Impact of integrated pest management technologies on farm revenues of rural households: The case of smallholder Arabica coffee farmers

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Abstract

Enhancing farmers' incomes through the utilisation of improved agricultural technologies is an important step towards poverty eradication among rural households in developing countries. Using empirical data from small-scale Arabica coffee farmers in Manafwa district in Uganda, this paper assesses the effect of integrated pest management (IPM) on net coffee revenue. The study also estimates the rural income multiplier of IPM adoption. After controlling for endogeneity and selection bias, we found that the multiplier effect of IPM use is positive and significant. The increase in income arising from the use of IPM leads to a more than proportional increase in demand for farm non-tradable and non-farm non-tradable commodities. Hence, coffee farming with IPM has a higher rural income multiplier than conventional coffee farming. These findings provide evidence that the incomes of smallholder coffee farmers and rural community economies can be raised through the use of production technologies that are less environmentally invasive than conventional coffee-growing technologies.

Keywords: multiplier value; net coffee revenue; integrated pest management; Uganda; Africa

1. Introduction

Agriculture had long been neglected by governments and investors in sub-Saharan Africa. Over the past decade, however, efforts to devote renewed attention to agriculture in sub-Saharan Africa have been spearheaded by the New Partnership for Africa's Development (NEPAD) through its Comprehensive Africa Agriculture Development Programme (CAADP). The goals of CAADP include allocating at least 10% of national budgets to agriculture to reduce poverty and hunger and to boost the growth of national economies. Agriculture is the main source of rural purchasing power for both agricultural and non-agricultural commodities in sub-Saharan Africa. However, farmers' incomes have been persistently low due to the use of obsolete technologies, missing markets for agricultural inputs and outputs, pervasive crop diseases, and unfavourable weather. In the World Development Report 2008, the World Bank (2008) recommends refocusing economic policy on the agricultural sector, contending that agricultural development is the fastest and most equitable path to national economic growth in countries with an agrarian base. The report focused on Africa in particular, calling for a productivity revolution in agriculture.

As agriculture is the main source of livelihood for poor inhabitants in the rural areas of sub-Saharan Africa, developing and disseminating improved agricultural technologies must be a central strategy and one that requires urgent attention (Deininger & Okidi, 2001; Otsuka & Kijima, 2010). Some studies, however, argue that, given the available technologies and inefficient marketing systems, characterised by high input prices and low crop yields, it is unprofitable for farmers to use capital-intensive methods (Pender *et al*. 2004; Otsuka & Kalirajan, 2005, 2006). Therefore, unless improvements are made in market systems as well as in the development of more profitable technologies, neither technology adoption nor agricultural output will be increased, resulting in persistently low productivity and unfavourable input prices.

Integrated pest management (IPM) is a type of agricultural technology designed to minimise environmental damage associated with crop yield improvements. IPM makes use of both chemical and biological methods to control insects, plant pathogens, weeds and vertebrates, thereby reducing the frequency and quantity of chemicals needed to keep pest populations to a threshold density (Radcliffe *et al*. 2009). By emphasising optimal crop mixes, plant spacing and human observation of patterns of infestation as a means of controlling pests, IPM reduces the need for chemicals and for the cash to buy them.

To improve farmers' yields and incomes while minimising the environmental disturbance caused by agriculture, USAID launched the Integrated Pest Management Collaborative Research Support Programme (IPM CRSP) in collaboration with the Uganda Coffee Research Centre (COREC), beginning in 2007. The programme adopted a participatory agricultural research (PAR) approach in which scientists and extension providers work with small groups of farmers, engaging them in each step of the research and technology development process, from problem identification to the on-farm testing of improved management practices. The project has a broad focus on integrated pest and crop management. Demonstration trials and training took place on-farm and during field days, when groups viewed and discussed various practices, including improved technologies. Following five years of implementation, an evaluation was launched to assess whether the introduction of IPM technologies increased the incomes of farmers in Manafwa District. Past evaluations of other IPM programmes in Uganda assessed the outcomes in terms of awareness, knowledge and adoption of IPM technologies (Erbaugh *et al*. 2011), but had not examined the impact of IPM-based Arabica coffee production on the livelihoods of farmers and their communities (Alston *et al*. 1995; USAID 2010).

