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Adoption of chemical fertilizer by smallholder farmers in the peanut basin of Senegal

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Farm productivity in the Peanut Basin of Senegal has been declining over time, requiring strategic interventions to reverse this trend. Using pooled cross-section time-series data and probit and Tobit models, this paper examines factors that influence the decision whether or not to use fertilizer (adoption) and the share of land on which fertilizer is used (intensity) in peanut and millet production. Our results show that the probability of using fertilizer increases where household heads have higher literacy, larger families and larger farms, but decreases where they have off-farm income. Fertilizer use is also positively associated with the amount of rainfall and varies by geographical location. The analysis indicates that both the adoption and the intensity of use of fertilizer by peanut and millet farmers have been declining over the study period 1998–2005. Our findings suggest that focusing on market oriented interventions that motivate farmers to invest in improved agricultural technologies is a sensible policy option.

Keywords: adoption; use intensity; chemical fertilizer; peanut; millet

JEL classification: Q16

Avec le temps, la productivité agricole du bassin arachidier sénégalais a diminué. Pour corriger cette tendance, des interventions stratégiques sont nécessaires. Grâce à des données issues de séries temporelles en coupe transversale groupées, aux modèles probit et Tobit, cet article examine les facteurs qui influencent la décision d'utiliser ou non des engrais (adoption) et le partage des terres qui reçoivent l'engrais (intensité) dans la production de l'arachide et du mil. Nos résultats montrent que les chances d'utiliser un engrais augmentent lorsque la capacité des chefs de ménage à lire et à écrire est plus importante, et lorsque les familles et les fermes sont plus grandes, mais qu'elles diminuent là où il existe un revenu hors exploitation. On associe aussi de manière positive l'utilisation d'engrais à la pluviométrie et

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cette utilisation varie selon la situation géographique. L'analyse indique que l'adoption et l'intensité de l'utilisation d'engrais par les fermiers cultivant l'arachide et le mil ont diminué pendant la période étudiée, de 1998 à 2005. Nos résultats suggèrent qu'un accent mis sur des interventions visant le marché et qui poussent les fermiers à investir dans des technologies agricoles améliorées, représente une option politique judicieuse.

Mots-clés : adoption ; intensité de l'utilisation ; engrais chimique ; arachide ; millet

Catégories JEL : Q16

1. Introduction

Agriculture contributes 17.4% to Senegal's GDP, and peanut production and processing represent about 2% of GDP and 9% of exports (World Bank, 2007). The peanut industry accounts for 70% of the rural labor force and 60% of households' agricultural income. Senegal's Peanut Basin is home to 75% of the country's active population and produces 80% of exportable peanut and 70% of the total cereal crop (Akobundu, 1998; Mbaye & Golub, 2002). Policy changes in Senegal contributed to a national decline in fertilizer consumption from 40 kg/ha in 1968 to 13.5 kg/ha in 1996–2000 (Akobundu, 1998; Jayne et al., 2003), resulting in environmental degradation, manifested as soil nutrient loss due to overcultivation (Hathie, 1997; Cisse et al., 2004).

The Senegalese economy relies on peanuts for foreign exchange and this has made the country vulnerable to external shocks (World Bank, 2007). Market liberalization led to the removal of input subsidies, which resulted in capital restrictions, while the scarcity of credit led to low fertilizer adoption rates (Akobundu, 1998; Cisse et al., 2004). But self-sufficiency in food production requires supportive policies that create incentives for technology adoption. Market oriented strategies could be an important element in motivating farmers to intensify agriculture.

This study contributes to the analysis of factors that influence a farmer's decision to intensify agriculture in Senegal. The aim was to analyze the determinants of chemical fertilizer adoption and use intensity among smallholder farmers in the Peanut Basin, using pooled cross-section time series data. Using data from 502 households in five regions of Senegal from 1998 to 2005, the study focused on fertilizer use by peanut and millet farmers, given the importance of these two crops within the Basin and also at the national level.

The remainder of the paper is divided into four sections. The analytical framework and economic research on technology adoption is discussed in Section 2. Data and empirical models are presented in Section 3, followed by the results in Section 4. Conclusions and policy recommendations are presented in Section 5.

2. Analytical framework and economic research on technology adoption

Adoption behavior models range from simple relationships to complex multivariate analyses. Logit, probit and Tobit models are commonly used to identify factors that influence decisions to use a new technology (Makokha et al., 2001; Imai, 2003). Logit and probit models are

appropriate when the dependent variable is dichotomous (0, 1), while the Tobit model is useful for continuous values that are censored at or below zero (Anley et al., 2007).

