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AGRICULTURAL TECHNOLOGY ADOPTION AND NONFARM EARNINGS IN UGANDA: A SEMIPARAMETRIC ANALYSIS

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ABSTRACT

Household diversification into nonfarm work activities is a major rural livelihood strategy in many developing economies. In this paper, we explore empirically if rural households in Uganda leverage their nonfarm earnings to overcome credit constraints and invest in high yielding maize seed varieties. We use a semiparametric estimator of binary outcomes that accommodates endogenous regressors straightforwardly to estimate the effect of nonfarm income on technology adoption decisions. Our results show that nonfarm income has a positive and significant effect on the adoption of improved maize seed.

JEL Classifications: O12, O13, C14
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INTRODUCTION

Technological improvements in the agriculture sector are believed to be the most important pathway for reducing rural poverty in many agrarian economies such as those in Sub-Saharan Africa (SSA) (Bourdillon et al., 2002; Mendola, 2007; Kijima et al., 2008; Kassie et al., 2011). For many of these countries, agriculture provides the leading source of employment and contributes large fractions of national income.[1] In the case of Uganda, the agriculture sector contributes at least 40% of the Gross Domestic Product, about 85% of the export earnings, and employs over 70% of the national labor force (Government of Uganda, 2009). Nearly 90% of the population of Uganda lives in rural areas, and directly derives its livelihood from subsistence farming (Ministry of Finance, Planning and Economic Development 2009).

In recognition of its importance, development partners and SSA Governments have invested in agricultural research and development to increase agricultural productivity and stimulate growth in these countries (Doss, 2006). In Uganda, the Government launched the Plan for Modernization of Agriculture (PMA), a holistic policy framework aimed at eradicating poverty by transforming subsistence farming to market oriented production. To achieve the PMA's mission, the National Agriculture Research System in collaboration with international research centers generated a wide range of improved technologies and management practices that have been disseminated to farmers through the National Agricultural Advisory Services and several other private service providers. Adoption of modern technologies such as high yielding varieties is expected to increase farm-level productivity and improve livelihoods of farm households in developing countries (World Bank, 2008). Several studies have reported that adoption of improved agricultural technologies enhances household well-being in developing countries (e.g. Bourdillon et al. 2002 in Zimbabwe; Mendola, 2007 in Bangladesh; Kijima et al. 2008; Ali and Abdulai, 2010 in Pakistan; and Kassie et al., 2011 in Uganda). In particular, Kijima et al. (2008) and Kassie et al. (2011), respectively, find that adoption of upland rice and modern groundnut varieties are important pathways for rural households to increase agricultural income and escape poverty in Uganda.

However, adoption rates of improved agricultural technologies in many SSA countries remain comparatively low (Tripp and Rohrbach, 2001). For instance, only 28% of the land area allocated to maize in SSA is planted with improved maize varieties (Langyintuo et al., 2010).[2] Further, an average farmer in SSA applies only about 8 kg per hectare of fertilizers compared to 101 kg per hectare in South Asia (Morris et al., 2007) and over 145 kg per hectare in the developed world (World Bank, 2010). The majority of rural farmers in SSA are unable to purchase modern inputs because they lack equity capital and have limited access to credit (Langyintuo et al., 2010).

In many of these economies, markets for credit and insurance are either not available or dysfunctional (Gruhn and Rashid, 2001). Available credit institutions mainly supply commercial loan products relative to risky agricultural loans (Gordon, 2000). Credit institutions set high collateral requirements and charge high interest rates, inhibiting farmers' access to credit (Gruhn and Rashid, 2001). Diversification into nonfarm income activities is an important strategy used by credit-constrained households to obtain investment capital (De Janvry and Sadoulet, 2001; Barrett et al., 2001; Reardon et al., 2007; Quinn, 2009). In Uganda, the share of total income from nonfarm activities for rural households increased from 46% in 2000 to 65% in 2006 (Uganda Bureau of Statistics (UBOS)). These shares are above the average of 35% reported for Africa (Haggblade et al., 2010). Further, the level of household participation in rural nonfarm activities has significantly increased from 49% in 2003 (Kijima et al., 2006) to about 59% in 2009 (UBOS, 2010). Rural nonfarm opportunities are a more reliable source of household income, and often fetch higher returns to labor and capital than the agriculture sector (Reardon et al., 2001). In addition, the risk covariance between nonfarm and farm portfolios is low making it possible for poor farmers to effectively insure against the risks and uncertainties in the agriculture sector and market failures (Reardon et al., 2001). The stream of income earned from nonfarm activities does not only enable farmers to smooth consumption (Kijima et al., 2006; De Janvry and Sadoulet, 2003) but may also provide them with liquid resources to purchase modern farm inputs (Reardon et al., 1997; Barett et al., 2001).

