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Market imperfections, access to information and technology adoption in Uganda: challenges of overcoming multiple constraints

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Abstract

Limited empirical evidence exists on how multiple binding constraints influence the adoption of improved technologies by smallholder farmers. This article uses the case of groundnut variety adoption in Uganda to investigate the role of information, seed supply, and credit constraints in conditioning technology uptake. New data from a household survey in seven groundnut growing districts ($n = 945$) indicate that 8% of farmers lack information on new varieties, while 18% and 6% of farmers, respectively, cannot adopt mainly due to seed supply and capital constraints. A tobit-type specification that considers all nonadopters as being uninterested in the technology (i.e., corner solutions) would lead to inconsistent parameter estimates and incorrect conclusions in this context. We therefore estimate a modified multi-hurdle specification of demand for new varieties, taking into account how information, seed supply, and capital constraints jointly determine adoption probability and intensity. The study reveals new empirical insights on why agricultural technology adoption in Africa has lagged behind: slow uptake is not mainly due to a lack of economic incentives, but rather a reflection of information, seed supply, and credit constraints that prevent farmers from translating their desired demand into adoption of modern varieties. Policy implications are discussed.

JEL classifications: Q10, Q16, Q18, O31, O33

Keywords: Technology adoption; Market imperfections; Information; Multi-hurdle model; Groundnuts; Africa; Uganda

1. Introduction

There is a vast literature on the topic of technology adoption in all areas of economics, including agriculture (Abdulai and Huffman, 2005; Adesina and Zinnah, 1993; Doss, 2006; Diagne and Demont, 2007; Feder et al., 1985; Griliches, 1957; Huffman, 1974; Kassie et al., 2011; Neill and Lee, 2001; Pitt, 1983; Staal et al., 2002). Following Griliches'(1957) seminal econometric work on diffusion of hybrid maize across the United States and subsequent landmark studies on adoption of fertilizer and new seeds (Huffman, 1974; Pitt, 1983), several studies have investigated how relative profitability, access to extension, education and other factors shape technology choice and diffusion. Feder et al. (1985) provide a more comprehensive review of the earlier literature on technological change and adoption in agriculture.

While a number of earlier studies (e.g., Dimara and Skuras, 2003; Feather and Amacher, 1994; Huffman, 1974) clearly recognize the role of education of farmers, access to and availability of information (agricultural extension), and producer exposure and perceptions in explaining adoption and productivity change, limited effort has gone into investigating adoption of agricultural technologies by smallholder farmers in the context of multiple binding constraints in the provision of information and in the availability of inputs and capital. In fact, many adoption studies assume that farmers have complete information and face unconstrained access to the technology (e.g., Edmeades et al., 2008; Kassie et al., 2011; Neill and Lee, 2001; Staal et al., 2002). Under such conditions, the zero (nonadoption) generating process for both divisible and nondivisible technologies leads to a clear rejection of the new technology by the informed user in the long term (Dimara and Skuras, 2003). Such an adoption response is modeled using probit and logit models for nondivisible technologies and tobit-type models for divisible technologies.

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In reality, smallholder farmers in sub-Saharan Africa often lack reliable information and knowledge about new technologies and have therefore not had a chance to make the adoption choice. Even when information is available and farmers can make an informed adoption decision, many farmers with a positive desired demand for new technologies may fail to realize this potential demand due to various constraints (Croppenstedt et al., 2003; Shiferaw et al., 2008). This implies that many nonadopting farmers could be adopters of new technologies, if the limiting constraints (e.g., input supply, credit, etc.) were addressed. Under such circumstances, using a model that accounts only for censorship but fails to consider the difference in desired and actual demand for new technologies leads to inconsistent parameter estimates (Coady, 1995; Croppenstedt et al., 2003). A few studies have looked at how information constraints affect technology adoption (e.g., Adegbola and Gardebroek, 2007; Dimara and Skuras, 2003; Saha et al., 1994), but rigorous analysis of how information, seed supply, and credit constraints jointly affect adoption behavior is limited.

The present study uses groundnut (peanut) variety adoption as a case to investigate the role of information, seed supply, and credit constraints in conditioning technology uptake by smallholder farmers in Uganda. Existing studies of groundnut technologies either assess only the potential for adoption (e.g., Freeman et al., 2001) or are based on small samples of respondents in project areas and cannot be used to understand the determinants of adoption and impacts in the wider growing region. Our study adds value to extant research by estimating the probability and intensity of adoption of improved rosette resistant varieties (RRVs) of groundnut, conditional on availability of information and other limiting constraints (seed supply and credit). Based on a recent large-scale survey of groundnut farmers in Uganda ($n = 945$), the study evaluates the spread and intensity of adoption of improved RRVs of groundnut, and analyzes the determinants of variety uptake and the key policy-relevant constraints faced by smallholder farmers. The multiple thresholds that farmers need to overcome in their technology choice and investment decisions are analyzed using a modified version of the multi-hurdle model (Coady, 1995; Cragg, 1971; Croppenstedt et al., 2003), which explicitly takes into account the effects of information and other adoption constraints.

The remainder of the article is organized as follows. Section 2 provides a conceptual framework for smallholder farm household technology adoption in the presence of multiple binding constraints. Section 3 presents the context and analytical methods with emphasis on production systems, data, empirical models, and hypothesized relationships. The main analytical results are presented and discussed in Section 4. We conclude in Section 5 by presenting the key findings and the policy implications for stimulating the adoption of groundnut technologies in Uganda.

2. Smallholder technology choice and adoption

Smallholder groundnut farmers in Uganda are simultaneously involved in both production and consumption decisions. As in many developing countries in Africa, smallholder farmers face imperfect input and credit markets. We particularly consider that credit markets for agricultural inputs are imperfect and rationed. Lack of employment opportunities in rural areas for many farm households also implies that labor markets are either missing or highly imperfect. These market failures result from poverty, underdeveloped nonfarm sector, asymmetric information, and high transaction costs, especially in credit and input markets. In such situations, the relevance of a separable household model, where consumption and production decisions are made independently, is questionable. The nonseparable household model provides a suitable framework for analyzing household micro-economic behavior under market imperfections. This implies that household resource allocation, including on-farm technology adoption and off-farm labor supply, is determined simultaneously rather than recursively (de Janvry et al., 1991; Holden et al., 2001). Accordingly, technology adoption is modeled using household decision making under imperfect information and a random utility framework.

We assume that farmers choose to adopt a groundnut technology based on the maximization of an underlying utility function. The difference between the expected utility from adoption (U_{hA}) and nonadoption (U_{hN}) of improved groundnut varieties may be denoted as A^d, such that a utility-maximizing farm household, h, will choose to adopt an improved groundnut variety, if the expected utility gained from adopting is greater than the expected utility of not adopting ($A^{d^*} = U_{hA} - U_{hN} > 0$). Since these utilities are unobservable, they can be expressed as a function of observable elements in the following latent variable model:

$$A^{d^*} = \beta Z_h + \mu_h, \tag{1}$$

where Z_h is a vector of the explanatory variables that influence the level of the latent variable through a vector of parameters, β, and μ is the stochastic error term. The farmers' demand for the new technology (adoption decision) is given by

$$A_h^d = \begin{cases} 1 & \text{if } E\left(U_{hA} - U_{hN}\right) \geq 0 \Leftrightarrow \beta Z_h \geq -\mu_h \\ 0 & \text{if } E\left(U_{hA} - U_{hN}\right) < 0 \Leftrightarrow \beta Z_h < -\mu_h \end{cases}. \tag{2}$$

