Social Networks and Technology Adoption

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Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Providence, Rhode Island, July 24-27, 2005

Abstract

This study analyzes social network effects on Kenyan smallholders' decision to adopt improved natural resource management techniques. These effects are decomposed into effects from social influence and learning through networks (strong ties), group effects, weak ties effects, informal finance, and conflicts arising from technological externalities, controlling for non-network effects.

JEL-codes: D62 Externalities, O33 Technological Change: Choices and Consequences; Diffusion Issues, Q16 R&D; Agricultural Technology; Agricultural Extension Services.

Acknowledgements

This research was made possible with a grant from the Social Science Research Council, with funding from John D. and Catherine T. MacArthur Foundation, and grants from The Pew Charitable Trusts, Mario Einaudi Center for International Studies and Cornell International Institute for Food, Agriculture, and Development. Partial funding was also provided by US Agency for International Development through grant LAG-A-00-96-90016-00 to the Broadening Access and Strengthening Input Market Systems/ Collaborative Research Support Program (BASIS CRSP), and the Strategies and Analysis for Growth and Access (SAGA) cooperative agreement, number HFM-A-00-01-00132-00, as well as the Coupled Natural and Human Systems Program of the Biocomplexity Initiative of the National Science Foundation, grant BCS - 0215890 (Pell).

Introduction

The Green Revolution did not leave the same mark on agriculture in Sub-Saharan Africa as elsewhere. The failure of African agriculture to feed her growing population along with increasing concern about natural resource degradation, combine to paint a bleak picture of the prospects for poverty alleviation on this continent. But beneficial innovations that can help bring African agriculture out of its current state of stagnation do exist. However, their adoption is slow, and a better understanding of the adoption process and constraints to adoption is needed to guide policymakers in designing appropriate policies to stimulate technology adoption. This study seeks to improve our understanding of the role social networks play in the adoption of new agricultural technologies.

This study looks at adoption of improved natural resource management techniques in two very densely populated sites in Kenya, Embu in Eastern Province, and Vihiga in Western Province. Both sites enjoy high, bimodal rainfall, and both are considered areas of high agricultural potential. The technologies considered in this study are soil and water conservation practices and soil fertility management practices that are components of integrated natural resource management. The soil and water conservation practices considered are terraces and drainage structures. The soil fertility management practices include chemical fertilizers, mulching and *tumbukiza*. *Tumbukiza* is a Swahili word that means "submerge", and refers to planting crops in deep manure-filled pits, a technique that leads to deep incorporation of organic fertilizers into the soil. Mulching (covering the soil surface with plant residues) is a technique that protects the topsoil from rain and wind erosion in addition to providing organic matter, so it may serve as both a soil conservation and a soil nutrient management technique.

Finally, trees on farms are part of an integrated natural resource management system. Trees may be planted for their products for human consumption as either food or medicine, such as fruits, nuts, or leaves (tree crops). Other uses are provision of biomass that can either be used as animal feed or organic fertilizers, as mulching material or supplementing other organic material used in composts (agroforestry trees). Nitrogen-fixating trees have the same beneficial effect on the soil nutrient balance as leguminous herbs, and in addition, trees supplement the nutrient mobilizing capacity of leguminous herbs by extracting soil nutrients from deeper strata of the soil, making them available for plants with shallower root systems, for example, through the leaves they shed. Trees can also be planted as windbreaks or for shade, thereby improving the microclimate on the farmers' plots, and their root systems help bind soil and prevent erosion. Thus, trees are useful components of both a soil conservation and a soil nutrient management regime. In this study 3 such techniques are considered. They are tree crops, agroforestry trees and windbreaks.

Some of these techniques are well-known, and have been practiced for generations. In colonial times, the British launched large-scale tree-planting and terracing projects in Kenya in response to observations of severe soil erosion problems. After independence, adoption of both trees and terracing picked up in many places, and as a result, areas that were deemed seriously degraded generations ago now support much higher population densities than before without additional damage to the environment (Tiffen *et al.* 1994). But terraces require costly maintenance, without which their benefits are gradually lost over time. Thus, ongoing maintenance becomes an issue, in particular when the agricultural sector experiences adverse changes in the terms of trade.