The underlying economic theory on factors that influence the decision to use chemical fertilizer is based on the assumption that farmers are motivated by utility maximization (Shakya & Flinn, 1985; Adesina & Zinnah, 1993). Farmers form expectations of the costs and benefits of a technology on the basis of own experimentation or through analysis of information from early adopters and key informants in their communities. Following Marenya and Barrett (2007) and Nkamleu and Adesina (2000), we assume that farmers behave consistently with utility maximization and that chemical fertilizer is adopted when the anticipated utility from adoption exceeds that of non-adoption. Although not observed directly, the utility (U_{ij}) for a given farmer (i) to use a particular practice (j) can be defined as a farm-specific function of a vector of explanatory variables (X), and an error term with zero mean (e_{ij}). This function can be represented as:

$$U_{ij} = \beta_j X_i + e_{ij} \quad j = 1, 0; \quad i = 1, \dots, n \quad (1)$$

where $j=1$ represents technology adoption and $j=0$ represents non-adoption. Thus, the i^{th} farmer adopts ($j = 1$) if $U_{i1} > U_{i0}$. For empirical purposes, the expected utility of adoption U_{ij} can be surmised from a farmer's observed binary choice of adoption or non-adoption, which implies a probit or logit model (Anley et al., 2007). In the context of the choice of whether or not to adopt chemical fertilizer, the probit model is specified (Fufa & Hassan, 2006) as

$$Y = F(\omega + \alpha X_i) = F(z_i), \quad (2)$$

where Y is the discrete adoption choice variable, F is a cumulative probability distribution function, α is a vector of unknown parameters, X is a vector of explanatory variables and z is the Z-score of the αX area under the normal curve. The expected value of the discrete dependent variable in equation (2), conditional on the explanatory variables, is given by

$$E[Y / X] = 0[1 - F(\alpha' X)] + [F(\alpha' X)] = F(\alpha' X) \quad (3)$$

and the marginal effect of each explanatory variable on the probability of adoption is given by

$$\frac{\partial E[Y|X]}{\partial X} = \phi(\alpha' X)\alpha \quad (4)$$

where $\phi(\cdot)$ is the standard normal density function (Fufa & Hassan, 2006).

The probit model is suitable for analyzing adoption decisions that have dichotomous values, but if the adoption choice has a continuous value range censored from below (and/or above) then the Tobit model is appropriate. In this paper, we are interested in analyzing not only the binary adoption choice but also the intensity of fertilizer use (Adesina & Zinnah, 1993; Kazianga & Masters, 2002; Anley et al., 2007). In this case, we can express the underlying Tobit model (McDonald & Moffit, 1980; Yilma et al., 2008) as

$$\begin{aligned} Y_i^* &= \beta X_i + e_i \\ Y_i &= Y_i^* \text{ if } Y_i^* > 0 \\ Y_i &= 0 \text{ if } Y_i^* \leq 0 \end{aligned} \quad i=1, 2, \dots, N \quad (5)$$

where Y_i^* is a latent variable indexing adoption, Y_i is the observable dependent variable, e_i is the residual that is independently distributed with zero mean and constant variance (σ^2) and N is the number of observations. The model assumes that the dependent variable has a limiting value that is only observed for positive cases and thus qualifies as a latent variable. The expected value of Y in the Tobit model (McDonald & Moffit, 1980) is specified as

$$E[Y] = \beta X F(z) + \sigma f(z) \quad (6)$$

and the expected value of Y for observations above the limit ($Y^* > 0$) is

$$E[Y^*] = \beta X + \sigma f(z)/F(z) \quad (7)$$

where z denotes $\beta X/\sigma$, $f(z)$ is the unit normal density, $F(z)$ is the cumulative normal distribution function, and X is a vector of independent variables (individual subscripts in equations (6) and (7) are omitted for convenience).

The Tobit model allows us to investigate the decision whether or not to adopt a technology and the conditional level of its use if the initial adoption decision is made (Adesina & Baidu-Forson, 1995). It also allows us to determine the effect of a change in the i^{th} variable on changes in the probability of adopting the technology and in its expected use intensity.