Despite the evidence of increasing importance of nonfarm income in Uganda, no empirical study has, to the best of our knowledge, analyzed its direct causal effect on the agriculture sector, the dominant sector of Uganda's economy. The few published studies available have generally focused on investigating the impact of nonfarm activities on rural poverty alleviation in general (Kijima et al., 2006). The main purpose of the study is to investigate if higher nonfarm earnings spur a greater likelihood of adopting improved maize seed technologies in Uganda. Our analysis reveals this to be the case, suggesting that nonfarm earnings constitute an alternative source of investment capital for farmers who wish to adopt improved technologies but are frozen out of credit markets or cannot borrow the desired level of capital.

An important econometric challenge to the estimation of a causal effect of nonfarm income is its potential endogeneity, arising from unobservables that affect both household participation in nonfarm activities and their adoption decisions. For example, decision-makers that are more entrepreneurial may be more likely to (i) engage in nonfarm activities and (ii) adopt improved agricultural technologies. If so, the effect of nonfarm earnings would be biased upward because of the positive correlation with unobservable entrepreneurial skills. Furthermore, the extant literature on agricultural technology adoption has heavily relied on distribution-dependent parametric methods (e.g., normal errors in the case of Probit) to estimate causal effects. In this paper, we primarily rely on a semiparametric estimator (Rothe, 2009) for dependent variables with binary outcomes such as ours. Rothe's estimator is consistent under mild regularity conditions, and unlike other semiparametric single index models of binary data (Klein and Spady, 1993; Ichimura, 1993; Ergün et al., 2011), it accommodates endogenous variables in a simple two-step process. The rest of the paper is organized as follows. The second section reviews the literature on the determinants of technology adoption in Africa; the third section outlines the conceptual model and estimation methods; the fourth section describes the data used; the fifth section presents the estimation results; the last section concludes.

LITERATURE REVIEW

The literature on technology adoption highlights a number of different explanations for low adoption of improved technologies in developing countries, ranging from credit and liquidity constraints, information barriers, costs, uncertain benefits, risk and taste preferences, and differences in agro-ecological conditions. In this section, we review select recent studies on agricultural technology adoption in Sub-Saharan Africa. We categorize and present the literature in three strands. One strand has emphasized social interactions as an important determinant of technology adoption. For example, Bandiera and Rasul (2006) study farmer's decisions to plant sunflower in the Zambezi province in Mozambique. Their findings show that adoption decisions are correlated within networks of family and friends. Moser and Barrett (2006) analyze farmers' decisions to adopt, expand and dis-adopt a high yielding low external input rice production method in Madagascar. They find that seasonal liquidity constraints and learning effects from extension agents and other households to be important. More recently, Conley and Udry (2010) investigated the role of social learning in the diffusion of a fertilizer among smallholder pineapple farmers in Ghana and find a significant relationship between farmers' use of fertilizers and news about input productivity in the information neighborhood.[3] Duflo et al. (2008) conducted an experiment to study the impact of being invited to observe a trial on a farmer's plot and of having a trial performed on one's own plot. Their findings show an increase in fertilizer users, further demonstrating that learning through social networks may be an important determinant of technology adoption.

The second strand focuses on the relationship between different forms of heterogeneity and technology adoption decisions. For example, in their analysis of fertilizer and improved seed adoption in Tanzania, Nkonya et al. (1997) find that farmer adoption decisions are significantly influenced by differences in biophysical, environmental, and socioeconomic conditions under which they operate. In particular, they report that adoption of improved seed was positively associated with the rate of nitrogen application, farm size, farmer education, and visits by extension agents. Abdoulaye and Sanders (2003) estimate a probit model to quantify the determinants of fertilizer use in Niger; they find experience of farmers and agricultural extension workers as key factors in promoting fertilizer adoption. Dercon and Christiansen (2007) analyze the impact of ex-post risk on adoption of fertilizers in Ethiopia and find that downside risk in consumption exerts a negative and significant effect on the rate of fertilizer application.