The adoption choice is a function of the expected benefits from switching the technology, which, in turn, depends on technology attributes (including quality traits such as taste, color, and nutrition) and profitability (cost of production, kernel size, market value, etc.). The expected utility of the technology is not, however, the only factor that determines actual adoption behavior of smallholder farmers under constrained socioeconomic environments. The key first-stage determinants are awareness and access to information to evaluate options and assess the relative expected gains from using the new technology. A farmer is considered to be aware of a technology when his information level on the technology exceeds a threshold level (Adegbola and Gardebroek, 2007). Following Adegbola and Garderbroek (2007), we define a latent variable $A_h^{f^*}$ as a function of the level of information acquisition I_h^A that allows the farmer to be aware of the technology, the minimum level of information

(information threshold level) I_h^m needed to make the adoption decision, and a vector of covariates X_h that influence the amount of information obtained. Assuming a linear specification for the latent variable, the household's observed level of awareness, A_h^f, is given as:

$$A_h^f = \begin{cases} 1 \ \text{if } A_h^{f^*} = \left(I_h^A - I_h^m\right) \geq 0 \Leftrightarrow \gamma X_h + u_h \geq 0 \Leftrightarrow \gamma X_h \geq -u_h \\ 0 \ \text{if } A_h^{f^*} = \left(I_h^A - I_h^m\right) < 0 \Leftrightarrow \gamma X_h + u_h < 0 \Leftrightarrow \gamma X_h < -u_h \end{cases}. \quad (3)$$

The producer is aware of the innovation and able to make an evaluation of the benefit streams, when the available information exceeds the minimum level needed to make such choices. Even when information is available, a farmer with a positive desired demand may not plant the new variety due to other factors, mainly seed supply and credit constraints. The seed and credit constraints can be similarly defined as in the adoption and awareness equations. If the underlying latent variable that defines access to seed is given by A^{s^*}, the observed pattern of access to seed (A^s) can be given as:

$$A^s = \begin{cases} 1 \text{ if } A^{s^*} > 0 \\ 0 \text{ if } A^{s^*} \leq 0 \end{cases}. \quad (4)$$

Similarly, if the underlying variable that indexes access to capital needed for buying key inputs is given by A^{c^*}, the observed access to capital for farmers with positive desired demand and access to seed may be given as:

$$A^c = \begin{cases} 1 \text{ if } A^{c^*} \geq 0 \\ 0 \text{ if } A^{c^*} < 0 \end{cases}. \quad (5)$$

This implies that what we usually observe in terms of whether the variety has been adopted or not can be given as:

$$A = A^f A^d A^s A^c = \begin{cases} 1, \ \text{if the variety is adopted} \\ 0, \ \text{if the variety is not adopted} \end{cases}. \quad (6)$$

Adoption occurs when several factors hold simultaneously: the farmer is sufficiently aware of the innovation($A^f = 1$); the expected utility differential is positive ($A^d = 1$); access to seed supply is ensured ($A^s = 1$); and capital is not a constraint ($A^c = 1$). Accordingly, the probability of adoption, $P(A)$, of the new varieties can be given by:

$$P(A) = P\left(A^f\right) * P\left(A^d\right) * P\left(A^s\right) * P\left(A^c\right). \quad (7)$$

This conceptual framework for farm household decision making under imperfect markets shows the importance of variables that condition access to information, profitability of the technology, and access to seed and liquidity in determining the adoption behavior of smallholder producers. In the following section of the article, we develop an empirical model for estimating Eqs. (6) and (7) in order to test the study's conceptual framework for several farm, household, and institutional factors.

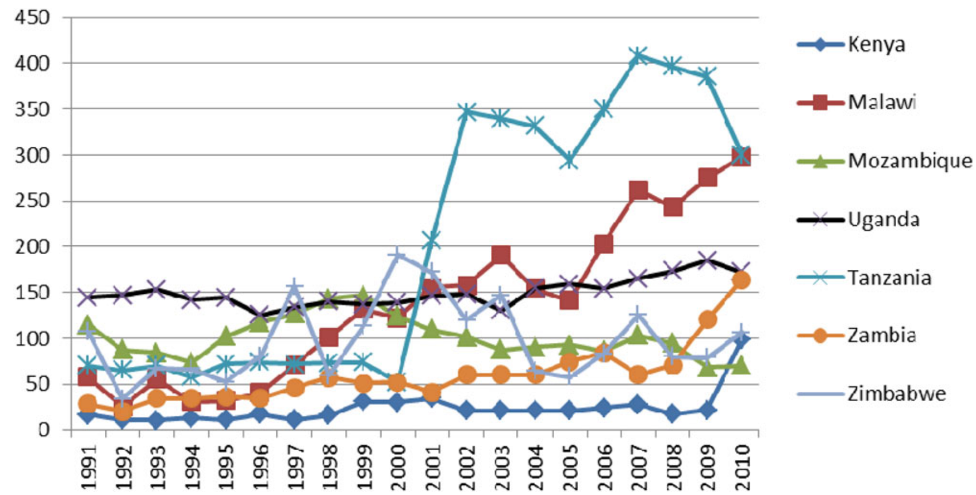
3. Data, study context, and empirical methods

3.1. Groundnut in Uganda

Uganda is one of the major producers of groundnut in eastern and southern Africa (Fig. 1). Groundnut is the second most widely grown legume in the country after the common bean. For households who can afford to produce a surplus for markets, it provides scarce cash income that can be used for investing in health, children's education, and other necessities. Although this study mainly focuses on groundnut technology adoption based on survey of groundnut producers, groundnut is an important food security crop in both rural and urban areas of Uganda. Widespread adoption of the technology can be expected to generate benefits to both producers and consumers. In rotation with cereals, groundnut also provides additional benefits by enhancing soil fertility through fixation of atmospheric, which is especially important given the high cost of chemical fertilizers. This contributes to increasing land and labor productivity for smallholder producers (Coelli and Fleming, 2004). Groundnut leaves and haulms (hay from the young stems and pods after shelling) also make nutritious animal feeds, while groundnut meal—a by-product of oil extraction—serves as an important protein supplement for livestock.

Despite the numerous benefits, groundnut production in Uganda has remained heavily constrained by diseases, pest pressure, and frequent droughts. Groundnut rosette virus (GRV) is one of the most serious problems limiting productivity growth.[1] The disease incidence may be reduced by insecticidal control of the vector (aphids) and other agronomic practices, but such practices are capital- or knowledge-intensive, and hence, are seldom adopted by smallholder farmers. Host-plant resistance to the disease is regarded as the most viable and sustainable solution. In partnership with the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT), the National Agricultural Research Organization (NARO) of Uganda identified and selected locally adapted RRVs that are tolerant to abiotic stresses, especially drought. By the end of 2002, a total of four improved RRVs (Igola, Serenut2, Serenut3, and Serenut4) had been tested and released by the Serere Research Center of NARO (at Soroti). This was followed by an aggressive promotion effort funded by the government of Uganda and several donors with the leadership of the National Agricultural Advisory Services (NAADS),

[1] Rosette is the most destructive viral disease of groundnut in sub-Saharan Africa. The rosette epidemic in 1994/95 Malawi and Zambia devastated the crop (e.g., crop area in Malawi declined from 92,000 ha in 1994/95 to 65,000 ha the following year). Overall annual loses in Africa due to rosette were estimated at about US$ 156 million (ICRISAT, 2005).



Source: FAOSTAT, accessed 2010.

Fig. 1. Trends in groundnut production (1,000 tons) in the major producing countries in eastern and southern Africa.

which offers demand-driven and farmer-led agricultural service and technology delivery systems.

3.2. Sampling procedure

This study uses primary data collected by ICRISAT (2005) in collaboration with NARO and NAADS in Uganda. The survey was done in two stages. First, a reconnaissance survey was conducted by a team of scientists to obtain an understanding of the production and marketing conditions in Uganda through discussions with farmers, traders, extension staff, and other service providers. The findings from this exploratory survey stage were used to refine the study objectives, sampling methods, and survey instrument.

