

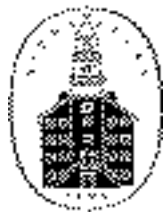
“The Effect of Social Capital on Fertilizer Adoption:
Evidence from Rural Tanzania”

by

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***The Effect of Social Capital on Fertilizer Adoption:
Evidence from Rural Tanzania***

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Do the characteristics of local social structures affect fertilizer adoption among rural households? This paper extends the model of technology adoption of Feder and Slade (1984) to incorporate social capital, and then tests the model with household data from two agro-ecological zones in rural Tanzania. Probit estimates of the model show that the probability of adoption of improved fertilizer in 1994-95 in the Central Plateau region is increasing in land under cultivation, cumulative adoption patterns, ethnically-based social affiliations, the adoption of improved seeds, the availability of credit and extension services, and the average years of residence in the village. In the Plains region, this probability is increasing in land under cultivation, ethnically based social affiliations and consultative norms. Overall, these results, which are robust after testing for the likely reverse causality of land under cultivation, support the finding that ethnically based and participatory social affiliations act as forms of social capital in the adoption decision.

Keywords: social capital, technology adoption, Tanzania

JEL Codes: Z13, Q16; 012

I. Introduction¹

Despite being perhaps the most important purchased input in African agriculture, fertilizer has not grown in use among Tanzanian smallholder farmers since the early 1980s (Kherallah *et al.* 2000).² In 1994, fertilizer use in Tanzania averaged 10 kilograms per hectare, as opposed to 18 kilograms in Africa and 94 kilograms in the world (World Bank 2000). Farm size, human capital, the availability of extension services, geographical characteristics, and relative prices are among the determinants of fertilizer adoption that have been identified in the last decade (Nkonya *et al.* 1997; Kaliba *et al.* 2000).

Fertilizer adoption in rural Tanzania is an excellent candidate for testing an economic model of information diffusion and technology adoption that incorporates social capital, “the set of elements of the social structure that affects relations among people and are inputs or arguments of the production and/or utility function” (Schiff 1992, p. 158).³ Nkonya *et al.* (1998) found that while seed technologies are normally

¹ I thank the Center for Institutional Reform and the Informal Sector (The IRIS Center) for financial support for this research; Deepa Narayan for permission to use the data from the Social Capital and Poverty Survey; and the staff of the Economic and Social Research Foundation for assistance in obtaining the National Sample Census of Agriculture. For their critiques and suggestions on earlier drafts of this paper, I thank Anand Swamy, Harry Kelejjan, Peter Murrell, Kurt Finsterbusch, Michael Woolcock, Ephriam Nkonya, and an anonymous referee. On this and related research, I thank Roger Betancourt for his guidance.

² Most Tanzanian smallholder farmers grow maize as a subsistence and cash crop. At high and intermediate altitudes, inorganic fertilizer (including urea, calcium ammonium nitrate, or sulfate of ammonia) can significantly increase returns to maize production as well as other staple crops (Hawassi *et al.* 1998; Katinila *et al.*, 1998).

³ Woolcock (1998) defines social capital as ‘the norms and networks that facilitate collective action’ and presents other definitions based on an extensive literature search.

adopted very rapidly, fertilizer is not adopted until farmers have compiled knowledge about its use. Katinila *et al.* (1998) find that farmers in southern Tanzania lack knowledge about using inorganic fertilizer, but that the main sources of information about its use are extension agents and other farmers.

Is information diffusion about inorganic fertilizer in Tanzania affected by characteristics of local social structures? Detray (1995) found that member-controlled participatory associations have a significant positive effect on farmers' market orientation in two regions in Tanzania. Narayan and Pritchett (1999), in their seminal study on poverty and social capital in rural Tanzania, find that households in villages with high levels of their 'social capital index' have greater use of modern agricultural inputs. They do not, however, test a formal model of technology adoption with a complete set of data that includes other potential determinants of adoption, including household-level land endowments and village-level adoption patterns. In addition, they did not test whether specific characteristics of social structures -- including group homogeneity, participatory norms, and leadership heterogeneity -- are the critical determinants of adoption.

In this paper, I extend the model of Feder and Slade (1984) in which the acquisition of information and the adoption of new technology are increasing in two household-level characteristics -- human capital and land -- and two village-level characteristics -- the cumulative proportion of adopters and social capital. The model is then tested using household data from two recent household surveys in rural Tanzania,

which include information on fertilizer adoption, selected household- and village-level characteristics, and characteristics of local social structures.