Following the proposed decomposition of the Tobit model by McDonald and Moffitt (1980) and Nkonya et al. (1997), the effects of the explanatory variables can be decomposed into the decision to adopt chemical fertilizer and the intensity of its use. Thus, a change on a given explanatory variable has two effects: 1) it affects the conditional mean of Y_i^* in the positive part of the distribution, and 2) it affects the probability that the observation will fall in that part of the distribution. Therefore, the marginal effect of an explanatory variable (X_i) on the expected value of the dependent variable (McDonald & Moffitt, 1980; Greene, 2003) is equal to

$$\frac{\partial E(Y)}{\partial X_i} = F(z)(\delta EY^* / \delta X_i) + EY^* (\delta F(z) / \delta X_i) \quad (8)$$

McDonald and Moffitt (1980) showed that the total change in Y can be disaggregated into two parts: 1) the change in the probability of adoption as the explanatory variable X_i varies, given by

$$\frac{\partial F(z)}{\partial X_i} = \frac{f(z)\beta_i}{\sigma} \quad (9)$$

and 2) the change in the intensity of adoption among users due to a change in an explanatory variable (McDonald & Moffitt, 1980; Norris & Batie, 1987; Fufa & Hassan, 2006), given by

$$\begin{aligned} \frac{\partial E(Y_i^*)}{\partial X_i} &= \beta_i + (\sigma / F(z)) \delta f(z) / \delta X_i - (\sigma f(z) / F(z)^2) \delta F(z) / \delta X_i \\ &= \beta_i [1 - zf(z) / F(z) - f(z)^2 / F(z)^2] \end{aligned} \quad (10)$$

The variables in equations (9) and (10) are as defined above, and β is a vector of parameters from the Maximum Likelihood estimation of the Tobit model.

Economists have provided considerable evidence about agricultural technology adoption and diffusion among farmers in developing countries (Sunding & Zilberman, 2001; Conley & Udry, 2003). A substantial body of literature analyzes farmers' adoption behavior and these studies reveal considerable variation in such behavior for agricultural technologies over time and across socioeconomic groups (Feder et al., 1985; Moreno & Sunding, 2005). Nonetheless, research on farm level technology adoption in Senegal is negligible.

Empirical models of technology adoption typically include socioeconomic, physical and agro-ecological variables as regressors (Zegeye et al., 2001; Knepper, 2002). Decisions to use a technology depend in part on how farmers receive, process and evaluate information about innovations. In environments where information acquisition and transfer are fraught with difficulties, the educational level of the farmer is critical (Wozniak, 1984; Ersado et al., 2004). Moreover, the incentives to adopt a technology depend on the expected benefits, and education facilitates the sourcing, the processing and its successful application. As a result, exposure to formal education is expected to increase technology adoption (Wozniak, 1984; Feder et al., 1985; Doss et al., 2003).

In theory, a large family in a rural farming community is indicative of abundant labor. New technologies may increase seasonal labor demand and labor shortages may constrain small-sized families, making technology adoption less attractive (Feder et al., 1985). In areas with undeveloped labor markets, family labor plays a key role in the adoption of labor-intensive technologies (Lee, 2005). Therefore, households with large families are more likely to adopt such technologies (Croppenstedt & Demeke, 1996; Zegeye et al., 2001; Doss et al., 2003).

Land is often used as a proxy for wealth in the technology adoption literature; however, this variable can have an ambiguous effect on adoption. Feder et al. (1985) suggest that small farms may be willing to adopt a technology to increase short-run profits, but financial constraints may impede such adoption. Households with larger farms are assumed to have easier access to credit and farm inputs and thus be more likely to be adopters. Moreover, extension services and agribusiness firms tend to target larger farms for trials of new agricultural technologies (Bacha et al., 2001; Kherallah et al., 2002). Nevertheless, Diederer et al. (2003) argue that smaller farms may be more likely to cooperate in trials and to accept the risks and costs associated with experimentation. Hence, small-scale producers would be more inclined to adopt improved practices and to intensify their operation.

Some researchers suggest that higher income increases household liquidity, making it possible to allocate more resources to improved technologies. Thus, the availability of off-farm income can offset credit constraints while enhancing the capacity to bear risk (Feder et al., 1985). By contrast, households with limited income or credit are likely to be capital constrained and less able to adopt riskier technologies (Adesina, 1996). Some of the adoption literature considers farm income as endogenous, which requires special treatment in the econometric estimation (Doss, 2006). A common alternative is to include off-farm income as a way of incorporating additional liquidity while minimizing the endogeneity problem (Adesina, 1996; Makokha et al., 2001; Chirwa, 2005; Doss, 2006; Anley et al., 2007).

The geographical location of the farm determines the land potential and thus the expected returns from a given technology (Chirwa, 2005; Doss, 2006). Prevailing agro-ecological conditions capture the potential risk of crop failure associated with rainfall dependency and soil quality, which affects adoption decisions. Researchers have shown that households located in zones where rainfall is low and erratic are less likely to use fertilizers than those in zones with more reliable rainfall (Freeman & Omiti, 2003; Chianu & Tsujii, 2004).