The household survey was conducted in seven districts, drawn from five farming systems where groundnut is widely grown. These districts represent the major groundnut growing region of Uganda. One district was randomly selected to represent each farming system, except for the banana–cotton–millet system, where three districts were randomly sampled owing to the large number of groundnut growing districts. A multi-stage stratified sampling technique was used to sample households in each of the selected districts. In each district, all groundnut growing subcounties were identified, and three subcounties were randomly selected. This was followed by random selection of three parishes from each subcounty, providing nine parishes per district, from which one village was randomly selected. A random sample of 15 households was selected from each village, providing a total of 135 households per district and 945 households across the seven sample districts.

Data were collected through personal interviews administered by trained investigators from October 2006 to December 2006, using pre-tested, semi-structured questionnaires, designed to capture diverse issues related to farmer technology adoption under constrained conditions.

3.3. Socioeconomic profile

Agriculture was the main occupation and livelihood strategy for 82% of the farm households in the Uganda study districts. The level of adoption of improved varieties was very high: about 59% of sample households grew improved varieties. About 62% of the groundnut area was planted to improved varieties, indicating a high intensity of adoption. On average, the income per hectare from improved varieties was about 80% higher than the income from local cultivars.[2] About 88% of the sample households were male headed. The mean age of the household heads was about 45 years, while the mean education level was about seven years. The average household size for all districts was very high, ranging from 6.4 in Busia district to 8.1 in Mbale district, with a mean of 7.1 persons. However, the total work force was relatively low—averaging only 2.5 adult equivalents per family, indicating high levels of dependency; for every productive member of a household, there were two nonproductive members.

The households were, on average, located about 2 km from the nearest village market, 5 km from the nearest main market, and 2 km from the nearest all-weather road. Using distance to proxy market access, Iganga district had the best access to markets, while Arua district had the worst. Based on distance to nearest all-weather road, Lira and Mbale districts had better access to markets than others, while Busia and Arua districts had relatively poor market access. Access to agricultural information, which is vital for creating awareness or reinforcing knowledge about an improved technology, also varied across districts and villages. Using distance to the nearest extension center as a proxy, farmers in Mbale and Iganga districts had relatively better access to information than others, while Tororo and Busia districts had poorer access. The majority of

[2] Summary statistics of selected variables for adopters and nonadopters are available on request.

the sample households (68%) owned some information and communication assets, mainly a radio, which was the major means of accessing outside information; a few sample households also possessed mobile phones and televisions (TVs).

The average size of owned farms across the study districts was about 2.6 ha. The estimated mean value of all nonland assets was about USh 838,000 of which livestock assets accounted for about 78%.[3] Livestock was a very important asset, especially in the districts where farm sizes were large and seasonal fallows served as pasture or grazing lands (e.g., Lira district). Districts with smaller farmland holdings seemed to be investing in nonlivestock assets, probably due to unavailability of pastures for livestock.

3.4. Empirical methods

The landmark paper by Feder et al. (1985) synthesized the vast adoption literature and defined adoption at the level of the individual farm or firm as the degree of use of a new technology in long-run equilibrium when the farmer has full information about the new technology and it's potential. Numerous applied econometric studies have accordingly used binary and censored regression models, such as probit and tobit, to study the technology adoption behavior of farmers (Feder et al., 1985)[4] . The key underlying assumptions of these models are that farmers have access to the information needed to make informed choices, and that farmers who, after evaluating the technology, would like to adopt are unconstrained to do so. When these assumptions hold, the zero (nonuse) values for both divisible and nondivisible technologies correctly indicate a clear rejection of the new technology by well-informed users in the long run (Croppenstedt et al., 2003; Dimara and Skurus, 2003; Shiferaw et al., 2008). However, in situations where farmers face information constraints or when agricultural extension services and seed supply and credit markets are underdeveloped, the probit and tobit models provide corner solutions (i.e., all farmers who did not adopt the innovation are considered as lacking positive demand), and hence, generate inconsistent parameter estimates.

Farm household surveys in developing countries show that many farmers are unable to access information, or face constraints in accessing seeds of improved varieties because of imperfections in local seed supply systems or lack of the capital needed to purchase inputs. These constraints must be overcome before a farmer can grow the new cultivars. Data in Table 1 show that about 59% of sample farmers did not face information, seed supply, or capital constraints, and had positive demand for the new varieties. This group of farmers adopted the technology (group 1). On the other hand, about 8% of the farmers lacked information about the new varieties and were unable to make the adoption decision (group 2). About 18% of the sample farmers had a positive desired demand for the new varieties, but could not access the seed due to input market imperfections (group 3). About 6% expressed a desire to plant the new varieties, but capital constraints prevented them from doing so (group 4). Only about 10% of the farmers did not want to adopt the new varieties because these varieties were judged to be unprofitable (group 5). Our survey results thus suggest that a constrained adoption model (Coady, 1995; Cragg, 1971; Croppenstedt et al., 2003) is more appropriate than a tobit specification that considers all nonadopters as having no interest in the new technology. The Double Hurdle model (Cragg, 1971) can provide consistent estimates of adoption parameters in situations where constraints on information, seed supply, and credit prevent farmers from adopting new technologies (Coady, 1995; Croppenstedt et al., 2003; Dimara and Skurus, 2003).

Table 1
Adoption constraints for groundnut farmers in Uganda

Choices and constraints	Groundnut adoption choices	
	N	%
1. Want to adopt	777	82.2
• Adopted	555	58.7
• Lack seed supply	170	17.9
• Lack credit	52	5.5
2. Lack information	72	7.6
3. Do not want to adopt	96	10.2
Sample (N)	945	100

We therefore develop and estimate a modified double hurdle model which accounts for the multiple constraints that Ugandan groundnut farmers face and makes use of survey information about the sample separation into multiple groups. The four-equation model that we develop accounts explicitly for the multiple hurdles (information, seed access, and capital constraints) farmers must overcome before they can choose how much land to allocate to improved varieties. The unobserved demand for improved seed for farmer i can be modeled as:

$$D_i^* = \beta^i X_i + u_i, \tag{8}$$

where X is a vector of variables that determine the demand function, β is a parameter vector, and u is a normal random variable with mean 0 and variance σ_u. Similarly, the latent variable underlying an individual farmer's access to information, improved seed, and capital needed to buy the required input can be modeled with Eqs. (9)–(11).

Access to information:

$$I_i^* = \alpha' g_i + \omega_i. \tag{9}$$

Access to seed:

$$S_i^* = \theta' z_i + e_i. \tag{10}$$

Access to cash capital:

$$C_i^* = \gamma' y_i + \varepsilon_i. \tag{11}$$

[3] The exchange rate at the time was 1,800 Ugandan Shilling (USh) to 1 US$.

[4] Feder et al.'s (1985) survey paper on adoption cites more than 70 studies directly related to technology adoption in agriculture.

In the above equations, g, z, and y are a vector of variables that affect access to information, seed, and capital, respectively; α, θ, and γ are the parameter vectors; and ω, e, and ε are random variables distributed as normal with mean 0 and variance 1. The observed improved seed demand (D_i) is characterized by the interaction of model (8) to (11). A positive use of improved seed is observed if three thresholds are passed in the decision-making process in such a way that the farmer has access to information ($I_i^* > 0$), passed the positive demand threshold ($D_i^* > 0$), has access to improved seed ($S_i^* > 0$), and is not capital constrained ($C_i^* > 0$). This comprises the first group in the sample. Group 2 consists of farmers who do not have access to sufficient information ($I_i^* < 0$) and hence cannot adopt improved seed ($D_i^* < 0$) no matter what—whether they have access to improved seed or not ($S_i^* > 0$ *or* $S_i^* \leq 0$) and whether they have access to capital or not ($C_i^* > 0$ or $C_i^* \leq 0$). The third group in the sample constitutes farmers who have access to information ($I_i^* \geq 0$) and want improved seed ($D_i^* > 0$) but cannot get it because improved seed is not locally supplied ($S_i^* \leq 0$). Group 4 farmers have access to information ($I_i^* \geq 0$) and want improved seed ($D_i^* > 0$) but they cannot adopt it because they are capital constrained ($C_i^* \leq 0$). The fifth group consists of farmers who do not have desired demand for new varieties ($D_i^* \leq 0$); access to information, seed, and capital is irrelevant for this group.