Farmer-level studies of the economic impact of IPM typically estimate economic impacts using estimated partial farm budgets or hypothetical willingness-to-pay surveys, while aggregate impact studies measure economic surplus by ex-ante shifting of supply curves in a demand-supply framework (Swinton & Norton 2009). No published studies to date have examined the relationship between farmer use of IPM in Africa and the resulting community-level income changes. Assessing community-level impacts is important for knowing the potential for IPM to contribute to rural economic growth.

This paper has two main objectives: 1) to assess whether IPM use has an effect on net coffee revenue, and 2) to estimate the rural income multiplier of IPM technologies compared to conventional coffee-growing technologies. Specifically, we examine whether farming with IPM technologies has a higher rural income multiplier than farming without IPM technologies. To achieve the second objective, we estimated how coffee income is re-spent on a mix of tradable and non-tradable agricultural and non-agricultural goods and services in rural Manafwa District. Manafwa is representative of the Arabica coffee-growing areas of Uganda. Some farmers in Manafwa use IPM technologies, while others do not and, therefore, we use an estimation procedure that accounts for farmer self-selection in IPM adoption. IPM in Manafwa entails a combination of crop management practices. These practices include biological methods (e.g. use of natural enemies of pests), cultural practices (e.g. mulching, planting of shade trees, organic manure application), and chemical methods (e.g. use of pesticides applied only after scouting).

Economic growth is generated through an initial exogenous income shock, such as technological change or improved infrastructure, resulting in extra income derived from stimulated indirect regional demand and production in the local non-tradables sector (Mellor 1976; Hendriks & Lyne 2003). When the extra coffee income is spent in local markets and shops, it spurs multiple rounds of spending in local and national economies. Studies reviewed by Haggblade *et al*. (1991) place regional agricultural income multipliers of Green Revolution technologies between 1.3 and 4.3. That is, a one-dollar increase in technologically induced agricultural income generates an additional \$0.30 to \$3.30 across all sectors of a rural region.

Section 2 presents the conceptual and methodological framework of the study. The results and findings are discussed in Section 3. Section 4 summarises and concludes the study findings, highlighting key results and policy implications.

2. Methodology

The study used rural survey data gathered to estimate the direct and indirect rural income of IPM-based coffee production. A multi-stage sampling procedure was used to select farmers from Bupoto and Bumbo sub-counties in Manafwa District for interviewing. A random sample of 21 farmers per sub-county was selected from lists of Participatory Agricultural Research (PAR) participants, and a control group of 21 non-participants per sub-county was selected from lists provided by the District Agricultural Office. The final sample of 84 households consisted of 42 participants and 42 non-participants. The survey instrument was pre-tested and adjusted. Each questionnaire was administered to the farmers in personal interviews. The questionnaire was designed to collect information on income sources, coffee inputs, harvests and sales. Different recall periods were used for foods, non-durable and personal goods, non-food items and services to minimise non-responses, memory errors and misreporting of information. Weekly recall was used for food and non-durable and personal goods, as these items are purchased frequently, while annual recall was used for rarely purchased items. These data were then projected to a period of one year. The survey period was from mid-July to mid-August 2011. Coffee inputs and yields were recorded for the two harvest seasons, namely the main and fly[1] seasons from September 2010 to August 2011.

[1] The fly season refers to a time when the coffee berries that were not ready in the main season are harvested.

2.1 Characterisation of the study area

Manafwa District is bordered by Bududa District to the north, the Republic of Kenya to the east and south, Tororo District to the southwest and Mbale District to the west. The district headquarters at Manafwa are located 26 km by road southeast of Mbale, the largest city in the sub-region. Agriculture is the main activity of the district, just as it is in the rest of the country. The major crops are Arabica coffee, bananas, cotton and maize. The estimated population of the district in 2010 was 153 000 inhabitants, with a density of 339 persons per square kilometre.

2.2 Model specification

2.2.1 Objective One

The first objective was to assess whether farmers who used IPM had higher net coffee revenues than those who did not. This was assessed by using a revenue function (Bolwig *et al*. 2009). If we conceive of this technology as a technological shock that is determined endogenously, it is evident that we face a "treatment effects" problem (Quandt 1972; Rubin 1974; Heckman 1979). The problem can be set up as a system of equations involving an outcome of interest (y) and a selection equation for treatment (t) over observations *i*. Following Maddala (1983), the model can be written in the following general form:

$$y_{1i} = x_i'\beta_1 + u_{1i} \tag{1}$$

$$y_{2i} = x_i'\beta_2 + u_{2i} \tag{2}$$

$$t_i^* = z_i'\beta_1 + v_i, \;\; where\; t_i = \begin{cases} 1\; iff\; t_i^* > 0 \\ 0\; iff\; t_t^* \le 0 \end{cases} \tag{3}$$

where y_{1i} refers to the outcome for treated respondents ($t_i = 1$) and y_{2i} refers to the outcome for a control group ($t_i = 0$); u_{ki} (k = 1, 2) is the error term, and x_i is a vector of explanatory variables. Participation Equation (3) is an indicator function that invokes a latent variable framework in which selection factors (z) capture the propensity to participate in IPM. The observed y_i is defined as:

$$y_i = y_{1i}\; iff\; t_i = 1 \tag{4}$$

$$y_i = y_{2i}\; iff\; t_i = 0 \tag{5}$$

The above equations can be summarised in the following general switching model:

$$y_i = x_i'\beta_2 + t_i x_i'(\beta_1 - \beta_2) + u_{2i} + t_i(u_{1i} - u_{2i}) \tag{6}$$

$$Cov(u_{1i}, u_{0i}, v_i) = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{1v} \\ \sigma_{12} & \sigma_{22} & \sigma_{2v} \\ \sigma_{1v} & \sigma_{2v} & 1 \end{bmatrix} \tag{7}$$

Differences in regimes between those who used IPM and those who did not use IPM refer to the extent to which the treatment had an effect only through the intercept of the joint-outcome equation.

Consequently, in Equation (6) we restrict $\beta_0 = \beta_1 = \beta$, excluding the intercept term and thus giving the familiar reduced form common-coefficient model for outcomes over a single treatment:

$$y_i = x_i'\beta + t_i\alpha + u_{2i} + t_i(u_{1i} - u_{2i}) \tag{8}$$

where α captures the treatment effect given by the difference in intercepts for Equations (1) and (2). If the assumption that the use of IPM is uncorrelated with the error term is not true, the OLS results will be biased and inconsistent, and either Instrumental Variable (IV) or Heckman selection models (Heckman 1979) will be appropriate. The latter are generally more robust for small samples, but they are sensitive to model specification and distributional assumptions (Heckman *et al*. 1999, Blundell & Costa Dias 2000). It therefore is recommended to augment vector z in Equation (3) with variables that do not enter the outcome Equations (1 and 2). Tests for heteroskedasticity and collinearity between the selection and outcome equations are advised to check for deviations from the underlying assumptions required for consistency and robust inference. The above discussion indicates that, unless selection on observables can be guaranteed, a Heckman model would be most appropriate. This is because Heckman selection estimators remain consistent under the assumption of heterogeneous effects. As there was no prior reason to discard the possibility of unobserved selection factors, the hypotheses were investigated via full information maximum likelihood (FIML) estimation of the Heckman model, although an OLS specification was estimated for comparison. A test for sample selection bias was applied to indicate whether the OLS results were biased. The FIML method differs from Heckman's original two-step estimation approach, as the selection and outcome equations are estimated jointly, thereby enhancing asymptotic efficiency and correcting for the high level of correlation in the residual series of both equations (Puhani 2000).

2.2.2 Empirical implementation of model for Objective One

The OLS estimates of IPM treatment effects are based on Equation (8), in which the exogenous regressors affect both the use of IPM and the outcome (net revenue) or IPM usage. The exogenous regressors include logarithmic functions of farm size, number of productive coffee trees, age of head of household, education of head of household, and size of household. The dummy variable for the use of IPM is also a regressor. The dependent variable (y) is the logarithm of net coffee revenue. The selection variable, (z), is an indicator variable that proxies for the orientation of the household toward agriculture. It is constructed by assigning a value of one to households whose largest source of income is agriculture, and zero otherwise. This indicator captures the "deep" structure of household revenue generation. We assumed that this variable would directly influence farmers' adoption of IPM. Households for whom agriculture is the most important source of income would be most likely to attend IPM training sessions, to have time available for labour-intensive observation of pest infestations, and to utilise IPM knowledge.

2.2.3 Objective Two

To estimate the rural income multiplier of IPM technologies, we used an expenditure-system version of the agricultural household model (Hazell & Röell 1983). Household expenditure functions were estimated for various classes of goods (farm and non-farm tradables and non-tradables). The functions measure the consumption effects of money brought into the local economy from outside the region from the sale of Arabica coffee, a tradable export commodity. The sectors that generally export products and services to non-regional purchasers are considered "basic", while sectors that circulate existing monies in the local economy but do not bring a significant portion from outside are considered "non-basic". Growth or decline in basic sectors has important implications, because basic-sector changes ripple across the entire local economy.