II. Information Diffusion and Technology Adoption

Adoption of improved technologies can dramatically improve the well-being of agricultural households, but many questions about the determinants of adoption remain unanswered (Feder, Just, and Zilberman 1985, Besley and Case 1993).⁴ Economic research on technology adoption in rural areas has only partially addressed the issue of how the social structure can affect adoption (Feder and Slade 1984; Case 1992; Foster and Rosenzweig 1995; Pomp and Burger 1995). These studies build their modeling or empirical estimation on a very likely assumption: that neighboring agricultural households are, *de facto*, members of a social structure who exchange information about improved agricultural practices. None of these studies models or tests how social structures, which vary from village to village, may affect adoption.⁵

However, much non-economic research suggests that the characteristics of social structures are critical determinants of information diffusion among rural households. Specifically, Rogers (1995) cites three characteristics of social structures that promote

⁴ Following Feder, Just, and Zilberman (1985), adoption is defined as “the degree of use of a new technology in long-run equilibrium when the farmer has full information about the new technology and its potential.”

⁵ In her study, for example, Case (1992) does note that if more information were known about the ‘amount of influence that each [neighboring] household wields,’ then this could be integrated into the estimation procedure. More recent research has looked at social networks and information diffusion in other settings: Barr (1997) finds empirical evidence that information

more rapid diffusion of innovations in rural settings. Group homogeneity⁶, the degree to which two or more individuals who interact are similar in certain attributes, promotes more information sharing. When individuals share common attributes and beliefs, communication between them is more likely to be effective. For example, Munshi and Myaux (1998) find evidence that information diffused among households with similar religious affiliations helps to explain the adoption of improved contraception methods in Matlab, Bangladesh.

Participatory norms, the degree to which local customs promote interactive decision-making, promote more rapid diffusion. In villages with such social norms, innovators are able to share their new ideas and influence the opinions of others -- through the established consultative mechanisms. Rogers (1995) presents a range of evidence that when norms favor communication and interaction among agents, 'early' adopters can share more rapidly their successful use of innovations.

Leadership heterogeneity, the degree to which leaders within a social structure differ in certain attributes, can also accelerate the diffusion of innovations. When villages leaders have dissimilar social and economic characteristics -- and therefore different contacts across social subsystems -- they can learn about the use of innovations from outside sources and then share this new information with other local villagers. In a range of settings, Granovetter (1973) has shown that when leaders have different professions or

diffused via social networks helps to explain productivity difference among Ghanaian enterprises.

⁶ Rogers uses the terms 'homophily' and 'heterophily', respectively, for homogeneity and heterogeneity within social structures.

higher socioeconomic status than other members of a social structure, this can provide an information link between two different sets of agents: such links are critical in information sharing about innovations across group.

III. Extending a Model of Technology Adoption

Feder and Slade (1984) present and test a model of technology diffusion that incorporates passive information accumulation through farmer's contacts with neighbors. Their model predicts that farmers with more schooling and greater land will have more knowledge of improved practices and will adopt these practices more rapidly. The extension of their model presented in this section includes characteristics of local social structures as a fixed input into the accumulation of household knowledge, which affects the adoption decision. This extended model is then estimated to test whether group homogeneity, participatory norms, and leadership heterogeneity promote the adoption of fertilizer.

A. The Model of Feder and Slade (1984).

The model of Feder and Slade (1984) begins by considering a single village of M farmers. An improved agricultural input has recently been exogenously introduced into the village, for example, by a trader in a local market or by an extension agent.

Each farmer's stock of knowledge in period t is defined as⁷:

$$(1) \quad K_t = K_{t-1} + A_t + I_t,$$

⁷ For notational simplicity, the index for each farmer is subsumed in this and all subsequent equations for the theoretical model.

where K_{t-1} is the carried-over stock from the previous period, A_t is private ‘actively acquired’ information, and I_t is public ‘passively acquired’ information.

Public information is available to all farmers without cost. Private information requires monetary resources (or time). Its cost is:

$$(2) \quad C_t = C(A_t),$$

where $C(\cdot)$ is a convex cost function, so that $C' > 0$, $C'' > 0$, and $C(0) = 0$.

Let agricultural production be a function of both the general and input-specific impacts of knowledge. Each farmer’s agricultural output Y_t depends on a positive stock of knowledge, a positive endowment of land (L), and a non-negative amount of the improved input (N_t) as follows:

$$(3) \quad Y_t = g(K_t) F(L, h(K_t) N_t).$$

Let a positive amount of N_t be characterized as household-level adoption of the improved input. The general impact of knowledge on productivity is represented by the knowledge function $g(\cdot)$. Assume that g is concave, so that $g' > 0$, $g'' < 0$. In addition, assume that $g(\cdot)$ converges to an upper limit (g^*) as cumulative knowledge increases to an upper limit (K^1). Likewise, the input-specific impact of knowledge on productivity is represented by the knowledge function $h(\cdot)$, with similar properties.