Another important strand relates adoption decisions to access to liquidity and credit. For example, Moser and Barrett (2006) analyze farmers' decisions to adopt, expand, and dis-adopt high yielding rice varieties in Madagascar. They fit a dynamic Tobit model of technology adoption under incomplete financial and land markets, and find that seasonal liquidity constraints discouraged adoption by poorer farmers. Similarly, Coppenstedt et al. (2003) estimate a double hurdle model to examine the role of credit and subsidies on farmers' decision to use fertilizer in Ethiopia; they find that credit was the most important constraint to adoption of fertilizers. It has been noted that subsistence farmers want to use advanced farm technologies but do not have financial resources to purchase them (Duflo et al., 2008). They have limited access to credit because it is either not available or they do not have collateral to get credit for farm investment (Hertz, 2009). Moreover, typical subsistence farmers are usually not able to save their farm earnings to purchase inputs later because they face several other needs that compete for the limited financial resources. In their recent experiment conducted in Kenya, Duflo et al. (2011) find that farmers could only use farm revenue to purchase fertilizers immediately after harvesting. Their findings show that the proportion of farmers using fertilizer increased by at least 33% when farmers were offered the option to buy fertilizer immediately after the harvest. We contribute to existing literature on technology adoption in SSA by exploring the linkage between nonfarm income and technology adoption under liquidity constraints. In the presence of imperfect credit markets, rural nonfarm income opportunities are expected to substitute for borrowed capital (Reardon, 1997; Ellis and Freeman, 2004), and can increase the collateral base of households (Reardon et al., 1994; and Barrett et al., 2001). This translates into increased availability of resources to farmers for financing the purchase of improved technologies.

Empirical studies investigating the effect of nonfarm income on technology adoption in Africa have reported mixed findings. Holden et al. (2004) use dynamic programming techniques to analyze the impact of improved access to nonfarm income on household welfare, agricultural production, and conservation investments in the Ethiopian highlands. Their results show that access to nonfarm income opportunities increased household income but reduced farmer incentives to invest in conservation, leading to rapid land degradation. Marenya and Barrett (2007) estimate a multivariate Probit model to quantify the determinants of adoption of natural resource management practices in Western Kenya, and find a positive and significant effect of nonfarm income on use of inorganic fertilizers. Clay et al. (1998) fit a random effects model to analyze the determinants of household intensification, emphasizing the effect of nonfarm income on farmers' investment in land conservation and soil fertility in Rwanda. Their results indicate that nonfarm income significantly increased investment in land conservation but had no effect on the use of chemical fertilizers. Chikwama (2010) uses panel data to analyze the effect of rural nonfarm employment among smallholder farmers in Zimbabwe. His findings show no evidence of contribution of income from rural wage opportunities towards raising households' farm investment, which he attributes to low savings from rural wage employment. Savadogo et al. (1994; 1998) study the relationship between animal traction use, productivity, and non-farm income in Burkina Faso.[4] They find non-farm income to be an important indirect determinant of farm productivity, and ability to intensify production, through its influence on farmer adoption of animal traction.

ECONOMETRICS

Model Specification

The major focus of this study is to provide an understanding of how farmers adjust their adoption decisions in response to changes in household nonfarm income. As discussed in the introduction, we treat nonfarm income as endogenous for the reasons enumerated therein. We define nonfarm income as the household revenue earned from wage employment and self-employment, as well as the income transfers and remittances received from members of the household working outside home. The study also controls for the effect of the endogenous household revenues generated from the sale of farm produce, and other exogenous variables. To obtain unbiased estimates of farm and nonfarm income coefficients, we consider four instruments. First, we use the status of the local nonfarm labor market captured by the share of nonfarm income in the total household income at village level as one of the instruments for nonfarm income. This variable was constructed by dividing aggregate household nonfarm income in a given village by the total income for all households in that village. A high share of nonfarm income indicates high prevalence of nonfarm employment opportunities in the village, and translates into greater potential of households to diversify into nonfarm income generating activities. We hypothesize that existence of nonfarm opportunities in villages increases the probability of household participation in nonfarm work, leading to increased household nonfarm income. One may argue that the share of nonfarm income likely affects household farm decisions via its negative effect on agricultural labor supply. We, however, control for the amount of family labor supplied to agriculture (proxied by household size) and argue that the only remaining pathway through which the instrument influences household adoption decisions is through the instrumented variables.