Several studies (Jones, 1992; Kimhi, 1999; Moffatt, 2005) have applied variants of the double hurdle model, where the independence of the equations is tested and the independence assumption could not be rejected. Smith (2003) shows that assuming dependency between the equations is not a worthwhile exercise as there is little statistical information available to support dependency in a double hurdle framework. Such lessons may suggest setting zero for some or all correlations between random disturbances $u, \omega, e, \varepsilon$ implying a partial or total independence between the above-specified hurdles.

To verify these claims in our setting, we employed model selection criteria that rely on the use of the test proposed by Vuong (1989). The hypothesis of no correlation between the desired demand equation and the three hurdles was performed using the Vuong test of selection between two models, differing only with respect to the value of the error correlation coefficients with each of the hurdles. The null hypothesis of zero correlation is accepted for each of these tests implying the independence of access and demand equations.[5] This means that while the observed demand for improved seed and the intensity of adoption are conditional on access to information, seed, and capital, the intensity of adoption is not necessarily determined simultaneously by unobserved factors that affect the demand equation and the hurdles.

[5] The null hypothesis was no pairwise correlation among random disturbances (correlation of the demand equation error term with error terms in each of the three constraints). The tests were performed in R software using the LR statistic. The P-values for these tests were 0.235, 0.203, and 0.382 for information, seed, and capital access equations, respectively. Hence, at the 5% significance level, the null hypothesis of no correlation and, hence, model independence cannot be rejected. Detailed test results can be obtained from authors on request.

Hence, the log likelihood function for the sample separated data can be expressed as:

$$\begin{aligned}
\ln L = & \sum_{G1=1} \ln\left[\Phi\left(\alpha' g_i\right)\cdot\Phi\left(\theta' z_i\right) c\Phi\left(\gamma' y_i\right)\cdot(1/\sigma_u)\cdot\varphi\left(\left(D_i - \beta' X_i\right)/\sigma_u\right)\right] \\
& + \sum_{G2=1} \ln\left[1-\Phi\left(\alpha' g\right)\right] \\
& + \sum_{G3=1} \ln\left[\Phi(\alpha' g)\cdot\Phi(\beta' x_i/\sigma_u)\cdot(1-\Phi(\theta' z_i))\right] \\
& + \sum_{G4=1} \ln\left[\Phi(\alpha' g)\cdot\Phi(\beta' x_i/\sigma_u)\cdot\Phi(\theta' z_i)\cdot(1-\Phi(\gamma' y_i))\right] \\
& + \sum_{G5=1} \ln\left[\Phi(\alpha' g)\cdot(1-\Phi(\beta' x_i/\sigma_u))\right], \qquad (12)
\end{aligned}$$

where ϕ and Φ are, respectively, the probability density and cumulative distribution function of the standard normal variable; $G_1, \ldots, G_5$ are indicator functions for whether a given observation belongs to group 1 to group 5, as described earlier. Equation (12) can be estimated using maximum likelihood (ML) techniques, resulting in consistent parameter estimates. Given that adoption decisions are made under imperfect markets, we include a number of household, farm, and institutional factors that capture the differential access to information, credit, labor, and other inputs needed in the adoption process. The overall probability of adoption is then computed according to Eq. (7). The descriptive statistics for the variables included in the multi-hurdle model are given in Table 2.

The choice of variables is informed by literature review and insights from farm household behavior under imperfect markets (de Janvry et al., 1991; Holden et al., 2001), which indicate that imperfections in information, credit, and labor markets will have a direct effect on the adoption decision and the intensity of adoption. Under such conditions, the marginal cost of adoption would be higher for credit- and labor-constrained households, when adoption requires more of these inputs. This will reduce the net gain from adoption and make the technology less profitable or limit the intensity of adoption. Accordingly, we include farm and household characteristics along with institutional factors in understanding the adoption behavior of farm households. The extent of adoption is modeled conditional on access to information, seed, and capital which, in turn, depend on specific social capital, institutional, and market access variables hypothesized to determine access to these resources. The key variables hypothesized to affect *access to information* include human capital variables, such as gender, age, and education; social capital variables, such as group membership and distance to agricultural center; and assets, such as ownership of information and communication technology (ICT) and farm size. Similarly, *access to seed* is expected to depend on institutional variables such as linkage to research, extension, markets, farmer-to-farmer seed exchange, and membership in farmer organizations. *Access to capital credit* is expected to depend on household assets and human capital (e.g., assets, wealth, education, etc.), past income, social capital, and distance to