Application of fertilizers is also a well-known technique that most farm households have experience with. But chemical fertilizers have become more expensive following the removal of government subsidies, discouraging their use. According to some studies, this shift in prices has caused a shift to more intensive utilization of organic fertilizers instead (Scoones 2001), but this shift may not compensate for the reduction in application of chemical fertilizers. The adoption rate of these technologies can hardly be attributed to the level of awareness of their benefits, but rather to other factors, mainly related to market incentives. But the technology packet considered in this study also includes less-known methods to improve traditional techniques, such as the use of agroforestry, mulching, or the deep incorporation of organic fertilizers into the soil that is achieved with *tumbukiza*.

Removal of trade barriers and improved terms of trade for the agricultural sector were high on the agenda for policymakers during the structural adjustment process in the past couple of decades, and experience confirmed that farmers do respond to market incentives (Sanders *et al.* 1996). However, after decades of structural adjustment, agricultural productivity remains stagnant. Part of the explanation may be that structural adjustment policies did not, in fact, improve terms of trade as much as anticipated (ref?), but another explanation may be that other barriers to technology adoption remain, and these may be related to non-market factors. Recently, there has been increased interest among development scholars in the importance of informal institutions to technology adoption.

The problem is that institutions are very diverse, and deeply embedded in social structures that are shaped by both the local environment and by non-material factors, such as culture. Thus, policies that have been proven successful in some institutional settings may turn out to be inappropriate in others. An example is the variable success of microfinance schemes throughout the developing world (Morduch 2000), once hailed as the key to unlock poverty traps in traditional economies. Another example is the perplexing multitude of contracts that are found among villagers, even in settings where according to economic theory they are inefficient, and yet, policy interventions to make people choose the assumed efficient contracts have had perverse outcomes (Hoff and Stiglitz 1993).

Social network effects on technology adoption have been demonstrated, and are often attributed to social learning, but other less studied network effects may also be involved. The services social networks provide that may interact with peasant farmers' technology adoption decisions are, at least, threefold. A social learning environment is one of those services, while the other two are informal finance that may relax the farmers' credit or risk tolerance constraints, and facilitation of collective action where coordination of adoption is needed due to technological externalities. Each of these services interacts with a farmer's adoption choice through its own set of mechanisms that may be complex and contradictory.

The classic studies of social learning showed that the aggregate adoption pattern follows a sigmoid curve, with adoption accelerating in an early stage, and then decelerating as adoption reaches an upper limit after some time. In the classical literature, adopters have been characterized as "innovators" or "laggards", depending on when during the adoption process any given adopter adopted (Rogers 1995). This sigmoid curve is also typical for the spread of diseases, and is often referred to as the "contagion model", which implies an underlying assumption about a social mechanism behind the adoption pattern. In a study of adoption of Green Revolution technologies in India, Foster and Rosenzweig (1995) found that learning externalities within social networks increased the profitability of adoption, but also that farmers appeared to be free-riding on neighbors' costly experimentation with the new technology. Bandiera and Rasul (2002) suggest learning externalities generate opposite effects, such that the more other people also engage in experimentation with a new technology, the more beneficial it is to join in, but also the more beneficial it is to free-ride on the experimentation of others. As a result of these contradictory effects, they propose an inverted U-shaped individual adoption curve, implying that network effects are positive at low rates of adoption, but negative at high rates of adoption.

Technical aspects of agricultural technologies themselves are often overlooked as factors that may drive adoption patterns. When technologies are complementary, and several technologies need to be adopted simultaneously to be successful, then adoption becomes complicated, and perceived as risky. Farmers prefer to adopt technologies gradually, one by one, to experiment with them on a small scale before applying them to the whole farm (Sanders *et al.* 1996). But the integrated natural resource management techniques that are needed to address natural resource degradation in Africa commonly fit the description of complementary technologies (Fernandes *et al.* 2002). It may be possible to adopt and apply them individually, but the full benefits of adoption are only achieved when they are all applied simultaneously.