Consumption goods and services were categorised into thirteen expenditure groups, and then further aggregated into four groups distinguished by "tradability" (local versus traded goods and services). The expenditure groups are food, household cleaning materials, transportation, entertainment, cloth and footwear, furniture and bedding, kitchen appliances, education, taxes, social obligations, rent, medical care issues, and fuel. The tradability groups are farm tradables, farm non-tradables, non-farm tradables, and non-farm non-tradables.

Tradability was determined on the basis of local boundaries. The local economy was defined as the area within a radius of 30 km of the household. This radius registers most of the commercial activity undertaken by the sampled respondents. Non-tradables were defined as those goods that were freely traded within the local area, but not traded outside of it.

2.2.4 Estimation of expenditure elasticities for tradables and non-tradables

Total household expenditure was calculated as the sum of consumption of farm tradables, farm non-tradables, non-farm tradables and non-farm non-tradables. Coffee was the sole income earner for most of the farmers in this region. Household expenditure was almost equivalent to income from coffee because saving is low among the rural households in Uganda. Household expenditure therefore was used as a proxy for income, as suggested by Alderman (1993), Devereux (1993), and Puetz (1993).

A variant of the Working-Leser model was used to estimate average budget share (ABS), marginal budget share (MBS) and consumption elasticities for each commodity group (Hazell & Röell 1983; Delgado *et al*. 1998). ABS measures the percentage of household expenditures for each group of goods, while MBS measures the impact of a unit change in income on the consumption of a group of goods. The independent variables used in the model include age of household head, household size, education of household head, coffee crop area (in acres), a dummy variable indicating whether or not farmers used IPM, and a term capturing the interaction between use of IPM and expenditure. Data on soil quality was not available.

The version of the Working–Leser model employed in this study allows for non-linear relationships between consumption and expenditure:

$$E_i = \alpha_i + \beta_i E + \gamma_i ElogE + \sum_j \left(u_{ij} Z_i + \lambda_{ij} EZ_j\right) \quad (9)$$

where E is total per capita consumption expenditure, Z_j denotes the j^{th} household characteristic variable, and α_i, β_i, u_{ij} and λ_{ij} are parameters to be estimated. A dummy variable was included to account for the effect of IPM use on yields. Furthermore, the model was estimated in share form to limit heteroskedasticity, as variability in E_i is likely to increase with total expenditure in cross-sectional data. Share equations in relative form were estimated by ordinary least squares:

$$S_i = \beta_i + {}^{\alpha_i}/_{E} + \gamma_i \, logE + \sum_j (u_{ij} Z_i/E + \lambda_{ij} Z_j) \quad (10)$$

where $S_i = E_i/E$ is the share of commodity *i* in total expenditure. MBS, ABS and expenditure elasticities for each category of expenditure were estimated using the following equations proposed by Delgado *et al*. (1998):

$$MBS_i = \delta E_i/\delta E = \beta_i + \gamma_i (1 + logE + \Sigma_j (\lambda_{ij} Z_j) \quad (11)$$

$$ABS_i = S_i \quad (12)$$

$$\zeta_i = MBS_i / ABS_i \quad (13)$$

To calculate the multiplier value, the following equation was used:

$$M = \frac{1}{1-(MBS_{nontradables} (1-s))} \quad (14)$$

where s is the savings rate.[2]

3. Results and discussion

3.1 Social-demographic and socioeconomic characteristics of the respondents

There was a relatively high proportion of men (76%) compared to women (24%), reflecting the fact that coffee is considered predominantly to be a "male crop", since it is cultivated purely for cash. However, women who are widowed or unmarried have recently taken up the cultivation of coffee. There was an almost equal distribution of men to women among the IPM and non-IPM group of farmers. On average, farmers who used IPM technologies were older (52 years) than those who had not used IPM (36 years). The mean age difference was significant at the one percent level. This is in contrast to many studies that have found young people to be more likely to adopt and implement new technologies. Young people, who generally have higher levels of education than their elders, may have other income-generating opportunities. Their opportunity cost of acquiring IPM knowledge and applying it thus may be higher and, consequently, their rates of adoption lower (see Table 1).