Table 2
Descriptive statistics for the variables used in the multi-hurdle model

Variable	Group 1: Adopters ($N = 555$)	Group 2: Lack information ($N = 72$)	Group 3: Want to adopt but seed constrained ($N = 170$)	Group 4: Want to adopt but capital constrained ($N = 52$)	Group 5: Do not want to adopt ($N = 96$)
Improved variety area (ha)	0.35 (0.3)	0.00 (0.0)	0.00 (0.0)	0.00 (0.0)	0.00 (0.0)
Aware of technology (yes = 1)	1.00 (0.0)	0.00 (0.0)	1.00 (0.0)	1.00 (0.0)	1.00 (0.0)
Seed supply unconstrained (yes = 1)	1.00 (0.0)	1.00 (0.0)	0.00 (0.0)	1.00 (0.0)	1.00 (0.0)
Capital unconstrained (yes = 1)	1.00 (0.0)	1.00 (0.0)	1.00 (0.0)	0.00 (0.0)	1.00 (0.0)
New varieties have preferred taste (yes = 1)	0.37 (0.5)	0.00 (0.0)	0.05 (0.2)	0.10 (0.3)	0.03 (0.2)
New varieties are late maturing (yes = 1)	0.17 (0.4)	0.24 (0.4)	0.15 (0.4)	0.17 (0.4)	0.20 (0.4)
New varieties have large grain (yes = 1)	0.37 (0.5)	0.00 (0.0)	0.11 (0.3)	0.13 (0.3)	0.03 (0.2)
New varieties are high yielding (yes = 1)	0.94 (0.24)	0.00 (0.0)	0.19 (0.4)	0.21 (0.4)	0.06 (0.2)
Farming is main occupation (yes = 1)	0.85 (0.4)	0.61(0.5)	0.80 (0.4)	0.86 (0.3)	0.81 (0.4)
Male head (yes = 1)	0.88 (0.3)	0.93 (0.3)	0.86 (0.3)	0.85 (0.4)	0.90 (0.3)
Age of head (years)	45.68 (13.5)	45.77 (13.2)	44.80 (13.5)	47.81 (15.2)	42.95 (12.2)
Education of head (years)	7.20 (4.1)	8.51 (4.2)	6.24 (4.0)	5.77 (4.0)	6.77 (4.2)
Education of family (years)	32.63 (22.9)	37.75 (26.6)	27.34 (20.2)	26.08 (18.2)	28.18 (19.0)
Belongs to groups (yes = 1)	0.71 (0.5)	0.46 (0.5)	0.53 (0.5)	0.48 (0.5)	0.59 (0.5)
Belongs to farming group (yes = 1)	0.63 (0.5)	0.25 (0.4)	0.39 (0.50)	0.38 (0.5)	0.49 (0.5)
Total family work force[a]	2.58 (1.22)	2.60 (1.5)	2.39 (1.2)	2.43 (1.3)	2.46 (1.3)
Operated farm size per capita (ha)	0.24 (0.5)	0.12 (0.1)	0.15 (0.1)	0.11 (0.1)	0.15 (0.2)
Pasture area per capita (ha)	0.30 (1.1)	0.09 (0.1)	0.17 (0.2)	0.14 (0.2)	0.17 (0.3)
Past experience with new varieties (yes = 1)	0.79 (0.4)	0.00 (0.0)	0.36 (0.5)	0.36 (0.5)	0.12 (0.3)
Distance to main market (km)	4.43 (3.4)	4.77 (2.8)	5.75 (3.8)	5.27 (3.3)	5.18 (4.6)
Distance to village market (km)	1.88 (1.9)	1.47 (1.6)	1.78 (1.7)	1.26 (1.3)	1.91 (1.7)
Distance to agric center (km)	3.63 (3.3)	3.61 (3.8)	4.26 (3.9)	4.04 (4.1)	4.28 (4.4)
Distance to nearest road (km)	1.64 (2.1)	1.39 (2.0)	1.99 (2.3)	1.66 (1.6)	1.85 (2.8)
Accessed initial seed from NGOs (yes = 1)	0.16 (0.4)	0.00 (0.0)	0.03 (0.2)	0.04 (0.2)	0.02 (0.1)
Accessed initial seed from extension (yes = 1)	0.52 (0.5)	0.00 (0.0)	0.16 (0.4)	0.13 (0.3)	0.07 (0.3)
Accessed initial seed from farmers (yes = 1)	0.35 (0.5)	0.00 (0.0)	0.16 (0.37)	0.15 (0.4)	0.04 (0.2)
Accessed initial seed from markets (yes = 1)	0.21 (0.4)	0.00 (0.0)	0.08 (0.28)	0.08 (0.3)	0.03 (0.2)
Number of owned oxen	0.47 (1.1)	0.14 (0.61)	0.18 (0.7)	0.08 (0.4)	0.20 (0.6)
Nonoxen livestock wealth per ha (1,000 Ush)	365.7 (651)	481.0 (523)	256.0 (398)	417.6 (673)	357.5 (567)
Previous crop income per ha (1,000 Ush)	376.9 (6,378)	166.9 (891)	87.66 (262)	71.20 (191)	71.48 (112)
Has iron roof house (yes = 1)	0.44 (0.5)	0.71 (0.5)	0.32 (0.5)	0.38 (0.5)	0.31 (0.5)
Owns transport asset (yes = 1)	0.80 (0.4)	0.58 (0.5)	0.60 (0.5)	0.58 (0.5)	0.75 (0.4)
Owns bicycle (yes = 1)	0.79 (0.4)	0.56 (0.5)	0.58 (0.5)	0.56 (0.5)	0.73 (0.4)
Owns ICT (yes = 1)[b]	0.69 (0.5)	0.81 (0.4)	0.60 (0.5)	0.60 (0.5)	0.76 (0.4)
Owns a mobile (yes = 1)	0.15 (0.4)	0.25 (0.4)	0.12 (0.3)	0.15 (0.4)	0.17 (0.4)

Notes: The numbers in brackets are standard deviation.
[a]Workforce = 1*(full time farm labor providing members aged 16–60 years) + 0.5*(Part time farm labor providing members aged 16–60 years) + 0.25*(Full time farm labor providing members aged 11–15 years).
[b]ICT = information and communication technologies (radio, phone, and television).

markets. Finally, once the information, capital, and seed access hurdles are overcome, the *intensity* or *extent of adoption* is expected to depend on technology characteristics, human capital, gender, distance to markets, and assets (oxen, farm size).

4. Estimation results

In this section, we present the results from the multi-hurdle model, where the intensity of adoption of groundnut varieties is estimated conditional on the farmer accessing information and overcoming seed supply and capital constraints. This approach allows the inclusion of different sets of explanatory variables in a jointly estimated model of the determinants of adoption intensity, information access, seed access, and capital access (Table 3).[6]

4.1. Access to information

Farmers must be aware of the availability of improved seed, if they are to test and determine its performance relative to other cultivars in use. In the absence of such information, the farmer will not have the opportunity to choose the technology. Yet, the full information assumption of binary and censored

[6] We also estimated the tobit model for comparison purposes. In our analysis, Vuong's statistics appear to favor the modified multi-hurdle model over the tobit for adequately describing the data (P-value was 0.193, so the null hypothesis that the modified DH model is preferred cannot be rejected).

Table 3
Multi-hurdle regression model (standard errors are in parentheses)

(a) Information access model	Coefficient	z-Statistic	Marginal effects
Male head (yes = 1)	−0.382 (0.260)	−1.470	−0.009
Age of head (years)	0.007 (0.006)	1.150	0.000
Education of family (years)	−0.003 (0.003)	−0.820	−0.000
Belongs to farming groups (yes = 1)	0.521 (0.149)	3.490***	0.019
Had contact with NGOs (yes = 1)	4.943 (218.949)	0.020	0.039
Distance to agric center (km)	−0.052 (0.022)	−2.360**	−0.002
Owns bicycle (yes = 1)	0.295 (0.170)	1.730*	0.010
Owns ICT (yes = 1)	−0.107 (0.190)	−0.560	−0.003
Operated farm size per capita (ha)	1.631 (0.729)	2.240**	0.050
Lira district	−1.624 (0.438)	−3.700***	−0.184
Tororo district	−1.305 (0.438)	−2.980***	−0.118
Busia district	−1.109 (0.419)	−2.650***	−0.086
Iganga district	−1.206 (0.439)	−2.750***	−0.101
Arua district	−0.005 (0.540)	−0.010	−0.000
Mbale district	−2.017 (0.430)	−4.690***	−0.289
Constant	2.323 (0.533)	4.360***	
(b) Seed access model	Coefficient	z-Statistic	Marginal effects
Male head (yes = 1)	0.087 (0.190)	0.460	0.025
Age of head (years)	0.009 (0.004)	2.130**	0.003
Farming is main occupation (yes = 1)	0.292 (0.160)	1.820*	0.087
Belongs to farming group (yes = 1)	0.571 (0.142)	4.020***	0.160
Distance to village market (km)	−0.020 (0.036)	−0.550	−0.005
Distance to agric center (km)	−0.021 (0.017)	−1.220	−0.081
Accessed initial seed from NGOs (yes = 1)	0.583 (0.297)	1.960**	0.129
Accessed initial seed from extension (yes = 1)	0.937 (0.150)	6.240***	0.229
Accessed initial seed from other farmers (yes = 1)	0.850 (0.155)	5.490***	0.192
Accessed initial seed from markets (yes = 1)	0.947 (0.187)	5.060***	0.189
Operated farm size per capita (ha)	0.291 (0.375)	0.780	0.081
Owns a mobile (yes = 1)	0.011 (0.190)	0.060	0.003
Owns bicycle (yes = 1)	0.327 (0.135)	2.430**	0.096
Tororo district	−0.291 (0.255)	−1.140	−0.087
Busia district	−0.985 (0.243)	−4.060***	−0.336
Lira district	−0.572 (0.264)	−2.170**	−0.183
Iganga district	−0.356 (0.269)	−1.320	−0.109
Arua district	−0.725 (0.234)	−3.100***	−0.239
Mbale district	−0.505 (0.271)	−1.860*	−0.160
Constant	−0.614 (0.394)	−1.560	
(c) Capital access model	Coefficient	z-Statistic	Marginal effects
Male head (yes = 1)	−0.059 (0.278)	−0.210	−0.005
Belongs to groups (yes = 1)	0.498 (0.198)	2.520***	0.052
Education of head (years)	0.036 (0.024)	1.510	0.005
Had contact with NGOs (yes = 1)	0.673 (0.366)	1.840*	0.040
Distance to main market (km)	−0.024 (0.028)	−0.850	−0.002
Distance to village market (km)	0.100 (0.078)	1.290	0.009
Distance to nearest road (km)	0.066 (0.049)	1.330	0.006
Total family workforce	0.006 (0.075)	0.090	0.001
Previous crop income (Ush 1,000/ha)	0.003×10^{-1} (0.001)	0.620	0.000
Number of owned oxen	0.142 (0.171)	0.830	0.013
Owns transport asset (yes = 1)	0.363 (0.199)	1.830*	0.039
Operated farm size per capita (ha)	3.965 (1.056)	3.750***	0.367
Pasture area per capita (ha)	0.119 (0.205)	0.580	0.011
Nonoxen livestock wealth (Ush 1,000/ha)	0.001×10^{-1} (0.000)	1.030	0.000
Has iron roof (yes = 1)	−0.063 (0.239)	−0.260	−0.006
Lira district	−0.174 (0.446)	−0.390	−0.018
Tororo district	−0.939 (0.388)	−2.420**	−0.150
Busia district	−0.650 (0.392)	−1.660*	−0.089
Iganga district	−0.047 (0.432)	−0.110	−0.004
Arua district	−0.782 (0.360)	−2.170**	−0.115
Mbale district	−0.505 (0.413)	−1.220	−0.064
Constant	0.112 (0.440)	0.260	