Let the production function $F(\cdot, \cdot)$ be concave and linearly homogenous (constant returns to scale) in its two arguments, land and the product of the improved input and the productivity-shifting knowledge function $h(\cdot)$. Assume also that $F(\cdot, 0) > 0$ and $F_L(\cdot, 0) =$

$F_0^* > 0$ (and is finite), so that farmers who use none of the improved input can still produce an output.⁸

With the assumption of constant returns to scale of $F(.,.)$ in its two arguments, the output per acre for each farmer is y_t :

$$(4) \quad y_t = g(K_t) f(h(K_t) n_t),$$

where n_t is the amount of the improved input per acre. From the assumptions about $F(.,.)$, $f' > 0$, $f'' < 0$, $f(0) > 0$, and $f'(0) = f'_0 > 0$ (and is finite).

The per-period profit for the farmer is:

$$(5) \quad \Pi_t = L [g(K_t) f(h(K_t) n_t) - pn_t] - C(A_t),$$

where p is the price of N_t and output price is unity. The farmer's myopic objective is to maximize (5) subject to (1) and $n_t \geq 0$, $A_t \geq 0$.

B. Extension of the Model of Feder and Slade (1984).

This model is extended here in three ways. Human capital is formally introduced into the model,⁹ and the quantity of public information is affected by the village-wide cumulative proportion of adopters and village-wide social capital.

To introduce human capital into the model, let the impact of knowledge be dependent on each farmer's level of human capital. First, the general impact of

⁸ The model of Feder and Slade (1984) does not consider the effect of labor inputs. How is this justified, as labor is clearly a necessary input into agricultural production? Labor and other (variable or fixed) inputs can easily be integrated into a more fully specified production function (where a concave and linearly homogenous production function $F^*(.,.)$ has n arguments -- land, the product of the improved input and the productivity-shifting knowledge function, and $n-2$ other inputs). But as long as there are no interactive effects between labor and the other possible inputs, the solutions for such a production function do not affect the fundamental results on knowledge and technology adoption that are the focus of this model.

knowledge on productivity is now represented by the productivity function $g = g(V, K_t)$, where V is each farmer's stock of human capital. Assume that overall productivity is increasing in both human capital and knowledge (so that $g_v, g_k > 0$, $g_{vv}, g_{kk} < 0$, and $g_{vk} > 0$). Let $g(\cdot)$ converge to an upper limit ($g^*|_V$) as cumulative knowledge increases to an upper limit (K^1). Note that the upper limit $g^*|_V$ is increasing in the level of human capital: with the stock K^1 , farmers with more human capital will achieve higher levels of productivity. Let the input-specific impact of knowledge on productivity now be represented by the knowledge function $h = h(V, K_t)$, with similar properties.

Let public information in each period be increasing in the village-wide adoption pattern and social capital, so that I_t is defined as:

$$(6) \quad I_t = I(M_t, S_t),$$

where M_t is the cumulative proportion of village-level adopters at the beginning of period t and S_t is village-level social capital. Assume that $I_m, I_s > 0$, $I_{mm}, I_{ss} < 0$, and $I_{ms} > 0$.

With these two modifications, per acre output and per period profit are, respectively:

$$(4)^* \quad y_t = g(V, K_t) f(h(V, K_t) n_t);$$

$$(5)^* \quad \Pi_t = L [g(V, K_t) f(h(V, K_t) n_t) - pn_t] - C(A_t).$$

Under this extended set-up, the maximization of profits will now be affected by human capital, the cumulative proportion of adopters and social capital.

⁹ Feder and Slade (1984) suggest that human capital can be integrated into their model but do not formally extend the model.

Based on these extensions, the farmer's myopic objective is to maximize (5)* subject to (1), (6) and non-negativity of the choice variables ($A_t \geq 0$, $n_t \geq 0$). The first order conditions (FOC) for an optimum of this Kuhn-Tucker problem are:

$$(7) \quad \Pi_a = L [gf'h_k n + g_k f] - C' \leq 0 \text{ and } A_t \Pi_a = 0.$$

$$(8) \quad \Pi_n = L [gf'h - p] \leq 0 \text{ and } n_t \Pi_n = 0;$$

Based on these conditions, there are four possible solutions for a maximum:

- No knowledge accumulation and no adoption ($A = 0$, $n = 0$), where

$$(9a) \quad \Pi_a = L g_k f - C' < 0 \text{ and } \Pi_n = L [gf'h - p] < 0;$$

- Knowledge accumulation and no adoption ($A > 0$, $n = 0$), where

$$(9b) \quad \Pi_a = L g_k f - C' = 0 \text{ and } \Pi_n = L [gf'h - p] < 0;$$

- Knowledge accumulation and adoption ($A > 0$, $n > 0$), where

$$(9c) \quad \Pi_a = L [gf'h_k n + g_k f] - C' = 0 \text{ and } \Pi_n = L [gf'h - p] = 0;$$

- No knowledge accumulation and adoption ($A = 0$, $n > 0$), where

$$(9d) \quad \Pi_a = C(0)' = 0 \text{ and } \Pi_n = L [gf'h - p] = 0.$$

The solutions of the model define a process of knowledge accumulation and adoption in a village where a new technology has been introduced. Farmers who acquire private information will do so until the value of its marginal product, through its effect on general productivity (equation 9b) or input-specific productivity (9c) equals its cost. Farmers who adopt a new technology (9c and 9d) will do so until the per-hectare value of its marginal product, through its direct effect on output, equals its unit price.