Second, we use 3 to 5 year lags of nonfarm income and farm revenue as instruments for nonfarm income and farm revenue, respectively. Past household income represents an important form of financial endowment, presenting households with an opportunity to invest in productive assets that generate income. We hypothesize that lagged (at least three years) nonfarm income affects current nonfarm income through its positive effect on investment in nonfarm activities (e.g., self-employment) but it is unlikely to have a direct effect on current farm production decisions because few rural subsistence farmers in developing countries, if any, operate savings accounts in formal institutions. It is also unlikely that subsistence farmers can keep cash savings for 3-5 years. Indeed, findings from a study of constraints to fertilizer adoption in Kenya by Duflo et al. (2011) show that farmers are unable to save money over even short periods of time, which is a major impediment of adoption. In practice, subsistence farmers including those in Uganda save money in form household assets, land, livestock and poultry. We therefore include the value of household assets to control for household savings.

Third, we use availability of migrant network in the district, defined as the percentage of households with at least one migrant, as an instrument for nonfarm income. According to the dynamic theory of migration, communities build migrant connections from interpersonal linkages involving migrants, former migrants, and non-migrants in the origin and destination areas (Massey et al., 1993). These networks facilitate migration because they lower the transaction costs and risks of movement, and provide information about the economic opportunities elsewhere (Massey, 1993; Mckenzie and Rapoport, 2009). We therefore argue that district-level migrant networks create social capital which facilitates household access to nonfarm work opportunities in other communities. A possible threat to validity of the instrumental variable is that availability of migrant networks is likely to influence household agricultural decisions via its negative effects on local farm labor supply. We address this concern by controlling for family agricultural labor supply using household size in our estimators.

Fourth, we use contemporaneous weather shocks to instrument for household farm earnings. The weather shock variable was captured as an index, constructed as the mean of three indictors (dummies) of severe weather conditions in a village: drought, floods and landslides. The index takes values from 0 to 1, corresponding to favorable weather and severe weather conditions, respectively. Severe weather shocks during the production season are expected to induce exogenous variation in farm earnings by reducing farm yields but have no direct effect on the adoption decisions in the current season or year.

The remaining (exogenous) regressors included in the model are drawn from the literature of nonfarm labor supply and agricultural technology adoption. Education of the household head measured in years of formal schooling, age of the household head, household access to agricultural extension and advisory services, and household size are included to capture the effects of human capital and risk tolerance (age) on the nonfarm income and technology adoption.[5] The effects of savings and wealth on adoption are captured using the value of household assets. In addition to lack of access to debt capital, riskiness of agricultural returns (primarily due to rainfall variation) has been identified in the literature as a critical impediment to wider adoption of improved agricultural technologies. We therefore use the (3 to 5-year) lagged weather shock index to capture the effect of weather risks on adoption decisions. We also include a dummy variable indicating whether a household has ever used any type of improved farm technologies, to capture farmers' adoption history. The effect of neighborhood experience on the adoption of improved maize seed was captured in the model by using the proportion of households in the village--excluding the household of interest--that had planted improved seed varieties. Consonant with the social network story, we expect households located in a village that has greater experience with improved seed to be more likely to adopt them. Furthermore, we control for the effect of competitiveness of maize enterprise in a household's land allocation decisions using the proportion of land size planted with maize. Finally, heterogeneous effects of adoption arising from location and agro-ecological characteristics are captured using regional dummies (northern, central, western, and eastern parts of the country).

Binary Adoption Model with Endogenous Covariates

Parametric models are problematic because violation of distributional assumptions is well known to lead to incorrect estimates due to misspecification error (Newey, 1985; Shafgans, 2004; Martins, 2001; Sam and Jiang, 2009; Sam and Ker, 2006; Sam, 2010). This would render the inferences drawn from such models potentially incorrect and misleading for policy prescriptions. A number of semiparametric methods for estimating binary choice models with endogenous regressors have been proposed (Newey 1985; Lewbel 2000; Blundell and Powell 2004; Rothe 2009). We implement Rothe's two-stage semiparametric estimator of binary response models which is an extension the semiparametric maximum likelihood estimator by Klein and Spady's (1993). The estimator is $\sqrt{n}$ nconsistent, asymptotically normal, allows a certain form of heteroskedasticity and, most importantly for our purpose, endogeneity of continuous regressors. Monte Carlo simulations in Rothe (2009) indicate that his estimator exhibits better finite sample performance relative to competing semiparametric alternatives.[6]

For robustness considerations, we also estimated the conditional maximum likelihood Probit estimator (Rivers and Vuong, 1988) which, like the semiparametric estimator, requires endogenous regressors to be continuous and is estimated in two-stages. In the first stage, the endogeneous variables are regressed on the instruments and the other exogenous variables. The residuals from these first-stage regressions are added as controls in the second stage to model the binary adoption decision.