Continued

Table 3
Continued

(d) Demand for new varieties model (intensity of adoption)			
Model/Variable	Coefficient	z-Statistic	Marginal effects
New varieties have preferred taste (yes = 1)	0.072 (0.024)	3.020***	0.047
New varieties are late maturing (yes = 1)	−0.038 (0.027)	−1.430	−0.024
New varieties have large grain (yes = 1)	0.025 (0.023)	1.060	0.016
New varieties are high yielding (yes = 1)	0.079 (0.028)	2.800***	0.050
Male head (yes = 1)	0.027 (0.032)	0.840	0.017
Education of head 6 to 8 years (yes = 1)	−0.030 (0.025)	−1.200	−0.019
Education of head 9 to 12 years (yes = 1)	0.051 (0.029)	1.780*	0.033
Education of head more than 12 years (yes = 1)	0.122 (0.038)	3.220***	0.084
Accessed initial seed from NGOs (yes = 1)	0.085 (0.032)	2.620***	0.057
Total family workforce	0.009 (0.009)	1.000	0.005
Number of owned oxen	0.030 (0.012)	2.580***	0.019
Nonoxen livestock wealth (Ush 1,000/ha)	0.003×10^{-2} (0.000)	−1.750*	−0.000
Operated farm size per capita (ha)	0.294 (0.028)	10.330***	0.187
Pasture area per capita (ha)	−0.014 (0.012)	−1.160	−0.009
Past experience with new varieties (yes = 1)	0.138 (0.025)	5.470***	0.086
Distance to village market (km)	0.002 (0.006)	0.390	0.001
Distance to main market (km)	−0.003 (0.003)	−0.860	−0.002
West Nile farming system	−0.147 (0.043)	−3.430***	−0.085
Teso farming systems	−0.151 (0.045)	−3.350***	−0.087
Lango farming systems	−0.150 (0.044)	−3.370***	−0.087
Banana-based systems	−0.108 (0.036)	−3.040***	−0.068
Constant	0.125 (0.052)	2.410**	
Equation (5)			
Cons	0.264 (0.008)	33.690***	
Log likelihood = −866.60886	Wald chi^2(21) = 420.89		
Number of obs = 945.00	Prob > chi^2 = 0.00		

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

technology adoption models ignores the possibility that some of the nonadopters are actually censored due to lack of information. This can lead to misleading conclusions. In estimating the demand for new varieties conditional on access to information, we use several variables to explain the variation in accessing information on groundnut technologies: gender, age, education, farmer group membership, ownership of information assets, distance to the nearest agricultural center, farm size, and district fixed effects (Table 3a). As expected, proximity to agricultural centers, group membership, farm size, and ownership of a bicycle have a positive and significant effect ($P < 0.05$) on the likelihood of accessing information. Interestingly, household education does not seem to affect access to information, perhaps because such information is not coming through the print media and does not require high skills to digest and implement. Compared to Soroti district, the level of awareness seems to be lower in almost all the other districts. The Serere Agricultural Research Institute, which developed the improved groundnut varieties, is based in this district and has been working closely with farmers for many years.

4.2. Access to local seed supply

As in the case of information access, the seed-supply-dependent variable is binary with a value of 1 indicating access to local seed supply, and 0 representing lack of access, irrespective of the capital constraint. We include several household-specific, institutional, and regional variables that are expected to determine access to seed (Table 3b). The institutional variables include linkage to research, extension, markets, farmer-to-farmer seed exchange, and membership in farmer organizations. We hypothesize that farmers with access to extension services, input markets and farmer organizations, or to nongovernmental organizations (NGOs) and research centers will face lower constraints in accessing quality seed. Indeed, the results show that prior experience of obtaining seed from research/extension centers and buying seed from traders have positive and highly significant effects on relaxing the seed access constraint. This indicates that farmers who obtained their initial seed stock from extension and local agro-dealers in the past are less likely to face seed supply constraints. This may be due to saving and recycling of seed, or to better relationships that allow farmers to access seed from a particular source. Experience in informal seed systems (farmer-to-farmer seed transfer) and membership in crop production groups also significantly reduce the probability of facing the seed supply constraint. Similar to findings from other studies, our results underscore the importance of both formal and informal seed systems in technology diffusion in rural areas and networking among farmers in overcoming the problem of access to improved seed (Arega and Manyong, 2007; Shiferaw et al., 2008).

Farmers' ability to access improved seed is also affected by their endowment of certain marketing assets and regional effects. In particular, ownership of bicycle (a proxy for market access) significantly increases the probability of a farmer having access to improved seeds. This indicates the role of low-cost transport systems in facilitating local mobility and linkages with input and output markets. In rural Uganda, bicycles represent the most important means of transport for moving grain to key markets and inputs to the farm. Rural assemblers often transport over 100 kg of grain procured from the farm to the nearest wholesale markets, offering key services in integrating isolated rural grain markets. We also expected distance to markets and agricultural extension centers to be negatively correlated with seed access. These variables had negative estimated parameters, but were not statistically significant. However, we find significant interdistrict differences in accessing seed: relative to Soroti district, Tororo and Arua seem to have a lower probability of access.

4.3. Access to capital to buy seeds

The seed requirements for groundnut are quite high (about 120–150 kg/ha). Many small farmers face significant challenges in financing such a high seeding rate. The dichotomous-dependent variable takes the value 1 when capital is not indicated by the farmer as limiting adoption, and 0 otherwise. The probability of facing a capital constraint in buying improved seed is expected to depend on several household factors (assets, wealth, education, etc.), market linkages, past income, social capital, and regional dummies (Table 3c). The key variables reducing the likelihood of facing the capital constraint include group membership, ownership of productive assets (farm size), and means of transport. Collective action in terms of membership in a crop production group is highly significant, indicating that such social capital improves access to liquidity for capital-constrained households to finance the purchase of improved seeds. Such groups are widely used to overcome some idiosyncratic capital and other constraints resulting from imperfections in rural markets. Similarly, farm size substantially reduces the likelihood of facing a capital constraint. Other variables related to market access, gender, previous crop income, and family education are not found to have a significant effect on overcoming the capital constraint. The regional dummies indicate that relative to Serere district, farmers in Tororo and Arua are more likely to face capital constraints.