On average, farmers who used IPM had more coffee gardens (2.2) than farmers who had not used IPM (1.5). The mean difference was statistically significant at the one percent level. Income levels of IPM farmers were higher (Ushs 4 568 131) than those of non-IPM farmers (Ushs 2 840 036). The mean difference was statistically significant at the five percent level. This could be because IPM farmers have more coffee gardens and because IPM use increases yields, and hence the value of coffee.

[2] Statistics from the Ministry of Finance in Uganda showed the average savings rate of Ugandans to be 6.2% in 2011. This value was used for s in Equation 14.

Table 1: Socio-economic characteristics of IPM and non-IPM participants in Manafwa District

Characteristic	Used IPM technologies (N = 42)	Did not use IPM technologies (N = 42)	T-test for difference in means
	Mean (std. dev.)	Mean (std. dev.)	
Age (years)	51.62 (16.39)	35.90 (10.95)	-5.170***
Education (years)	7.81(4.02)	7.45 (3.09)	-0.4567
Household size	8.31 (3.58)	7.55 (3.56)	-0.98
Number of gardens	2.24 (1.71)	1.52 (0.74)	-2.487***
Incomes (Ushs)[3]	4568131 (5593165)	2840036 (2934126)	-1.7732**
Land (acres)	1.81 (1.23)	1.33 (0.87)	-2.085**
Household has male head	0.76 (0.07)	0.79 (0.06)	0.2608
Are you household head?	0.81 (0.06)	0.83 (0.06)	0.2849

Note: Values in parentheses are standard errors; *, ** and *** indicate significance at the 10%, 5% and 1% levels.

3.2 Empirical results for net coffee revenue

It is important to examine whether IPM usage is endogenous, as farmers who adopt IPM and those who do not may differ fundamentally in their characteristics. The results in Table 2, arising from a binomial probit model, reveal the extent to which the observed levels of the treatment variable can be attributed to regressors measuring structural differences. The results show that farm size, number of productive trees, age of household head, and a dummy variable for whether income is attained primarily from non-agricultural sources, are significant predictors of the use of IPM. This implies that the use of IPM is non-random; hence, there is a need to account for endogenous selection in further analysis. The statistical significance of the exclusion restriction variable (income source) supports the feasibility of using the Heckman selection method.

Table 2: Probit analysis of factors affecting adoption of IPM technology

Independent variables	Beta	Robust SE
Farm size in acres	-0.500*	0.293
Number of trees	0.508**	0.235
Education	0.065	0.048
Household size	-0.018	0.063
Age of head	0.050***	0.013
Income mainly from non-agricultural sources	-0.708**	0.351
Constant	-5.429***	1.561
N		83.000
Log likelihood		-42.354
Chi^2		23.85*
Adjusted R^2		0.264

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels. Standard errors are robust (Huber/White/Sandwich). The sample excludes missing observations

Table 3 presents the results of the OLS and FIML estimators. The OLS results do not adequately explain the variation in net coffee revenue, given the evidence of self-selection in Table 2. Only one variable, namely number of trees, is statistically significant, and the R-squared value of 20% is relatively low. In contrast, the FIML model accounts for self-selection. The chi-squared statistic is significant at the one percent level, the estimated coefficients have the expected signs, and three of the

[3] All costs were measured in local currency, the Uganda shillings; the exchange rate at the time the data were gathered was $1 = Ushs 2 500.

regressors in the outcome equation are statistically significant. Age of household head and use of IPM are significant at the 5% level, and number of trees is significant at the 10% level. The results of the selection equation are similar to those of the binomial probit model.

The endogenous selection term is the adjusted rho statistic, which measures the correlation between the residual errors in the selection and outcome equations. The hypothesis, that the selection and outcome equations are independent, is rejected at the 10% level. It therefore may be concluded that selection bias exists and that the OLS results are likely to be unreliable. Robust standard errors were generated to address heteroskedasticity, which was tested using the Breusch-Pagan test and found to be present and significant at the 10% level. Based on the sign and coefficient of the IPM (treatment) variable, we conclude that use of IPM has a positive and significant effect on the net revenue from coffee. The coefficient of the IPM variable implies that, all else being equal, that net coffee revenues of IPM farmers are 118% higher than the revenues of non-IPM farmers.