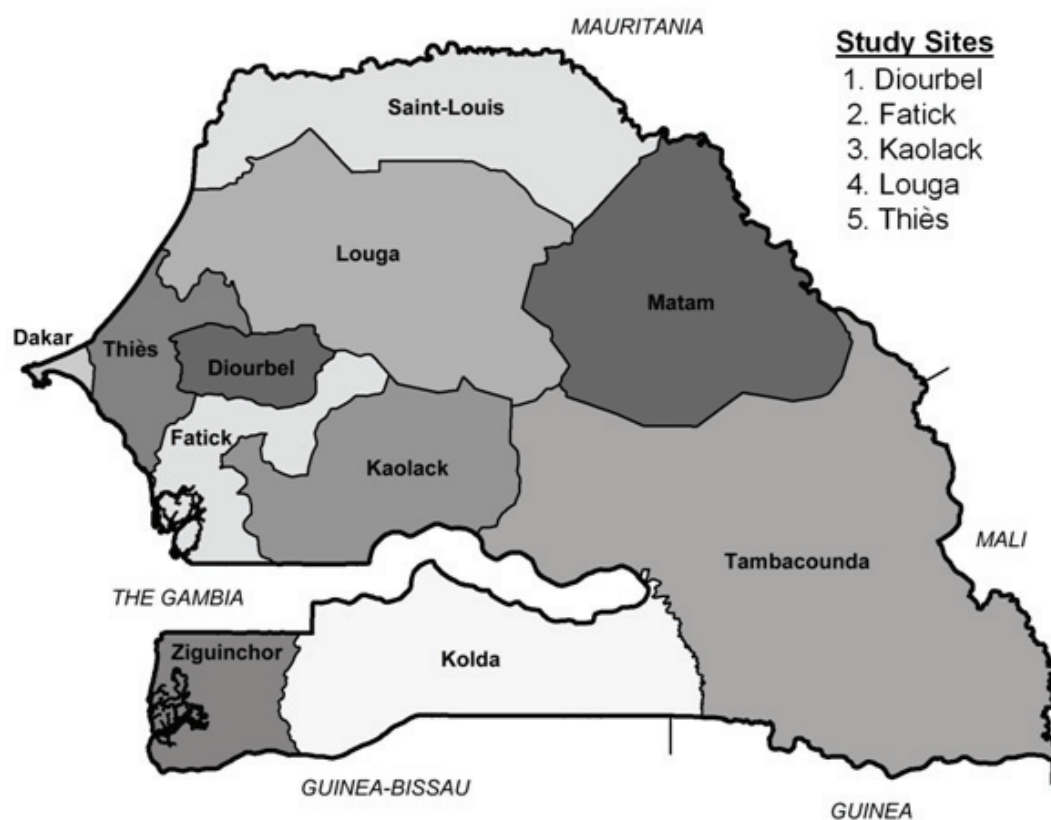
3. Data and empirical models

Data for this study comes from annual surveys conducted by the National School of Applied Economics (ENEA) in Dakar, Senegal. Each year, the ENEA targets rural communities to conduct an annual survey as part of its training program for first-year students. Selected sites vary annually to account for diversity in local characteristics (e.g. rainfall level, demography, agricultural activities). The most representative villages within the targeted rural communities are selected by the ENEA faculty for detailed study. ENEA students then conduct a village level census to collect data on geographical, economic, and demographic characteristics, which serve as the frame for sample selection. In each village, households are classified according to the number of economically active members, level of equipment and farm size as follows:

$$HE = \frac{\left(FS * \frac{AP}{TP} \right)}{EQ}$$

where HE = household endowment; FS = farm size; AP = active population; TP = total population and EQ = level of equipment measured on a scale from 1 (lowest) to 4 (highest).

Using the average and standard deviation of the HE variable, households are distributed into three groups (low, average and high). Next a subset of households from each category is randomly selected for the survey, which lasts for four months during the rainy season. After all the information has been coded, a comprehensive dataset is compiled at the end of each period. This study covers the 1998–2005 period for five regions: Diourbel, Thies, Kaolack, Louga and Fatick (see Figure 1) and includes 35 rural communities, 86 villages and a total of 631 households. A total of 129 observations were discarded because these farms do not produce peanuts or millet, and/or have incomplete data. The total number of households included in the analysis was 502, as shown in Table 1. Of this total, 411 households produce peanuts, 454 produce millet and all 502 planted at least one of the two crops, hereafter ‘peanut-millet’.