This set of solutions defines a process of knowledge accumulation and adoption in a village where a new technology is introduced. Four propositions about the determinants

of knowledge accumulation and adoption at the household level can be derived from these solutions¹⁰:

Proposition 1: Farmers with greater land will obtain more private information and adopt more rapidly.

Proposition 2: Farmers with more human capital will obtain more private information and adopt more rapidly.

Proposition 3: Farmers with neighbors that adopt will have higher levels of cumulative information and adopt more rapidly.

Proposition 4: Farmers in villages with higher levels of social capital will have higher levels of cumulative information and adopt more rapidly.

The intuition behind these propositions is as follows. *Ceteris paribus*, farmers with higher levels of land and higher levels of human capital will obtain more private information: with more land or education, a small increase of knowledge will have a greater marginal effect on farm productivity. *Ceteris paribus*, farmers in villages with more adopters among neighboring farmers and with higher levels of social capital have more cumulative information: each of these characteristics are associated with knowledge spillovers. Both of these increases of information will lead to a more rapid adoption of the new technology.¹¹

To estimate this model, begin by letting K_{ij}^* be a latent random variable for household i in village j which is some measure of the household's stock of knowledge

¹⁰ The proofs of these propositions are available from the author.

¹¹ Note that this model is consistent with the possibility that some elements of the social structure can have negative effects on the availability of public information and the adoption of new technologies. For example, in villages with high levels of inequality and norms that

about improved agricultural practices in a given year t . Assume that K_{ij}^* is a linear function of a set of non-stochastic household-level independent variables and an error term. These household-level covariates include (as predicted by propositions 1 and 2) human capital (H_{ij}) and land (L_{ij}) as well as a vector of other household-level variables (X_{ij}^h) that could affect the accumulation of knowledge (including household demographics and agricultural practices).

Let K_{ij}^* also be a function of a village-level fixed effect (W_j) which affects all households within village j , so that:

$$(10) \quad K_{ij}^* = \beta_0 + H_{ij}\beta_1 + L_{ij}\beta_2 + X_{ij}^h\beta_3 + W_j + \mu_{ij},$$

$$i = 1 \dots m_j, j = 1 \dots n^*$$

where μ_{ij} is iid $\sim N(0,1)$.¹²

Let the fixed effect W_j be a linear function of non-stochastic village-level independent variables and an error term. These covariates include (as predicted by propositions 3 and 4) the cumulative proportion of adopters (P_j) and social capital (S_j) as well as a vector of other village-level variables (X_j^v) that could affect the accumulation of knowledge (including agricultural resources and village wealth and migration). Accordingly,

$$(11) \quad W_j = \alpha_0 + P_j\alpha_1 + S_j\alpha_2 + X_j^v\alpha_3 + \varepsilon_j,$$

$$j = 1 \dots n^*,$$

discourage social contacts between the rich and the poor, these norms would hinder the flow of public information about agricultural practices from the rich to the poor.

where ε_j is iid $\sim N(0, \sigma_\varepsilon^2)$.

Combining (10) and (11) yields:

$$(12) \quad K_{ij}^* = \beta_0 + \alpha_0 + H_{ij}\beta_1 + L_{ij}\beta_2 + P_j\alpha_1 + S_j\alpha_2 + X_{ij}^h\beta_3 + X_j^v\alpha_3 + \mu_{ij} + \varepsilon_j,$$

$$i = 1 \dots m_j, j = 1 \dots n^*.$$

Assuming that the process (ε_j) is independent of the process (μ_{ij}) , (3) has the structure of a random effects model (Greene 1993). Propositions 1 - 4 of the model predict that β_1 , β_2 , α_1 and α_2 in (3) will be positive.

Unfortunately, K_{ij}^* , some measure of the total amount of knowledge about improved agricultural practices of each household, is not observed. Instead, only the adoption decision about improved fertilizer of each farmer is observed. Let $F_{ij} = 1$ if the measure of knowledge exceeds a certain amount K^f and the improved fertilizer is adopted, and let $F_{ij} = 0$ if the measure is less than K^f and the improved fertilizer is not adopted:

$$(13) \quad F_{ij} = \begin{cases} 1 & \text{if } K_{ij}^* > K^f \\ 0 & \text{if } K_{ij}^* \leq K^f \end{cases}.$$

Formal estimation of (12) requires data on fertilizer adoption (F_{ij}), human capital (H_{ij}), land (L_{ij}), cumulative proportion of adopters (P_j), social capital (S_j), as well as other possible household-level (X_{ij}^h) and village-level regressors (X_j^v).