Table 3: Regression results for effect of IPM on net coffee revenue

	OLS		FIML	
	Beta	**SE**	**Beta**	**SE**
(i) Outcome equation				
Farm size in acres	0.059	0.271	0.201	0.341
Number of trees	0.627***	0.220	0.459*	0.273
Education	-0.042	0.043	-0.064	0.050
Household size	0.050	0.046	0.057	0.050
Age of head	-0.016	0.011	-0.035**	0.017
Use IPM	-0.083	0.346	1.183**	0.575
Constant	10.533***	1.345	11.871***	1.746
(ii) Selection equation				
Farm size in acres			-0.480**	0.223
Number of trees			0.456**	0.198
Education			0.071	0.048
Household size			-0.002	0.061
Age of head			0.048***	0.012
Income mainly from non-agricultural sources			-0.878***	0.305
Constant			-6.074***	1.248
Rho			-0.571*	0.259
Log_likelihood			-179.351	
F-statistic/Chi^2			22.300***	
Adjusted R^2			20.240	
N			83.000	
Heteroskedasticity test			10.771*	

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

In the selection equation of the FIML system, the coefficient of age of household head variable is positive and significant at the one percent level. This confirms our earlier result that older farmers are the ones most likely to use IPM. On the number of trees per acre, the coefficient was positive and significant at the five percent level.

3.3 Results for ABS, MPS and the rural income multiplier

Table 4 presents the results on average household consumption behaviour, showing differences between IPM and non-IPM farm households. The results were obtained from an estimation of Equations 11 and 12 at sample mean values for total expenditure and all other household variables.

Table 4: Consumption behaviour in Manafwa District

Variable	Whole sample			IPM farmers			Non-IPM farmers		
	ABS	MBS	Elasticity	ABS	MBS	Elasticity	ABS	MBS	Elasticity
Food	0.658	0.662	1.006	0.652	0.671	1.030	0.701	0.684	0.975
Cleaning materials	0.041	0.041	1.001	0.048	0.045	0.949	0.039	0.035	0.905
Transportation	0.150	0.145	0.967	0.129	0.111	0.864	0.139	0.145	1.039
Clothing & footwear	0.022	0.022	0.997	0.024	0.023	0.955	0.023	0.024	1.043
Furniture & bedding	0.014	0.014	0.964	0.020	0.020	1.000	0.006	0.009	1.611
Kitchen appliances	0.002	0.002	0.974	0.002	0.002	1.090	0.001	0.002	1.503
Education	0.035	0.033	0.960	0.044	0.047	1.061	0.026	0.024	0.930
Taxes	0.003	0.003	0.952	0.000	0.000	0.954	0.000	0.003	11.457
Social obligations	0.018	0.018	0.979	0.025	0.026	1.049	0.009	0.011	1.249
Rent	0.000	0.000	0.952	0.000	0.000	0.872	0.000	0.000	-2.173
Medical care issues	0.013	0.013	0.971	0.018	0.017	0.934	0.012	0.010	0.846
Entertainment	0.012	0.017	1.341	0.006	0.006	0.940	0.014	0.024	1.653
Fuel	0.032	0.032	0.986	0.032	0.031	0.968	0.030	0.029	0.996
Farm non-tradables	0.083	0.089	1.071	0.087	0.093	1.069	0.080	0.066	0.831
Farm tradables	0.081	0.085	1.050	0.066	0.069	1.037	0.124	0.095	0.770
Non-farm tradables	0.671	0.663	0.988	0.681	0.686	1.006	0.661	0.697	1.055
Non-farm non-tradables	0.165	0.164	0.990	0.165	0.153	0.924	0.135	0.141	1.043

Source: Authors' estimates from survey data.

The food category was the most important group in the overall budget. Both IPM and non-IPM farm households spent on average more than 65% of their income on food. The budget share revealed that households that used IPM spent 67% of additional income on food, while those who did not use IPM spent 68% of additional income on food. Although the marginal budget shares were quite close, the composition of the incremental food basket was different. Households that used IPM technologies tended to eat three meals per day and spend a greater share of additional income on livestock products, while those that do not use IPM technologies ate one or two meals per day and most of their food budget was spent on crops and crop products. The food consumption elasticity of income was near 1.0 for both the IPM and non-IPM households.