In general, externalities are not internalized by economic decision makers, leading to “too much” or “too little” adoption in the absence of external intervention. A stark example is vaccination against a communicable disease, which interferes with the cycle of transmission of the disease, generating positive externalities that may be of greater social importance than the protection the vaccination provides for the individual. Where public benefits of a technology outweigh the private ones, people are less likely to adopt them (Miguel and Kremer 2003). Similar dynamics also exist for improved natural resource management techniques.

Where a sloping terrain and precipitation combine to generate problems with soil erosion, well constructed terraces may have positive externalities, while poorly constructed drainage structures may have negative externalities on downhill neighbors. For a farmer in need of soil conservation measures, having an uphill neighbor who drains excess water onto her land, or who has not terraced, can make terracing unprofitable, because excess water from the neighbor may damage these structures. Similarly, irrigation water that is returned to a river and is reused downstream becomes increasingly more saline with each time it is used, creating an externality that affects downstream water users. In the Colorado River Basin such problems have been addressed through costly public interventions intended to protect the interests of post-irrigation water users (Lee and Howitt 1996). Similar interventions to improve aggregate productivity of farmland through socially optimal investments in soil and water conservation structures are beyond the economic capacity of most countries in Sub-Saharan Africa.

In the rural economy in Africa, few have access to formal finance. Instead, many rely on informal finance. The most important sources of informal finance in rural Africa are (or have been) (i) interlinked contracts, where input purchases and output sales are made through the same marketing channels, (ii) private money lenders, and (iii) transfers within social networks. Much of the interlinked inputs and outputs trade used to take place within inefficient parastatals, which were targeted for dismantling during the structural adjustment process. As a result, this source of credit has diminished in importance during the last couple of decades (Kherallah *et al.* 2000). Furthermore, this source of credit only applies to a limited range of purposes directly relevant to the objectives of the parastatals. Private moneylenders are known to charge very high interest rates (Aleem 1993), at levels that often preclude the use of credit from this source for financing investments in smallholder farming. So for the purposes considered in this paper, i.e., investments in farm productivity, credit through social networks may be the most important source available to smallholders in Africa.

Borrowing through social networks takes two main forms - either as a collective arrangement organized as a rotating savings- and credit association (ROSCA), in Kenya popularly known as a “merry-go-round”, or as bilateral transfers between individual social network members. The former is a wide-spread, well-organized institution that has been shown to be important within the kinship-based rural economy in Sub-Saharan Africa, while the latter tends to be very informal, with no written contracts, and no explicit agreements about the terms of repayment, rather in the spirit of generalized reciprocity (van den Brink and Chavas 1991). Udry (1994) found in a study of bilateral informal credit through social networks in Northern Nigeria that both duration of loans and repayment amounts tended to be state contingent, with more favorable terms for borrowers who had experienced adverse shocks. Thus, he made the very interesting observation that informal credit could not be clearly distinguished from informal insurance. Indeed, the most important role of this kind of informal finance may be to complement the more rigid ROSCAs in situations of emergencies, i.e., to couple informal credit with informal insurance.

While in the concept of the market in classic economic theory, agents are anonymous, that is not the case within social networks. Many analytical studies have looked at endogenous formation of insurance networks, and how selection into networks leads to inclusion and exclusion of people according to individual characteristics. Empirical studies uniformly reject Pareto-efficient risk pooling in low-income rural villages (e.g., see Townsend 1994). Murgai *et al* (2002) propose that the configuration of mutual insurance groups and the level of insurance achieved within those groups are functions of transactions costs related to group formation and maintenance, i.e., “association” costs, and costs related to using these links when needed, i.e., “extraction” costs. Genicot and Ray (2003) propose that when a mutual insurance group has grown beyond some minimum number of members, it may be destabilized by coalition formation because a subset of group members finds it more beneficial to form a group of their own, leading to social exclusion. In a study using data from Ghana, Goldstein *et al* (2005) seek to explain who is successful in getting cash assistance and who is not, and from what source the assistance comes for those who succeed. In their data, they observe that individuals do not obtain assistance from both the spouse and community members, but from either one or the other. Based on this, they postulate two decision trees in seeking assistance, either ask the spouse first, and then others, or others first, and then the spouse. Spouses’ responsibilities towards each other are defined by the conjugal contract, and whether the spouse or others are more likely to provide a transfer depends on what item the individual is seeking assistance to obtain. Goldstein *et al* find that inability to find cash assistance is pervasive in low-income rural communities, and, just like many other empirical studies on informal insurance, that those who have difficulties obtaining assistance are not perfectly insured.