DATA AND SUMMARY STATISTICS

Our study utilizes the Uganda National Household Survey (UNHS) data collected by UBOS. The UNHS 2009/10 is a survey of a nationally representative sample of households drawn from 322 enumeration areas (villages) distributed over 54 districts in Uganda.[7] Our dataset is comprised of 1,218 maize farming households, about 22% of whom planted improved maize seed varieties.[8]

Table 1 presents a summary of variables included in the econometric model, characterizing households in terms of adopters and non-adopters of improved maize seed. The descriptive statistics show that adopting households have better access to markets and advisory services and are more endowed with financial, physical and human capital than the non-adopters. In particular, adopters report higher amounts of nonfarm income, assets and a larger proportion of land planted with maize; they have more years of formal education, more interactions with agriculture extension workers, and better access to credit. On average, adopters reported $1,269 in annual nonfarm income in the year 2009 vs. $1,080 for non-adopters.[9]

Adopters reported significant levels of past earnings from the farm and the non-nonfarm subsectors relative to the non-adopters. Adopters resided in villages with higher proportions of farmers using improved seed varieties than non-adopters. Non-adopters experienced more severe past weather shocks relative to the adopters. Severity of contemporaneous weather shocks was, however, comparable between the communities of the two famer categories. Further, adopters are closer to trading centers by about 5 km on average. Households that are located close to trading centers may have better access to purchased inputs and are thus more likely to use these technologies. The summary statistics also show that percentage of male adopters is higher (83.1%) than that of male non-adopters (69.7%).[10]

ESTIMATION RESULTS

Table 2 presents the results of the first stage equations and F-tests for the relevance of the instrumental variables used in this study. The results show significant coefficients on the instrumental variables in the expected direction as discussed above, indicating that the excluded variables satisfy the relevance requirement. In particular, lagged nonfarm income and the village level share of nonfarm income have a positive and significant effect on current nonfarm income. On the other hand, occurrence of severe weather conditions exert a negative and significant effect on household farm revenue while lagged farm revenue positively affects current revenue. The F-tests suggest that the chosen instruments are relevant in explaining the exogenous changes in the endogenous variables. We also perform the Amemiya-Lee-Newey test of over-identification, and fail to reject the null hypothesis that the instruments are uncorrelated with the error term.[11] We do not focus on the results of the first stage since they are only needed to generate consistent coefficients estimates for farm and nonfarm income.

In the second step, we include the residuals generated from the first step as controls in the parametric and semiparametric models of adoption. Table 3 presents the estimated coefficients.[12] We note that the first-stage residuals are highly significant in the Probit model lending some support to our treatment of farm and nonfarm income as endogenous regressors. It is also important to note that while both the Probit and semiparametric models exhibit highly significant coefficients in general, the standard errors for the semiparametric estimates are substantially smaller. These efficiency gains may be the result of the true link function being far from the normal distribution in which case the semiparametric estimator dominates the Probit (Martin, 2001; Klein and Spady, 1993; Bludell and Powell, 2004; Rothe, 2009; Sam and Zheng, 2010; Diiro et al., 2014). We performed the Lagrange Multiplier test of normally distributed errors (Bera et al., 1984; Wilde, 2008) to establish if the Probit functional specification is appropriate for the data. The test rejects the Probit specification with a p-value of 0.0049, indicating that Probit model may not capture the true adoption behavior of the sample of maize farmers.