For food and most other goods there were relatively small differences in expenditure patterns between IPM and non-IPM households. However, there were observed differences in expenditure for human and social expenditure. IPM households devoted nearly twice as much of their overall budget to education and had a higher education elasticity of income. For IPM households versus non-IPM households, the average budget share was 4.4% versus 2.6%, and the education elasticity of income was 1.06 versus 0.93. Regarding medical expenditure, IPM households spent approximately 50% more than non-IPM households – 1.8% of the overall budget versus 1.2%. The medical care elasticity of income was 0.93 for the IPM households versus 0.85 for the non-IPM households. For social obligations, the average budget share of IPM households was 2.5%, more than twice that of the 1.0% of budget share of non-IPM households.

IPM technology requires farm households to invest in new skills that non-IPM households do not have. IPM households also invest more heavily in education, health care and social obligation expenditure than non-IPM households. We therefore can conclude that IPM households have a larger investment portfolio, spending a higher percentage of their income on investment and a lower percentage on consumption than non-IPM households.

3.4 Income multipliers

Table 5 presents rural income multipliers calculated using Equation 14. It reports the increases in purchases of farm and non-farm non-tradables in the region when household income rises by one Uganda shilling. The income increase is viewed as an exogenous shock, arising in this case from the use of IPM. The multiplier estimates reveal that an income increase of one Uganda shilling results in purchases of 0.09 shillings of farm non-tradables and 0.18 shillings of non-farm non-tradables. When added together, the increase in purchases of local, non-tradable goods and services is 0.27 shillings following a one shilling injection into the local economy.

Table 5: Rural income multipliers

Sample category	All tradables	Farm non-tradables	Non-farm non-tradables	Total multiplier
Overall sample	1.00	0.091	0.1818	1.2728
IPM farmers	1.00	0.096	0.1676	1.2636
Non-IPM farmers	1.00	0.066	0.1525	1.2185

Source: Authors' estimates from survey data[4]

A one shilling increase in income in IPM households resulted in a 0.26 shilling increase in purchases of locally produced goods and services. A similar increase in income of non-IPM households increased purchases of local goods and services by 0.22 shillings. Our multiplier value was close in value to the estimate of 1.35 by Belete *et al*. (1999) for a sample of smallholder farmers in the Eastern Cape Province, South Africa, and close to the multiplier value obtained by Ngqangweni (2000) for the local economy of Middle Drift in the Eastern Cape, South Africa.

From Table 5 it is evident that a shilling of injected income results in twice as much spending on non-farm non-tradables (Ushs 0.1818) compared to farm non-tradables (Ushs 0.091). These results are nearly identical to the South Africa rural income multipliers of Hendriks and Lyne (2003), which showed R0.09 of spending on farm non-tradables and R0.19 of spending on non-farm non-tradables.

We reported earlier that, after controlling for other factors, the use of IPM technology resulted in a 118% increase in net coffee incomes. Non-IPM farmers, on average, earn 2 840 036 shillings (US$1 141). Thus, *ceteris paribus*, the income of these farmers would rise to 3 351 242 (US$1 346), an increase of 511 206 shillings (US$205), if they adopted IPM technology. Our estimated rural income multiplier of 1.27 implies that, for each coffee-producing household that adopts IPM, spending on locally produced goods and services rises by 139 457 shillings (US$56) compared to what spending would be without IPM adoption. Hence, our results suggest that IPM technology contributes to rural economic growth in Manafwa District.

[4] All figures represent the household income increase induced by an increase of one unit Uganda shilling in income from tradable agriculture production of farmers who used IPM technologies and those who did not use IPM technologies.

4. Conclusion and policy implications

Enhancing farmers' incomes through the utilisation of improved agricultural technologies is an important step towards poverty eradication among predominantly smallholder agricultural households in developing countries. This paper used cross-sectional data from small-scale Arabica coffee farmers in Manafwa District in Eastern Uganda to test the hypothesis that the use of IPM has a positive and significant effect on net coffee revenue after controlling for other relevant factors.

As farmers' incomes obtained from the sale of tradable Arabica coffee increases, it is re-spent on farm and non-farm tradable and non-tradable products. This implies that the non-farm portion of the local economy also benefits when income from coffee production increases. If these growth rates were attained, the objective of reducing both the proportion and absolute numbers of poor people would not only be achieved at the national level, but also for most household categories.

The results obtained here support the notion behind the CAADP agenda, namely that agricultural growth is an engine of economic growth across all sectors. Investment in IPM and other improved technologies ultimately is an investment in the entire economy. Finally, our results provide evidence that it is possible to intensify agricultural production with methods that are environmentally friendly, profitable for farmers, and growth-inducing for the entire rural economy.

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