**Figure 1: Map of Senegal and study sites***Source: DIVA-GIS, 2011***Table 1: Regional survey data by year (1998-2005)**

Year	Region	No. of rural communities	No. of villages	No. of households
1998	Diourbel & Thies	3	9	81
1999	Thies	4	12	67
2000	Louga	4	9	73
2001	Kaolack	4	13	56
2002	Kaolack	6	11	47
2003	Fatick & Thies	4	11	71
2004	Fatick	4	9	37
2005	Fatick	6	12	70
Total		35	86	502

The choice of variables included in the models is based on the available data as well as on the rationale derived from both the theoretical and empirical literature related to technology adoption, as reviewed in the previous section. The dependent variable for the probit (adoption) models is equal to one if the household used fertilizer on peanuts, on millet, or on peanut-millet, and zero otherwise. Fertilizer application rates in peanut and millet production vary by type; hence, the dependent variable for the Tobit models is defined as the proportion of land planted with peanuts, millet or peanut-millet that received applications of chemical fertilizer relative to all cultivated land (intensity). Therefore, the dependent variable in the Tobit models is continuous, but bounded between zero and one.

The probit (equation 11) and Tobit (equation 12) models are specified as

$$Y_{iA} = \alpha X + e_i \quad (11)$$

$$Y_{iR} = \beta X + v_i \quad (12)$$

where Y_i is the response variable for the peanuts, millet or peanut-millet models, the subscript A denotes adoption and R intensity of use, X is a vector of explanatory variables, α and β are the parameters to be estimated, and e_i and v_i are the error terms.

On the basis of the preceding discussion, the expected signs for the respective parameters are: age of the household head (\pm), family size (+), literacy level of the household head (+), off-farm income (+), cultivated land (+), rainfall level (+), time trend (\pm), and regional dummies (\pm) representing north (Louga), south (Kaolack and Fatick), and central (Diourbel and Thies). The central region, comprising the Diourbel and Thies regions, is used as the reference category and is the omitted region.

4. Results and discussion

Table 2 presents the definition of the variables included in the analysis and their descriptive statistics. The mean age for household heads is about 55 years and household size is close to 15 members. The average literacy levels vary, but roughly 56% of all farmers are able to read and write in French, Arabic or a native language. There are regional differences in the availability of off-farm income, but on average 47% of the farmers who planted peanut and/or millet report having off-farm income. Farming in the Peanut Basin is rainfed, with a wide variation between north and south. The overall average annual rainfall is 534 mm. Land cultivated (owned, borrowed or rented) is roughly 7.0 ha and on average 3.2 and 2.9 ha are devoted to peanuts and millet respectively, which is consistent with the recommended rotation practice in the Basin.

Table 2: Variable definitions and descriptive statistics

Variable	Description	Peanut-Millet (N=502)					Peanut (N=411)					Millet (N=454)				
		North	Central	South	Ave	Freq (%)	North	Central	South	Ave	Freq (%)	North	Central	South	Ave	Freq (%)
<i>Peanut, millet or peanut-millet</i>	Peanut, millet or both with fertilizer (%)	3.00	7.80	32.00	-	42.00	.00	6.30	17.80	-	27.50	3.00	5.70	16.10	-	22.00
<i>Age</i>	Age of household head (yrs)	55.99	56.22	52.84	55.02	-	55.86	56.75	52.87	55.16	-	55.72	56.14	52.57	54.81	-
<i>Literacy</i>	Ability to read and write in French, Arabic or national language (1 if literate and zero otherwise) %	70.15	46.99	49.60	-	55.58	69.23	45.32	62.80	-	59.12	69.44	45.98	61.07	-	58.83
<i>Family size</i>	# of household members residing in the farm	16.07	14.68	14.84	15.00	-	16.22	15.71	15.97	16.00	-	15.61	14.80	14.98	15.00	-
<i>Land</i>	Total cultivated land (ha)	7.85	6.35	6.04	6.75	-	8.08	7.62	6.82	7.51	-	9.13	6.31	6.14	7.19	-
<i>Rainfall</i>	Amount of rainfall (mm)	438.59	513.71	648.42	533.57	-	438.66	494.33	642.53	525.17	-	441.42	519.37	647.15	535.98	-
<i>Off-farm income</i>	1 if a household receives off-farm income (%)	38.80	49.18	52.38	-	46.78	36.92	48.20	49.76	-	44.96	38.89	48.28	52.45	-	46.54
<i>North</i>	1 if Louga (%)	-	-	-	-	13.35	-	-	-	-	15.82	-	-	-	-	7.93
<i>Central</i>	1 if Diourbel or Thies (%)	-	-	-	-	36.45	-	-	-	-	33.82	-	-	-	-	38.33
<i>South</i>	1 if Kaolack or Fatick (%)	-	-	-	-	50.20	-	-	-	-	50.36	-	-	-	-	53.74
<i>Observations</i>		67	183	252	-	-	65	139	207	-	-	36	174	244	-	-