¹² Households are indexed from 1 to m_j since the number of households surveyed per village varies from 10 to 15.

IV. Data for Estimating the Model of Technology Adoption

In order to estimate this model, two data sets -- from surveys conducted in overlapping villages but not in the same households -- were merged.¹³ The Social Capital and Poverty Survey (SCPS), conducted in 1995, was a stratified random sample of households in 87 villages across Tanzania. In addition to collecting a limited amount of household data on family demographics, household expenditures and some agricultural practices and characteristics (but not on land under cultivation), this survey collected detailed information about local social structures within these villages. To assess the characteristics of social structures, the survey primarily focused on household activity in local organizations: social organizations as well as religious and economic groups.¹⁴

The National Sample Census of Agriculture (NSCA) was conducted in two consecutive agricultural seasons (1993-94 and 1994-95) in households in 540 villages. It contains detailed information on the use of fertilizer, land under cultivation and land availability, human capital, and other household demographics.

¹³ The variables in each of these data sets were collected by teams of local enumerators who were trained by members of the department of economics of the University of Dar es Salaam. After tests of the survey instruments, each enumerator was able to interview about five households per day. Detailed documentation of the methodology for the HRDS can be found in World Bank (1995).

¹⁴ This was the first household-level survey that integrated the collection of household data on the causes and consequences of economic decisions (compatible with the World Bank's Living Standards Measurement Study (LSMS)) and data on local social structures. Since its implementation in 1995, there have been three other such surveys conducted in Bolivia, Burkina Faso and Indonesia (World Bank 1998).

Based on the merging of these two data sets, the model can be tested in two different agro-ecological zones: the central plateau (297 households from the 1994-95 season in 23 villages) and the plains (142 households from the 1994-95 season in 11 villages).¹⁵ For these households, means and standard deviations of selected household- and village-level variables are presented in Table 1.

¹⁵ Data from additional households was available from one other agro-ecological zone -- the highlands -- but the model is inestimable among the six villages in this zone because of the presence of four village-level regressors (the three social capital variables and 'years in village', as detailed below) and the lack of village-level variance of 'cumulative adoption' (since three villages had complete adoption, and three others had no adoption.)

Table 1: Selected Summary Statistics in Rural Tanzania

	<u>Variable description</u>	<u>Summary statistics</u>	
		<i>Central Plateau</i>	<i>Plains</i>
Dependent variable	Fertilizer adoption	0.26 (0.44)	0.09 (0.29)
	Predicted determinants of adoption	Education (in years) Land (in log hectares) Cumulative adoption Ethnic affiliations Consultative norms Leadership heterogeneity	4.64 3.40 0.24 0.23 0.66 0.29 (2.82) (1.21) (0.35) (0.21) (0.17) (0.15)
Other possible determinants of adoption	Female	0.13 (0.33)	0.23 (0.42)
	Age (in years)	44.7 (15.4)	46.6 (15.3)
	Improved seeds	0.23 (0.42)	0.23 (0.42)
	Credit availability	0.09 (0.29)	0.07 (0.26)
	Extension activity	0.15 (0.36)	0.20 (0.40)
	Years in village	18.4 (2.5)	18.0 (2.3)

Note: Means and (standard deviations) of selected variables. See text for description of variables.

As listed in Table 1, the dependent variable is ‘fertilizer adoption’, a dichotomous variable that indicates whether households surveyed in the HRDS report using some inorganic fertilizer in the 1994-95 season.

The variables that are used to test the first three propositions of the model, derived from the HRDS, are as follows. ‘Years of education’ is the years of education of the head of the household, calculated from the self-reported highest grade completed. ‘Land’ is the log of hectares of cultivated land, calculated from self-reported estimates of land per household¹⁶. ‘Cumulative adoption’ is the village cumulative proportion of adopters in the 1994-95 season, excluding the farmer concerned.

The village-level variables that are used to test the fourth proposition of the model are derived from the SCPS. From this survey data, three different variables were created to measure the three characteristics of social structures identified by Rogers (1995) that promote diffusion of innovations: group homogeneity, participatory norms, and leadership heterogeneity. All of these variables were derived from self-reported household activity in social organizations and religious and economic groups. When a household was a member of more than one organization, these variables were derived from average group characteristics.

‘Ethnic affiliations’ is the village share of households that report that their local organizations include only members of the same clan (as opposed to different ethnic groups). Note that this measure might differ from the overall ethnic fractionalization of

the villages themselves. For example, if a village was ethnically heterogeneous but the social groups within the village were ethnically homogeneous -- so that villagers tend to socialize only with their own ethnic group -- the variable would capture this difference. 'Consultative norms' is the village share of households that report that members vote and discuss decisions within their local organizations, as opposed to having decisions made by leaders alone. 'Leadership heterogeneity' is the village share of households that report that their local organizations have leaders with different livelihoods than other village members.