Clearly, the threat of exclusion from transfer or insurance networks can function like a Nash reversion strategy as a mechanism for contract enforcement, which would be particularly credible and powerful towards the vulnerable and poor. An interesting question following this observation is whether those with the power to exclude exert stronger social influence than others, and whether such influence also extends to decisions related to farm management and adoption of agricultural technologies.

Hypotheses

The three types of social network services identified above may all interact with technology adoption, but through different mechanisms. Moreover, these may be contradictory. Competing models that may or may not be mutually exclusive also exist.

Bilateral transfers effects:

Bilateral transfers through social networks complement other sources of finance, or even substitute for them where they are missing, and if this informal financial market functions the same way as a formal financial market does, it should have the same expected effect on farm management decisions. Better access to finance, of any kind, should relax farmers' cash constraints, and enable them to invest more in their farms' productivity. This could be termed the economic "enabling" model, implying that more credit means more economic freedom and higher ability to adopt, and leads to the first testable hypothesis:

H1: Those who have better access to informal credit (or insurance) through social networks are more likely to adopt new agricultural technologies.

But, following the discussion above, due to the non-anonymous nature of informal finance, and the possibility of power relations within social networks, a different model, that may be termed the economic "power" model, can be pitted against the first model. In the power model, net borrowers depend economically on their lenders, and must somehow signal creditworthiness. From the formal economy we know that in a competitive credit market lenders will balance risk and price to achieve zero expected profit. Indeed, the distribution of risk between lender and borrower is an important component of formal credit contracts. The issue of risk rationing is an emerging issue for development economics research for more informal and less competitive financial markets (ref? Michael Carter?). Due to an assumed general unwillingness for informal lenders to carry risk, it is assumed that risk is disproportionately pushed over on the borrower, who therefore is forced to abstain from perceived risky, but potentially beneficial experimentation with new technologies, making borrowers more conservative than lenders with respect to technology adoption. This leads to the alternative testable hypothesis:

H2: The borrowers who are most likely to become excluded from transfer networks need to be more conservative than their lenders, so they become adoption laggards.

These hypotheses are not mutually exclusive. Economic enabling may dominate in the absence of economic dependence and a credible power to exclude, while the pressure to behave conservatively may dominate where exclusion is a credible threat. The existence of these opposite effects may generate complicated adoption patterns.

Learning effects:

The most important and best-known model for social learning is the “learning from others” model, where information about new technologies spread from mouth to mouth through collective experimentation, discussion and persuasion or by direct observation of neighbors’ experiments (Foster and Rosenzweig 1995). Conversely, if a community has become disenchanted with a new technology, community members may succumb to conformity pressure and disadopt it (Moser and Barrett 2002). This model implies the following testable hypothesis:

H3: The more adopters a farmer knows and interacts with through social networks, the more likely that farmer is to also adopt the new technology.

Where social interaction within networks is of less importance, farmers are expected to learn about technologies, experiment with them, and decide whether to adopt more on an individual basis, and their source of knowledge about new technologies becomes the main issue of study. Traditionally, farmers have been assumed to be passive recipients of knowledge that is provided to them by change agents, such as extension officers or sales agents representing producers of, e.g., new machinery, seeds, or other farm inputs (Rogers 1995). But farmers may also be actively trying to figure out new ways to solve their own problems themselves, and instrumentally use social networks to seek information they need as inputs in their own experimentation process. Since useful sources of information are likely to be found outside the social networks people participate in on a daily basis, this will often involve mobilization of weak social ties (Granovetter 1973). The ability to locate useful sources of information can be tested experimentally. Thus, two competing hypotheses emerge:

H4: The more a farmer interacts with extension officers, the more likely she is to adopt new technologies.

H5: A farmer with a greater ability to mobilize networks instrumentally (by using weak ties) is more likely to adopt new technologies.