There is a wide variation in fertilizer use (see Tables 2 and 3), with less than a third of the farmers applying fertilizer on the peanut or millet crop. The application rate for farmers who use fertilizer on peanuts ranges from 0.03 to 250 kgs/ha across all five regions, with an average rate equal to 72 kgs/ha. This average is well below the recommended rate of 200 kgs/ha or more for gypsum (i.e. calcium topdressing) (FAO, 2006; Ntare et al., 2008), while the average recommendation for NPK (nitrogen, phosphorous and potassium) for Senegal is 150 kgs/ha (Gascho, 2011). The average application rate on millet is roughly 63 kgs/ha, with observations ranging from 0.31 to 205 kgs/ha across regions. Again, this average rate is far less than the recommended 200 kgs/ha of NPK for the millet production systems in the Sudano-Sahelian agro-ecological regions (Hayashi et al., 2008). These low fertilization rates are consistent with findings from Kelly (1988), who argued that farmers fail to follow recommended practices, especially those relating to fertilizer application.

Table 3: Fertilizer application rates for adopters by region

Peanut production (kgs/ha)					
Region	Sample	Min	Max	Mean	Std dev.
North	1	-	-	12.5	-
Central	26	2.94	165	74.7	38.31
South	86	0.03	250	70.98	55.99

Millet production (kgs/ha)					
Region	Sample	Min	Max	Mean	Std dev.
North	14	7.66	205.3	64.24	58.31
Central	13	0.31	152.42	52.62	55.68
South	73	2.16	203	74.3	46.46

Three probit and three Tobit models, one each for peanut, millet and peanut-millet, are estimated and the coefficients and standard errors are presented in Table 4. Table 5 provides the marginal effects for variables included in the probit and Tobit models. The same basic variables are included in the adoption and the intensity of fertilizer use models. The dependent variable for the probit models is dichotomous ('use' and 'non-use' of fertilizer) and for the Tobit models it is the share of land planted and treated with chemical fertilizer (under peanut, millet or peanut-millet) with respect to all cultivated land. Unlike the binary model, the Tobit model provides estimates of both the likelihood of technology adoption and the intensity of use.

Table 4: Results for adoption and use intensity

Variable	Probit						Tobit					
	Peanut		Millet		Peanut-Millet		Peanut		Millet		Peanut-Millet	
	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
Age	.002	.42	-.004	-0.75	-.001	-.15	.0045	.39	-.0036	-.35	-.0006	-0.20
Family size	.003	.37	.024***	2.84	.021***	2.83	-.0036	-.20	.0345**	2.24	.0107**	2.22
Literacy	.245	1.54	.125	0.87	.232*	1.76	.2013	.61	.2844	1.03	.1331	1.52
Off-inc	-.273*	-1.77	-.237*	-1.67	-.408***	-3.13	-.6816**	-2.06	-.4200	-1.54	-.2362***	-2.72
Farm size	.026*	1.87	.008	0.56	.019	1.50	.0526*	1.84	.0106	.41	.0044	0.54
Rainfall	.001***	2.53	-.0002	-0.41	.0001	.27	.0021*	1.86	.0002	.23	.0003	1.27
Trend	-.128**	-2.36	-.174***	-3.38	-.161***	-3.46	-.3030***	2.56	-.3968***	-3.71	-.1081***	-3.49
North	.611**	2.37	-.376	-1.00	.125	.55	1.3083**	2.37	-1.2951	-1.46	.1367	0.89
South	1.252***	4.18	1.423***	5.19	1.367***	5.51	2.569***	3.66	2.7288***	4.53	.8901***	5.29
Constant	-2.208***	-4.61	-.856***	-2.11	-1.051***	-2.81	-3.641***	-3.29	-1.7551**	-2.16	-.6866***	-2.73
Sigma							2.167	6.98	1.9788	7.90	.7393	14.13
Likelihood ratio	65.20		64.70		82.70		-253.10		-291.30		-331.01	
Sample size	411		454		502		411		454		502	
z-score	0.62		-0.01		0.56		.549		-.178		.627	
$f(z)$.343		.393		.327	

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Parameter signs tend to be quite consistent across the probit and Tobit models, although significance levels do vary. In general, the level of statistical significance of the parameters for family size, off-farm income, farm size, rainfall, region (north and south) and the time trend is high for both the probit and Tobit models, while the parameter for literacy is statistically significant only for the adoption model.