TABLE 1. DESCRIPTIVE STATISTICS

Variable	All households (n=1,218)		Adopters (n=272)		Non-adopters (n=946)		T-statistics
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Annual farm revenue per hectare (thousand US$)	1.640	5.234	1.104	1.318	1.794	5.888	1.917*
Annual nonfarm earnings (thousand US$)	1.128	3.235	1.269	1.971	1.080	3.532	-0.910
District migrant network (proportion of households with a migrant)	0.239	0.098	0.227	0.096	0.242	0.099	2.182**
Credit (1=household received credit, 0 otherwise)	0.865	0.342	0.864	0.343	0.865	0.342	0.031
Size of household (number of persons)	6.859	3.202	7.081	3.070	6.795	3.238	-1.298
Distance to the nearest trading center (km)	4.305	8.920	3.685	6.077	4.483	9.577	1.301
Gender of head of household (1=male; 0=female)	0.727	0.446	0.831	0.376	0.697	0.460	-4.410***
Age of head of household (years)	47.659	14.687	44.985	13.700	48.428	14.877	3.422***
Formal education level of household head (years)	5.710	5.827	6.787	6.606	5.401	5.549	-3.473***
Agriculture extension (number of visits received per year)	0.443	2.047	0.843	3.294	0.328	1.491	-3.681***
Village level nonfarm earnings as a proportion of total income	0.518	0.196	0.527	0.202	0.516	0.194	-0.844
Contemporaneous weather shock index (1=severe, 0=not shock)	0.195	0.179	0.183	0.183	0.199	0.177	1.313
Value of household assets (thousand US$)	7.203	47.011	12.583	95.484	5.656	14.861	-2.145**
Neighborhood effects^{+}	0.288	0.244	0.417	0.249	0.251	0.230	-10.22***
Lagged annual farm revenue per hectare (thousand US$)	0.051	0.094	0.067	0.119	0.046	0.083	-4.475***
Lagged annual nonfarm income (thousand US$)	0.429	8.968	0.528	0.136	0.399	0.821	-1.749***
Lagged weather shock index (1=severe, 0=not severe)	0.336	0.346	0.269	0.308	0.350	0.352	3.361***
Adoption history (1=ever used other improved technologies, 0=No)	0.788	0.409	1.000	0.000	0.743	0.437	-8.648***

***, ** *and* * *indicate significance level at 1%, 5% and 10%, respectively.*

$^{+}$ *Proportion of adopters in the village except the* i^{th} *household*

TABLE 2. FIRST-STAGE REGRESSIONS (N=1,218)

	Nonfarm Income Equation		Farm Revenue Equation	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Intercept	-0.601	0.573	5.145***	0.933
Lagged annual nonfarm income (thousand US$)	0.530***	0.104	0.03	0.17
Lagged annual farm revenue per hectare (thousand US$)	0.719	0.972	3.387**	1.583
District migrant network (proportion of households with a migrant)	-0.256	1.067	-5.780***	1.737
Village level nonfarm earnings as a proportion of total income	2.809***	0.48	-2.974***	0.781
Value of household assets (thousand US$)	0.016***	0.002	-0.001	0.003
Contemporaneous weather shock index (1=severe, 0=not severe)	-0.155	0.522	-1.942**	0.849
Lagged weather shock index (1=severe, 0=not severe)	0.157	0.258	-0.285	0.421
Household access to credit (1=member received credit, 0 otherwise)	0.461*	0.253	0.129	0.412
Adoption history (1=ever used other improved technologies, 0=No)	0.118	0.215	-0.912***	0.35
Gender of head of household (1=male; 0=female)	0.002	0.206	0.306	0.335
Agriculture extension (number of visits received per year)	-0.011	0.046	-0.079	0.074
Age of head of household (years)	-0.001	0.006	0.019*	0.01
Formal education level of household head (years)	0.01	0.016	0.032	0.026
Size of household (number of persons)	0.055*	0.029	-0.107**	0.047
Log of distance to the nearest trading center (km)	-0.074	0.059	-0.216**	0.096
Neighborhood effects	0.790**	0.400	-0.005	0.652
Share of farm size allocated to maize crop production	-0.367	0.498	6.039***	0.81
Eastern region	0.104	0.321	-1.513***	0.523
Central region	-0.447	0.283	-2.556***	0.461
Western region	-0.276	0.314	-1.836***	0.512
F-statistic	11.370***		10.460***	
Adjusted R-squared	0.146		0.135	

****, ** and * indicate significance level at 1%, 5% and 10%, respectively*

We therefore focus mostly on the semiparametrically estimated coefficients in the ensuing analysis. Starting with our key variable of interest, we find that an increase in nonfarm income is positively and significantly associated with an increase in the likelihood of adoption of improved maize seeds. These findings corroborate previous related studies that nonfarm income induces adoption of modern farm inputs in developing countries (e.g. Savodogo et al., 1998; Fernandez-Cornejo et al., 2005; Goodwin and Mishra 2004; Phimister and Roberts, 2007; Marenya and Barrett, 2007; Hertz, 2009). To evaluate the impact of change in the coefficient of nonfarm income on adoption, we follow standard practice (Blundell and Powell, 2004; Rothe, 2009) and report the average structural functions (ASF), which represents the marginal probability that the dependent variable takes a value of 1 for exogenously determined values of the regressors.[13]