The variables that are used to measure other household- and village-level characteristics that could effect the adoption decision are: 'age', the self-reported age of the household head, and 'age squared'; 'female', a dummy variables for female headed-households; 'improved seeds', a dummy variable for households that reports using this technology;¹⁷ 'credit availability', a dummy variable for households that report that credit is available to their household; 'extension activity', a dummy variable for households that report that they were visited by an extension agent; and 'years in village', the average years of residence in the village. All but the last of these variables was derived from the HRDS: the years of residence in the village were not part of the HRDS survey instrument, so the village-level mean from the SCPS is used as 'years in village.' The choice of these variables as regressors in the basic model is based on literature reviews of the

¹⁶ This is the same measure of land used by Feder and Slade (1984). Using the logarithmic transformation imposes a decreasing effect of land endowments on the probability of adoption.

determinants of adoption (Feder, Just and Zilberman 1985, Besley and Case 1993) and recent research on Tanzania (Nkonya *et al.* 1997; Hawassi *et al.* 1998; Kaliba *et al.* 2000).

V. Empirical Results

Table 2 reports the results of standard probit estimation of the model -- adjusted for possible heterogeneity with Huber-adjusted standard errors. As noted in section III, the presence of a village-level error term in (13) calls for the use of random effects probit to estimate the model. Using the estimating equation (GEE) approach of Liang and Zeger (1986), a likelihood ratio test reveals that the village-level variance component is negligible, so that the random effects probit estimate is not significantly different from the standard probit model.

Estimation of the model also accounts for the likely endogeneity of the amount of land under cultivation, because there may be reverse causality: adoption of fertilizer makes a farmer wealthier, which may allow the farmer to cultivate more land.¹⁸ Probit estimation with instrumental variables (using the technique of Newey (1987)) can correct for reverse causality. The challenge is to find suitable instruments: variables that are

¹⁷ Both Nkonya *et al.* (1998) and Kaliba *et al.* (1998) present empirical evidence that Tanzanian smallholders tend to adopt improved seeds before inorganic fertilizer.

¹⁸ I thank an anonymous referee for this suggestion. In a previous draft of the paper, instruments for 'ethnic affiliations' and 'consultative norms' were also used to estimate the model. Many readers reacted that reverse causality -- household-level fertilizer adoption in 1994-95 affecting the composition of groups that have been in these villages for many years -- was unlikely and that measurement error problems were no more likely with these variables than with other variables in the model. For the model estimated in this draft, two different tests -- based on Smith and Blundell (1986) and Rivers and Vuong (1988) -- cannot reject the null of the

positively correlated with ‘land’ -- the log of land under cultivation -- and not strongly correlated with the household-level error term in (13). Using additional data from the HRDS survey, the following four household-level variables were constructed and used as instruments for ‘land’: the total amount of land available to the household for cultivation that is owned; rented; leased from the government; and borrowed from a relative. These variables, like ‘land’, were derived from detailed documentation on land use and availability provided by the household head and tabulated by the survey enumerator.

Accordingly, Table 2 is organized as follows. Columns 1 and 3 list standard probit estimates for the Central Plateau and the Plains, respectively. Columns 2 and 4 list the probit estimation with instrumental variables.

The theoretical model included four propositions about the determinants of adoption: that the probability of adoption is increasing in human capital (proposition 1), land (proposition 2), cumulative proportion of adopters (proposition 3), and social capital (proposition 4). The estimation of the model shows first that proposition 1 can be rejected. These results do not support the conclusion that human capital is a large and significant determinant of adoption.¹⁹ This is consistent with one of two recent studies of adoption in Tanzania: while Nkonya, Schroeder and Norman (1997) present empirical evidence that years of education are a significant determinant of adoption in Northern

exogeneity of ‘ethnic affiliations’, ‘consultative norms’, and ‘leadership heterogeneity’. By contrast, both tests can easily reject the null of the exogeneity of ‘land’.

¹⁹ This can also be rejected when ‘literacy’, a dummy variable for the achievement of literacy in reading and writing, is used as an alternative human capital measure.

Tanzania, Kaliba *et al.* (1998) present empirical evidence that years of education are not a significant determinant in the intermediate and lowland zones.

Second, proposition 2 cannot be rejected (using the 10 percent level of significance): households with greater land under cultivation are more likely to have adopted improved fertilizer, in both the regular probit and the IV probit estimations.²⁰

Third, proposition 3 cannot be rejected in the Central Plateau: in this agro-ecological zone, households are more likely to have adopted fertilizer in the 1994-95 growing season in the presence of greater adoption among their neighbors. By contrast, proposition 3 can be rejected in the Plains. One likely explanation for this result is that the overall use of fertilizer in this agro-ecological zone is still relatively low. The mean for ‘cumulative adoption’ among these households is 0.08: this translates into about 1 household per village sample. Consequently, there are few neighbors from whom one can yet learn about the benefits of fertilizer adoption.²¹

²⁰ This is a case where the two-tail test used here is particularly demanding: it seems unlikely that greater land endowments will be negatively associated with fertilizer use.