Family size is used as a proxy for labor availability and has a positive effect on fertilizer adoption and intensity of use in the millet and peanut-millet models. The coefficient is statistically significant at the 1% level in the probit model and at the 5% level in the Tobit model for millet and peanut-millet, respectively. These findings confirm that labor availability has an impact on the decision to adopt and intensify fertilizer use. These results are consistent with those reported by Zegeye et al. (2001) for adoption of improved maize technology in Ethiopia, indicating that labor availability increases the rate of technology adoption, but contrary to findings by Freeman and Omiti (2003) for fertilizer use by smallholder farmers in Kenya. The results in Table 5 indicate that a unit increase in household size raises the probability of fertilizer use among non-adopters by 0.9% and 0.7% for the millet and peanut-millet models, respectively.

Table 5: Marginal effects for probit and Tobit

Variable	Probit			Tobit								
	Peanut	Millet	Peanut-Millet	Peanut			Millet			Peanut-Millet		
	M.E	M.E	M.E	$\delta EY/\delta X$	$\delta EY^*/\delta X$	$\delta F(z)/\delta x$	$\delta EY/\delta X$	$\delta EY^*/\delta X$	$\delta F(z)/\delta x$	$\delta EY/\delta X$	$\delta EY^*/\delta X$	$\delta F(z)/\delta x$
Age	.001	-.0016	-.0002	.0005	.0023	.0007	-.0004	-.0012	.0007	-.0002	-.0003	-.0003
Family size	.001	.0095	.0072	-.0004	-.0018	-.0006	.0004	.0112	.0068	.0029	.0056	.0047
Literacy	.088	.0477	.0830	.0316	.1007	.0318	.0541	.0923	.0564	.0611	.0696	.0589
Off-inc	-.081	-.0950	-.1217	-.0963	-.3411	-.1078	-.0834	-.1362	-.0833	-.0942	-.1234	-.1045
Farm size	.008	.0031	.0063	.0053	.0263	.0083	.0012	.0035	.0021	.0012	.0023	.0019
Rainfall	.001	-.0001	.0000	.0002	.0010	.0004	.0000	.0001	.0000	.0001	.0002	.0001
Trend	-.041	-.0715	-.0519	-.0461	-.1516	-.0479	-.0794	-.1288	-.0787	-.0447	-.0565	-.0478
North	.228	-.1483	.0423	.2327	.6546	.2070	.1409	-.4201	.5413	.0647	.4652	.3938
South	.468	.4196	.5033	.4477	1.2857	.4065	-.2558	.8851	-.2569	.4537	.0714	.0605

The coefficient for literacy has the expected positive sign for all models, but is statistically significant only at the 10% level for the peanut-millet adoption case. This result supports the hypothesis that human capital plays a positive role in the acquisition and evaluation of new ideas. Moreover, programs and materials promoting technological change typically favor literate farmers. This result is consistent with other findings in Africa, including Cameroon (Nkamleu & Adesina, 2000), Ethiopia (Bacha et al., 2001; Zegeye et al., 2001), Malawi (Chirwa, 2005) and Nigeria (Chianu & Tsujii, 2004).

Off-farm income is hypothesized to compensate for any additional financial resources that are associated with new technologies. The coefficient for off-farm income has a negative effect for both the adoption and intensity of use models. The parameter is statistically significant at the 1% level (peanut-millet), and at the 10% level for both peanut and millet (probit models). For the intensity of use, the coefficient is negative and statistically significant at the 1% and 5% levels for the peanut and peanut-millet models, respectively. Results on adoption are contrary to what is reported by Chirwa (2005) but support findings by Makokha et al. (2001) for determinants of fertilizer and manure use in Kenya. This negative effect could be attributed to the higher relative returns from other investments. If off-farm enterprises have higher returns, then households might prefer to invest in options that have better returns, given the risk involved in agriculture. Availability of off-farm income decreases the likelihood of adopting and intensifying fertilizer use among non-adopters by 9.6%, 8.3% and 9.4% in the peanut, millet and peanut-millet models, respectively.