In Figure 1, the estimated ASF for the semiparametric model is plotted over the 1% to 99% quintile range of the nonfarm income, given the sample average values for the remaining variables. As seen in the graph, the choice probabilities monotonically increase over the distribution of nonfarm income. The estimated probabilities imply that a farmer with annual nonfarm income of $4,363.276 (about the 95% percentile)[14] is 32.8% likely to adopt improved seed. Given the average adoption rate of 22.3%, probability estimates imply that one standard deviation increase in average nonfarm income increases the likelihood of adoption by 47%.[15]

Other significant determinants of adoption include farm revenue, history of adopting technologically advanced inputs, neighborhood effects, extension education, age of the farmer, credit and previous weather shocks. In particular, the amount of farm revenue per hectare generated by farmers wields a significant impact on adoption.[16] Having adopted one or more modern agricultural inputs in the past is a statistically significant positive predictor of adoption of improved maize seeds. Presence of farmers who have used improved seed in the neighborhood also increases a farmer's probability of adopting improved maize seed-suggesting that learning from other farmers plays a significant role in technology adoption. We also find that the probability of adoption increases with the number of interactions between the farmer and the agricultural extension agents. This underscores the role played by the extension system and the development projects in dissemination and promotion of improved technologies in Uganda. The results further show that probability of adoption significantly decreases with farmer’s age, probably due to aversion to risk. Experimental studies such as that by Yesufu and Bluffstone (2007) in Ethiopia, have found that farmers become more risk averse as they age. Our results also show that farmers who experienced severe weather shocks in the recent past were less likely to adopt improved seed, suggesting that weather risk discourages farmers to invest in risky farm technologies.

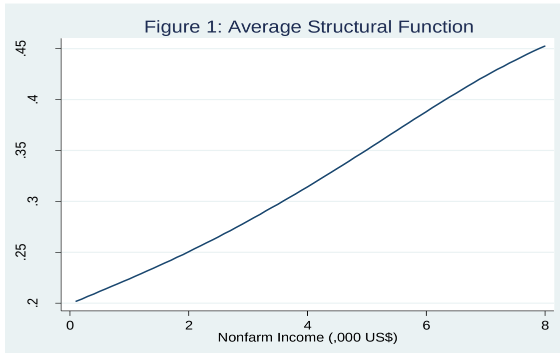
Interestingly, we find a negative and significant relationship between receipt of credit and adoption of improved seed in the semiparametric estimates. The negative effect could be due to risk averse behavior of farmers. Because of high cost of credit, small scale farmers may be reluctant to allocate debt capital to risky farm enterprises to avoid losing their collateral (Hertz, 2009). We find significant and positive coefficients on the three regional dummies suggesting that farmers in these agro-ecological zones are more likely to adopt improved seed relative to farmers in Northern region (the base region for the model).

TABLE 3: SECOND STAGE REGRESSIONS (N=1,218)

Variable	**Two-stage Probit estimates**		**Semiparametric estimates (Rothe)**	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
Annual nonfarm earnings (thousand US$)	0.112*	0.066	0.176***	0.045
Annual farm revenue per hectare (thousand US$)	0.130***	0.058	0.162***	0.029
Value of household assets (thousand US$)	0.001	0.003	-0.001	0.004
Lagged weather shock index (1=severe, 0=not severe)	-0.041	0.133	-0.461***	0.185
Household access to credit (1=member received credit, 0 otherwise)	0.077	0.133	-0.247*	0.151
Size of household (No. of persons)	0.015	0.016	-0.030	0.020
Adoption history (1=ever used other improved technologies, 0=otherwise)	0.276***	0.122	0.385***	0.147
Gender of head of household (1=male; 0=female)	0.310***	0.113	0.197	0.137
Agriculture extension (Number of visits received per year)	0.067***	0.021	0.068***	0.021
Age of head of household (years)	-0.013***	0.003	-0.007*	0.004
Formal education level of household head (years)	0.005	0.008	0.010	0.010
Log of distance to the nearest trading center (km)	0.034	0.035	0.105***	0.040
Share of farm size allocated to maize crop production	-0.493	0.407	-0.493	N/A+
Neighborhood effects	1.084***	0.201	1.015***	0.251
Eastern region	1.176***	0.247	1.391***	0.186
Central region	1.575***	0.264	1.648***	0.186
Western region	1.108***	0.264	1.193***	0.203
Residuals predicted from nonfarm equation	-0.119***	0.065		
Residuals predicted from farm equation	-0.158**	0.056		
Log likelihood value	-542.798		-468.574	

****, ** and * indicate significance level at 1%, 5% and 10%, respectively.*

+ The coefficient of the share of maize was not estimated in the nonparametric model; see endnote 12.



