 159–209.
- TBK. 2015. Crop Production Statistics for 2013. http://www.teaboard.or.ke/statistics/ production.html
- Wijeratne, M. 2003. Harvesting policies of tea (Camellia sinensis L.) for higher productivity and quality. *Tropical Agricultural Research and Extension* 14: 91–97.

Winship, C. and Mare, R. D. 1992. Models for sample selection bias. Annual Review of Sociology 18: 327–350.