In this study, farm size in hectares is taken as a proxy for wealth. The coefficient for land is positive as expected in all models, but is statistically significant only at the 10% level for the peanut model (probit and Tobit models). A unit increase in farm size increases the probability of fertilizer adoption for non-adopters by 0.8% while the same change increases the expected area under fertilizer by 0.1% (peanut models). These results are contrary to what Croppenstedt and Demeke (1996) found on adoption of chemical fertilizer in Ethiopia, but consistent with other studies carried out on adoption of agricultural technologies especially in Ethiopia (Zegeye et al., 2001), Zambia (Knepper, 2002), Tanzania (Isham, 2002), and Malawi (Chirwa, 2005). The

findings support the notion that farm size influences fertilizer adoption and intensity of use, which is compatible with the notion that access to agricultural inputs and other services is easier for larger producers.

Adoption rates, especially for fertilizer, are further linked to the availability of rainfall. Consistent with this expectation, the coefficient for rainfall for the peanut and peanut-millet models has a positive sign as anticipated, and is statistically significant at the 1% and 10% level in the peanut model for adoption and use intensity, respectively. As observed by Freeman and Omiti (2003), regions with better soil quality and higher water availability are more likely to adopt and intensify fertilizer use.

Location-specific dummy variables are used to capture overall agro-ecological conditions, which are also expected to influence fertilizer use. The positive and statistically significant results for the southern region parameter (1% level) for all models and that of the northern region (5% level) for the peanut models confirm our prior expectation that farmers located in areas with better soil conditions and more rainfall are more likely to use fertilizer (Kherallah et al., 2002; Chianu & Tsujii, 2004). The likelihood that non-adopters in the southern region would use fertilizer increased by roughly 42% for the peanut and millet models, and by 50% for the peanut-millet model as compared to households in the central region (the reference category). However, the probability that adopters in the southern region would intensify fertilizer use increased by as much as 40% for peanut, but decreased by 26% for the millet model.

In the probit models, the coefficient for the time trend variable is negative in all cases and statistically significant at the 1% level for the millet and peanut-millet models, and at the 5% level for the peanut model. However, for the Tobit model the coefficient is negative and statistically significant at the 1% level in all three models. Farmers in the Basin experience a host of factors that constrain use and intensification of fertilizer, including limited cash, lack of inputs, unfavorable weather conditions and difficulty accessing information. The results in Table 4 indicate that the likelihood of adopting and intensifying fertilizer use decreased by 5%, 8% and 5% over the study period 1998 to 2005 for the peanut, millet and peanut-millet models, respectively. This suggests that market liberalization policies, which caused government support to the agricultural sector to diminish during the period analyzed, led to lower fertilizer use.

5. Conclusions and policy implications

The paper contributes to the debate on the adoption of agricultural technologies in Africa. The study it describes examined some factors involved in adoption of new technologies, specifically those that influence the adoption and intensity of use of fertilizer by peanut and millet farmers in the Senegalese Peanut Basin. The results revealed both low adoption and low intensity of use of chemical fertilizers, with less than a third of the households in the Basin applying this input. Note that the Basin lies within the Sahel region, which means that these low adoption rates seem inadequate to sustain agricultural productivity and self-sufficiency in food production.

The results revealed that the decision to adopt and intensify fertilizer use is specific to a particular crop or a combination of crops (peanut, millet, or peanut and millet combined) and also depends on family size, literacy level, farm size and availability of rainfall. The finding that off-farm income has a negative effect on fertilizer adoption and use intensity suggests that agriculture is not very profitable for small farmers in Senegal. These results contradict expectations but support the notion that farmers with off-farm income prefer not to use it to buy

fertilizer. These findings could be attributed to low returns in agriculture, suggesting that policies that support value-added agricultural enterprises could increase reinvestment in farming.

Education plays a crucial role in technology adoption and this study revealed a positive relationship between education and fertilizer use by peanut and millet farmers. Literacy level influences farmers' ability to interpret information about recommended practices, which in turn affects their decision to adopt. Designers of agricultural programs should keep in mind that a significant number of farmers in the Basin have a low level of education.

Regional characteristics are also important in the decision to adopt and intensify the use of fertilizer, as evidenced by the differences found across the northern and southern regions. Policy makers should therefore take regional differences into consideration when promoting agricultural programs. For example, market oriented alternatives that aim to reduce production costs, and thus provide incentives for farmers to invest in agricultural technologies, deserve close scrutiny. It is also important to consider fertilizer adoption as part of a technology package along with other inputs, such as irrigation, within the Basin.

Lack of suitable data unfortunately made it impossible to evaluate the effect that extension services and social capital might have on information acquisition and the subsequent adoption of new technologies, or what the role of women might be in this regard, which suggests the need for further research in these areas in the Basin.

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