CONCLUSIONS

This paper investigates the effects of nonfarm income on farm level adoption of improved maize seed varieties in Uganda. We test the stylized fact that nonfarm income is a source of capital for credit constrained farmers. Departing from the conventional parametric paradigm, we analyze adoption behavior using a semiparametric estimator. Our results provide evidence that nonfarm income is a critical determinant of adoption of improved maize seed. The findings suggests that in presence of credit constraints, nonfarm income, including remittances, can induce investment in modern agricultural inputs. Strategic interventions aimed at promoting increased adoption and uptake of purchased agricultural technologies in SSA countries should consider the important drivers of nonfarm income and agricultural earnings.

Moreover, we find that extension education, peer effects (neighborhood influence) and prior experience with technologically advanced inputs increase the likelihood of adoption whereas drought reduces the likelihood of adoption. Thus, adoption of improved seed varieties can be further improved by implementing policy interventions aimed at strengthening the agricultural extension and advisory system (including village level extension contact farmers) and reducing systemic risk induced by drought events, for example through crop insurance schemes.

ENDNOTES

We are grateful to the editor, Professor Wahid, and an anonymous referee for very helpful suggestions. The usual disclaimer applies.

[1] Agriculture contributes a third of the regional “GNP” and employs at least two-thirds of the labor force (World Bank, 2011).
[2] Maize is a major staple crop enterprise in many SSA countries.
[3] In particular, they report four key findings that: "a given farmer is more likely to change his fertilizer use after his information neighbors who use similar amounts of fertilizer achieve lower than expected profits; he increases (decreases) his use of fertilizer after his information neighbors achieve unexpectedly high profits when using more (less) fertilizer than he did; his responsiveness to news about the productivity of fertilizer in his information neighborhood is much greater if he

has only recently begun cultivating pineapple; and he responds more to news about the productivity of fertilizer on plots cultivated by veteran farmers and farmers with wealth similar to his."

[4] In their empirical model, they assume that nonfarm income is exogenous to input demand, which is a strong assumption.

[5] In rural areas in Uganda, household heads are the main decision makers in the households. The age of head of household can increase or decrease risk aversion.

[6] Technical details about the estimator are omitted due to space limitations. The interested reader is directed to Rothe (2009) or an earlier draft of this article (available upon request from authors) for a fuller discussion of the estimator.

[7] The survey covered 72 enumeration areas in each of the four regions in the country: Eastern, central, western and northern.

[8] As explained above, we used lagged farm revenue, nonfarm income and weather shocks from the 2005/06 wave of the UNHS survey to obtain instruments for contemporaneous farm revenue and nonfarm income. The sample of 1,218 households is obtained by matching the two UNHS waves using unique household identifiers.

[9] The median income is however much lower than the average income: The median nonfarm income is about $587 for adopters and $453 for non-adopters. Median farm revenue is $755 for adopters and $684 for non-adopters.

[10] Diiro et al. (2014) delve further into the effect of gender on fertilizer adoption in Uganda by estimating separate regressions for male and female headed households.

[11] Chi-sq(2)= 0.464 , P-value = 0.792.

[12] Identification of second-stage coefficients requires location-scale restrictions. For the Probit, the location-scale normalization is imposed by setting the first and second moments of the error term to zero and one, respectively. For the semiparametric estimator, the normalization is imposed by constraining the intercept to zero and one of the coefficients on continuous regressors to a constant. Hence the model is estimated without a constant and the coefficient on the share of land planted with maize is normalized to its Probit counterpart**.**

[13] Marginal effects are not straightforward to compute in binary choice models with endogenous regressors. Following Blundell and Powell (2004) and Rothe (2009), we compute the average structural function (ASF).

[14] We assume a standard deviation increase in nonfarm income for the average household which translates to total nonfarm income of $1,128.38+$3,234.88=$4,363.28 per columns 2 and 3 of the descriptive statistics table (Table 1).

[15] The proportional marginal effect of 47% is obtained by dividing the probability of adoption (32.8%) for a farmer with an annual nonfarm income of $4,363.28 (see previous endnote) by the baseline adoption probability of 22.3%.

[16] A better measure of farm income would have been farm profits which we unfortunately do not have because of lack of reliable input cost estimates from the survey.

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