4.4. Demand for improved varieties

Once the information, seed, and capital hurdles are overcome, a farmer with a positive demand for new varieties will need to decide how much improved seed to use and determine the extent of technology adoption. The intensity of adoption or the realized demand for improved varieties is therefore modeled conditional on accessing information and overcoming the seed supply and capital constraints. Following previous studies (Kaliba et al., 2000; Sall et al., 2000; Shiferaw et al., 2008), we investigate the determinants of actual demand for improved varieties (intensity of adoption) using farmland planted to new groundnut varieties. Several explanatory variables capturing the effect of farming systems, technology attributes, household characteristics, distance to markets, and assets (labor, education, oxen, and farm size) are included (Table 3d). The extent of adoption seems to vary by farming system, technology attributes, education, contact with NGOs, ownership of productive assets (oxen and farm size), and prior experience in planting new crop varieties. From the technology attributes, better taste and higher expected yield increase the intensity of adoption. Among the household assets, higher education, farm size, and oxen ownership (traction power) increase the demand for new varieties. Farmers with past experience and knowledge in growing new varieties of all crops, and having regular contact with NGOs, seem to have higher demand for new seeds.

Among the institutional variables, membership in crop production groups[7] increases the intensity of adoption of improved varieties. Nevertheless, unlike in the probit adoption model, the proxy variables for market access are not significant determinants of the intensity of adoption. The inverse relationship between distance to main market and the decision to plant new varieties suggests that high transaction costs impede the first-level decisions, but not necessarily the degree of adoption of improved technologies. These findings are consistent with previous studies on adoption of improved technologies (e.g., Feleke and Zegeye, 2006).

The results also show that area allocated to improved varieties is affected by household endowment of certain productive assets. The number of oxen and farm size significantly affect the size of land planted to improved varieties. Unlike the adoption equation, however, family labor endowment was not significantly correlated with the intensity of adoption. These findings imply that, conditional on overcoming access to information, seed supply, and capital constraints, perception of valuable technology traits possession of key productive assets that ease seasonal resource constraints, social capital, education, and prior experimentation with new technologies play an important role in determining the demand for and the actual extent of adoption of improved groundnut varieties.

Under the constrained stepwise process of adoption, the probability of adopting the new varieties is given as the multiple of the probabilities of having access to information, positive demand for new seeds, access to seed supply, and overcoming the capital constraint. Using per capita farm size as

[7] It is, however, worth noting that membership in crop production groups can arguably be endogenous to the technology adoption decision. In fact, we have performed a Wu–Hausman specification test to test the null hypotheses that this variable is exogenous in the technology adoption function. The P-values of the estimated F-test statistics show that the exogeneity hypothesis cannot be rejected at the 10% level of significance.

Table 4
Effect of farm size on probability of adoption and intensity of adoption

Farm size	Probability of information access		Probability of seed access		Probability of credit access		Probability of seed demand	Probability of adoption	
	Group = 1	Group = 0	Group = 1	Group = 0	Group = 1	Group = 0		Group = 1	Group = 0
0.01	***0.984***	***0.948***	***0.857***	***0.689***	***0.870***	***0.735***	***0.791***	***0.580***	***0.380***
0.05	0.986	0.954	0.859	0.693	0.900	0.784	0.804	0.614	0.417
0.1	0.989	0.962	0.862	0.698	0.931	0.837	0.819	0.650	0.461
0.16	0.992	0.969	0.866	0.705	0.957	0.889	0.836	0.687	0.508
0.20	**0.993**	**0.973**	**0.869**	**0.709**	**0.970**	**0.916**	**0.847**	**0.708**	**0.535**
0.5	0.998	0.992	0.886	0.738	0.999	0.995	0.913	0.807	0.665
0.75	1.000	0.998	0.900	0.761	1.000	1.000	0.949	0.854	0.720
1	1.000	0.999	0.912	0.783	1.000	1.000	0.972	0.887	0.761
1.25	1.000	1.000	0.923	0.804	1.000	1.000	0.986	0.910	0.792
1.75	1.000	1.000	0.942	0.841	1.000	1.000	0.997	0.939	0.839
2	1.000	1.000	0.950	0.858	1.000	1.000	0.999	0.949	0.857

Note: About 30% of the farmers have per capita farm size less than 0.1 ha, 64% have less than 0.2 ha, 82% have less than 0.3 ha, 90% have less than 0.4 ha, and 95% have less than 0.5 ha. Only 5% of the sample households had above 0.5 ha. Group = 1 indicates farm households who are members of local collective action groups. Group = 0 refers to those who are not members.

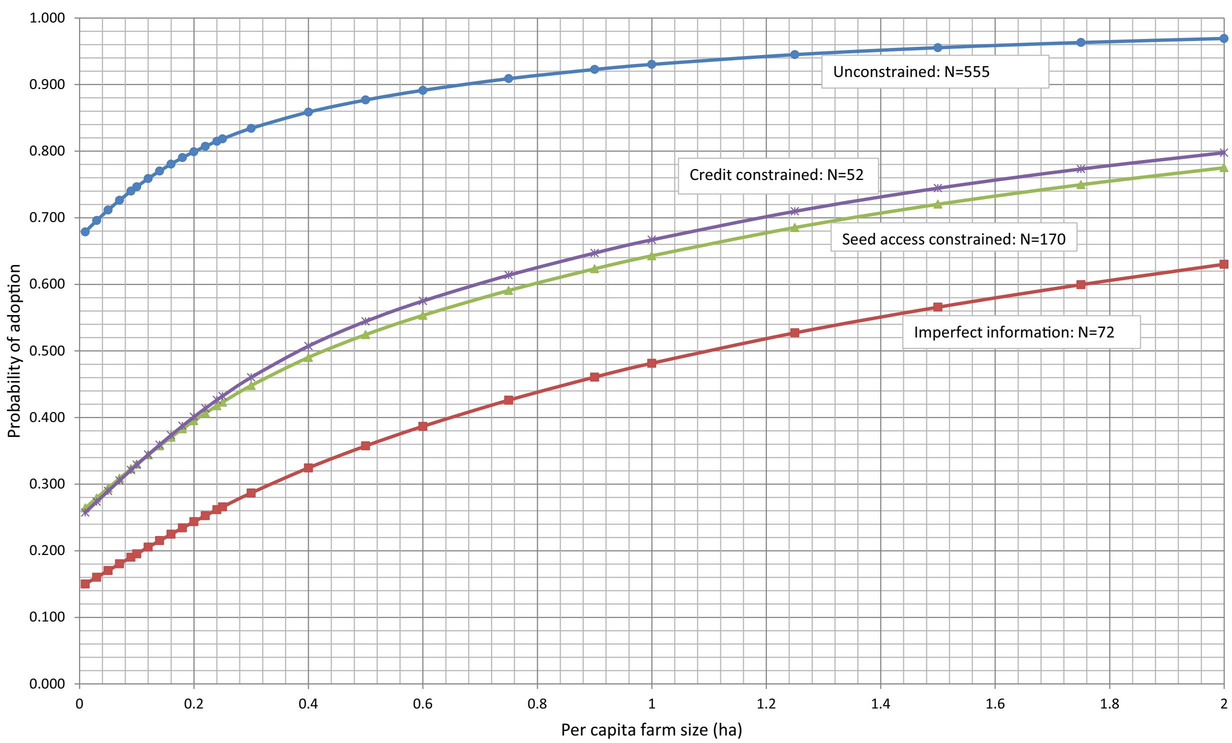


Fig. 2. Probability of adoption for different household groups.

the key variable,[8] the effect of these factors on the probability of adoption and the intensity of adoption for the average household is presented in Table 4. Since farm size and membership in collective action groups are significant in several of the hurdle models, the probabilities are evaluated for the different values of farm size (with and without group membership) at the average values of all other model variables. For the lowest value of 0.01 ha per capita, *ceteris paribus*, the probability of positive seed demand is 79%, the probability of access to information is 98%, access to seed 85%, and access to capital is 87%. This means that for a land-constrained small farmer, the probability of adoption is quite low, ranging from 38% to 58%, depending on the membership in collective action groups. For

[8] Land selling and rental markets in Uganda are underdeveloped, making farm size per person an important productive asset. The 1998 Land Act defined the rights of four classifications of tenure: freehold, leasehold, mailo, and customary. Except for freehold rights, there are restrictions and limitations set out by the government (leasehold), mailo owner (mailo), or communities (customary rights) on whether existing land rights can be transferred, mortgaged, or rented out (Petracco and Pender, 2009).