²¹ Rogers (1995) documents, in the case of many different forms of technology adoption, an ‘S’ shaped (cumulative) curve of adoption which is consistent with this explanation. In many cases, adopter distribution rise slowly in the early stages of diffusion, then accelerates with more rapid distribution, and then slows when the diffusion is almost complete.

Table 2: A Test of the Model of Technology Adoption in Two Agro-Ecological Zones

Region	Central Plateau		Plains	
	Probit	ProbitIV	Probit	ProbitIV
Estimation technique				
Years of education	0.0035 (0.063)	0.0020 (0.061)	0.074 (0.095)	0.0401 (0.118)
Land	0.35 *** (0.12)	0.55 * (0.34)	0.63 *** (0.21)	0.98 * (0.57)
Cumulative adoption	3.17 *** (0.56)	2.99 *** (0.82)	-3.63 (2.56)	-3.06 (3.39)
Ethnic affiliations	2.98 ** (1.24)	2.58 * (1.50)	8.88 * (4.85)	9.20 * (5.21)
Consultative norms	1.64 (1.38)	1.44 (1.89)	5.88 *** (2.01)	5.78 ** (2.81)
Leadership heterogeneity	1.65 (1.38)	1.86 (1.30)	0.48 (1.10)	0.71 (1.34)
Female	0.25 (0.35)	0.46 (0.57)	-0.652 (0.54)	-0.49 (0.89)
Age	0.075 (0.050)	0.065 (0.065)	-0.093 (0.074)	-0.119 (0.095)
Age squared	-0.00089 * (0.00048)	-0.00079 (0.00064)	0.00083 (0.00079)	0.00108 (0.00093)
Improved seeds	1.11 *** (0.35)	1.04 ** (0.44)	0.68 * (0.37)	0.56 (0.64)
Credit availability	0.74 ** (0.37)	0.52 (0.64)	0.74 (0.60)	0.94 (0.74)
Extension activity	2.01 *** (0.54)	1.97 *** (0.59)	1.02 *** (0.39)	0.90 (0.57)
Years in village	0.44 *** (0.12)	0.41 *** (0.14)	0.10 (0.11)	-0.04 (0.28)
Adjusted R-squared	0.71	--	0.43	--

Notes: Dependent variable is 'fertilizer adoption'. See text for description of variables.

Fourth, in the case of ‘ethnic affiliations’, proposition 4 cannot be rejected in both agro-ecological zones: households are more likely to have adopted fertilizer in the presence of ethnically homogenous social structures. Replacing ‘ethnic affiliations’ with ‘ethnic fractionalization’, a measure of village-level ethnic heterogeneity, leads to a similar result (with p-values of 0.10 and 0.01, respectively, in the Plateau and the Plains). While providing additional evidence that the local ethnic composition affects fertilizer adoption, one cannot isolate in this model any difference between the ethnic composition within social structures in a village and the ethnic composition across a village. Overall, this evidence is consistent with the general evidence detailed by Easterly and Levine (1997) that ethnic fractionalization is associated with poor development outcomes in Africa.

In the case of ‘consultative norms’ in the Plains, proposition 4 cannot be rejected: in this zone, households are more likely to have adopted fertilizer in the presence of participatory social structures. (The p-values for ‘consultative norms’ in the Plateau are 0.24 and 0.39, respectively.) It is not obvious why this aspect of the model is so region specific. These results -- in a region where the average adoption rate is only nine percent – do raise the possibility that participatory norms may be particularly important in the early stages of adoption.

Among the other independent variables, ‘improved seeds’ and ‘extension activity’ are significant determinants of adoption in the first three specifications; ‘years in village’ is also a positive and significant determinant in both specifications in the Central Plateau,

whereas ‘credit availability’ is significant in the first specification. In the Probit IV model for the Plains, the lack of significance of the other agricultural inputs -- ‘improved seeds’, ‘extension activity’ and ‘credit availability’ – may again be explained by the relatively low rate of overall adoption. It seems unlikely that these inputs are not positively associated with the eventual adoption of improved fertilizer.

Table 3 presents the marginal effects²² and point elasticities of ‘land’, ‘cumulative adoption’ and the two significant social capital variables in the cases where they are significant determinants of adoption. Following Grootaert (2001), these elasticities show the effect of a one percent increase of each independent variable on the probability of adoption. In each agro-ecological zone, the elasticities for the social capital variables are comparable to those of the other significant variables: in the Central Plateau, ‘land’ has about twice the effect as ‘cumulative adoption’ and ‘ethnic affiliations’; in the Plains Plateau, ‘land’ has about the same effect as ‘ethnic affiliations’ and about half of the effect of ‘consultative norms.’

²² The marginal effects are calculated as $\left. \frac{\partial \Phi(X\beta)}{\partial X_i} \right|_{X_d}$, where X_i is the regressor associated with each of the propositions. This expression and the point elasticities are evaluated at the mean of all regressors.

Table 3: Effects of selected independent variables on the probability of adoption

	Central Plateau		Plains	
	Marginal effect	Point elasticity	Marginal effect	Point elasticity
Land	0.033	0.036	0.017	0.0053
Cumulative adoption	0.303	0.020	--	--
Ethnic affiliations	0.285	0.018	0.237	0.0049
Consultative norms	--	--	0.157	0.0107

Notes: Dependent variable is 'fertilizer adoption'. See text for description of calculations.

In summary, the estimation of the model in this section shows that the probability of adoption of improved fertilizer in 1994-95 in the Central Plateau region is increasing in land under cultivation, cumulative adoption patterns, and ethnically-based social affiliations: in the Plains region, this probability is increasing in land under cultivation, ethnically-based social affiliations and consultative norms. Selected characteristics of social structures in two regions of Tanzania are significant and relatively large determinants of fertilizer adoption among rural households.

VI. Conclusion

Building on the qualitative results of Rogers (1995) and the theoretical approach of Feder and Slade (1984), this paper has modeled and tested how specific characteristics of social structure affect a distinct economic decision: the adoption of a new technology. This section concludes with observations about the methodological and policy relevance of the results presented in this paper.

The first micro-empirical studies that used survey data with information about local social structures relied on aggregate measures of social capital as determinants of a range of development outcomes. For example, using the same SCPS data from Tanzania, the research strategy of Narayan and Pritchett (1999) was to create a single ‘index of social capital’ from weighted means of eight variables measuring vastly different characteristics of social structures, and then to test whether this composite index was associated with different indicators of well-being.

The limitation of this approach is that it does not detail how distinct forms of social capital may affect economic outcomes through different mechanisms: for example, by diffusing information, reducing collective action dilemmas, affecting transactions costs, or increasing risk mitigation (Isham 2002). In fact, one of the variables included in Narayan and Pritchett’s ‘index of social capital’ is membership *heterogeneity*, which, according to the results presented in this paper, has a negative affect on fertilizer adoption. Yet ethnic heterogeneity may have a positive effect on other development outcomes in Tanzania, depending on the underlying economic mechanism. For example,

using similar survey data from rural Indonesia, Grootaert (2001) finds that the highest participation in local collective action--for example, building schools and maintaining roads--comes from members of more *homogenous* organizations, but that membership in internally *heterogeneous* organizations provides benefits to individual households in terms of access to credit and pooled savings.

Accordingly, the results presented in this paper suggest that measures of social capital should be as narrowly defined as possible -- or that econometric models that use composite indices should at least verify these results with alternative measures of social capital (as in Isham and Kähkönen 2002). Had a composite index been used in this case, it would not have been possible to distinguish among the effects of group homogeneity, participatory norms, and leadership heterogeneity.²³

What are the policy implications of the research presented in this paper for development assistance in Tanzania--and in the rest of Sub-Saharan Africa? Households with ethnically based and participatory social affiliations may be more likely to diffuse new information successfully -- and to adopt new technologies. Such information does not provide a *prima facie* justification to avoid investing in development projects to promote improved technologies -- for example, via extension programs -- in communities with high ethnic fragmentation or less participatory social affiliations. Many poor

²³ For example, replacing the three measures of social capital in the estimation of the model with a single composite index that includes 'ethnic affiliations', 'consultative norms', and 'leadership heterogeneity' can easily generate positive and significant determinants of adoption in both the Central Plateau and the Plains.

communities with the most urgent need for improved agricultural techniques may be ethnically diverse and non-participatory.

Instead, the allocation of investment resources for development projects may need to be adjusted to account for the characteristics of local social structures. Possible adjustments include more direct follow-up with individual farmers to counteract patchwork patterns of adoption in ethnically diverse areas, and investments in the strengthening of local organizations (for example, through direct training about new agricultural techniques). For example, under FAO's 'Special Programme for Food Security' in the Dodoma and Morogoro regions of Tanzania, farmers groups, input suppliers and other local stakeholders were consulted using participatory rural appraisal (PRA) techniques. Subsequently, eighty-six percent of targeted farmers adopted a set of recommended production technologies -- including improved seeds and fertilizer application (FAO 2000).

Like all potential investments in a development project, the expected net benefits of such investments should be compared to the expected net benefits of others: for example, in project infrastructure. At least, knowledge of the composition of local social structures can provide development practitioners in Sub-Saharan Africa with more complete information to guide their potential investments.

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