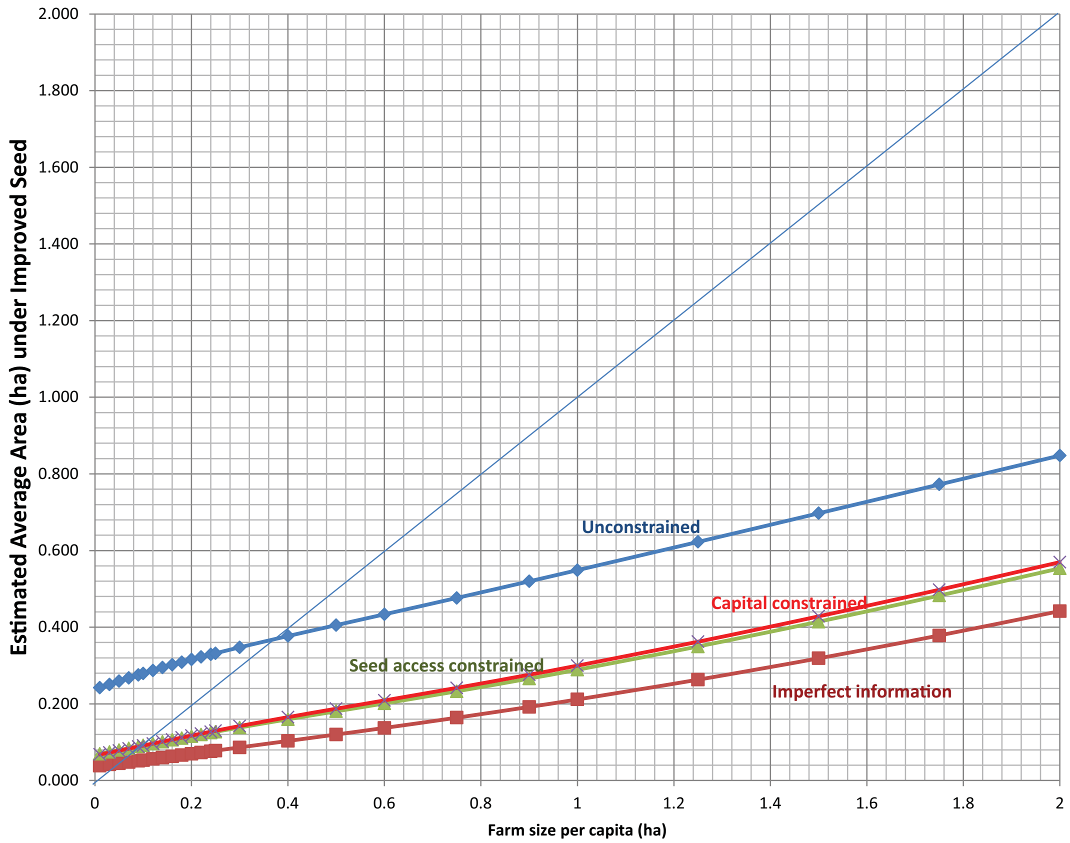


Fig. 3. Intensity of adoption for different household groups.

the average farm size of about 0.2 ha per person in the data, the estimated values for the probability of adoption of improved varieties increase to 53% and 70%, depending on access to collective action. If the farm size increases to about 1 ha per person, the probability of access to information and credit increases to about 100%, and the probability of adoption ranges between 76% and 88%, mainly because farm size does not ensure access to seed or necessarily enhance the profitability of new varieties. This shows how relatively large (land abundant) farmers who belong to groups for accessing information, seed, and capital are better able to benefit from new technologies.

In order to show the effect of information, seed access, and capital constraints on the probability and the intensity of adoption for the different household groups, we plot the relationships against farm size (Figs. 2 and 3). For the average per capita farm size of 0.2 ha, the probability of adoption is just 24% for those lacking reliable information, 39% for those lacking access to seed, 40% for those facing capital constraints, but as high as 80% for the unconstrained farmers. As indicated in Table 4, an increase in farm size enhances the probability of overcoming these constraints, and increases the probability of adoption for the different household groups (Fig. 2). For example, for unconstrained farmers with 1 ha per person, the probability of adoption increases to about 93%. The same results apply for the intensity of adoption. For the average per capita farm size of 0.2 ha, the intensity of adoption is just 0.07 ha for those lacking reliable information, 0.11 ha for those lacking access to seed or credit to invest in improved technologies, but 0.32 ha for the unconstrained farmers (Fig. 3). Interestingly, the figure shows that unconstrained farmers with small farmland per capita seem to allocate a larger proportion of their farm to groundnut production than those who have relatively large farms. These stylized results show the importance of access to information, seed, and capital, and the role of farm size and some collective action in easing these constraints, and in determining the probability of adoption and area planted into new varieties. Small farmers with limited capital are particularly constrained and are likely to lag behind in the adoption process.

5. Conclusion

This article documents the determinants of the intensity of modern variety adoption for the case of groundnut varieties in Uganda. The study finds that adoption of groundnut technologies in Uganda is constrained by imperfect markets for information and access to improved seed and capital. Many previous studies assumed that nonadopting farmers make decisions on technology choice under full information and that nonusers of the technology are disinterested in the innovation, after having made an informed comparative assessment of its performance on-farm. Failure to account for the fact that farmers often lack information to make informed choices, and to separate farmers who have a positive desired demand for the new technology, but face binding constraints to its use, from those who do not face adoption constraints, can lead to inconsistent parameter estimates and misleading conclusions. In this article, the adoption behavior of smallholder groundnut farmers in Uganda is modeled as a flexible multi-hurdle model taking into account various constraints facing farmers, notably information, seed supply, and capital access.

The results from the multi-hurdle analysis offer unique policy-relevant insights on the importance of imperfect information, capital, and seed access constraints in conditioning the intensity of adoption of improved varieties. About 8% of the sample farmers lacked information about new varieties, and hence, could not make any adoption decisions. About 18% wanted to plant new varieties, but did not adopt, mainly due to lack of local seed supply, while some 6% were constrained by lack of capital to buy improved seeds. The multi-hurdle regression analysis identifies the specific factors that determine access to information, seed supply, and capital constraints, and the overall demand for new varieties conditional on overcoming these hurdles. Social capital through local farmer groups and networks and distance to information centers are found to be critical for accessing variety information. Study findings suggest that seed supply constraints are overcome through strong links with local seed sellers, extension, and membership in seed production groups. Interestingly, we also find that group membership is a key factor in overcoming capital constraints. Productive assets like farmland and ownership of bicycles for increased mobility are also related to improved access to information, seed, and capital, which, in turn, enable adoption of new varieties. The importance of market access, household assets, human capital, and farm size in overcoming certain constraints to adoption indicates that in the absence of public intervention, resource-poor and marginal farmers may lag behind or face stiff barriers that exclude them from harnessing new technologies. This may lock some households, especially resource-constrained small-scale farmers, into stagnating subsistence production and extreme poverty. Given the significantly high but poorly understood and hidden demand for new technologies, improvements in farmer education and supply of improved seed and rural finance can make substantial changes for farmers currently constrained from using modern technologies, and could make a difference in improving productivity, nutrition, and food security for overcoming rural poverty.

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