Again, these hypotheses are not mutually exclusive, but may instead represent effects that complement and reinforce each other. A disentangling of these effects is not a problem worth worrying about, but it may be of interest which of these effects appear to be at work in the data, and which has the greater impact on adoption.

Technological spill-over effects:

In the presence of technological spill-over effects, or externalities, hidden incentives and disincentives to adoption may exist, that the adoption researcher may not observe. For the natural resource management techniques that are considered here, such externalities are probably only felt by the geographically proximate neighbors, and less so, the larger their farms are. Positive externalities should make people more likely to adopt if a proximate neighbor has adopted, while negative externalities should lead to less adoption if a neighbor has adopted. Negative externalities may also lead to conflicts between neighbors, which are easily observable, and can be used to instrument for it. This brings us to the final hypotheses:

H6: When adoption of a technology generates externalities that lead to observable conflicts between neighbors, a farmer is less likely to adopt it.

H7: When adoption of a technology is likely to prevent externalities that lead to observable conflicts between neighbors, a farmer is more likely to adopt it.

Econometric Model

Manski (2000) identifies three sources of predictive power of a social influence model that cannot easily be disentangled, creating an identification problem. Those are (i) endogenous network effects, (ii) exogenous network effects, and (iii) correlated (non-network) effects. It is the endogenous network effect that is usually referred to as a network effect, i.e., an effect generated by the network as a result of direct interaction between network members. Exogenous network effects are features of social networks that are not a result of the internal dynamics of the network, but rather a result of factors that are at play during the network formation process, i.e., how people get selected into networks. Correlated effects are effects that are external to networks, but that network members share with each other and with people who are not members of their networks, i.e., environmental factors, including institutional environment, mass media, etc. Moreover, correlated factors at the individual level may be driving endogenous network formation resulting in exogenous network effects. All of these can make members of the same networks choose to make similar technology adoption decisions, but only the endogenous effects are truly generated by the network.

To identify endogenous effects, the analysis needs to control for exogenous and correlated effects. This will require data about all relevant features of all network members in all networks, and about all relevant environmental factors that may vary between or even within localities. But endogeneity of network formation probably does not affect all networks equally. People may choose their "friends", but not their neighbors.

An adoption decision can be viewed as either a binary decision, to adopt or not to adopt, or as a continuous decision, whether to adopt a little or a lot, i.e., what proportion of the farm the technique will be applied to. In this study, only binary data about the adoption decisions are available, which drives the choice of a Probit or a Logit model for the econometric analysis. But the techniques included in this study can be clustered into sets of complementary techniques whose adoption are probably simultaneous, so an analysis of their adoption through multivariate regressions should be considered.

Data

The data used in this study were collected during 2003-2004 in two sites in Kenya: Manyatta Division in Embu District, and the former Madzuu Division (now divided between several new political entities) in Vihiga District, in Eastern and Western Provinces, respectively. Both sites enjoy high, bimodal rainfall patterns, and are considered high-potential areas for agricultural production. Both sites are also extremely densely populated areas. But the ethnicity of the population differs between the two sites, with Embu dominated by the Embu tribe, while the population in Vihiga belongs to the

Luhya tribe[1]. These two tribes are culturally different, with different languages and histories, including different histories of interaction with the English during colonial times. Embu also has somewhat more favorable economic conditions than Vihiga, because of generally less degraded soil, and better market access. Embu is situated about 120 km from Kenya's capital city, Nairobi, while Vihiga is about 400 km from Nairobi, but about 25 km from Kenya's third largest city, Kisumu.

The sample of research subjects was given in both sites, as this study was conducted under the umbrella of a larger interdisciplinary study, which I will here refer to as the BASIS study, involving about 120 households in each site[2]. The objective of this larger study is to investigate the dynamic interactions between subsistence agriculture and the natural resource base it depends on, and it involves building a panel data set for the sample households. In both sites a procedure of cluster sampling within multiple villages had been employed. The Vihiga sample was originally surveyed for an unrelated study in 1989, which serves as a baseline for the new study now nearing completion. The sample households in Embu were chosen because they were surveyed in 1998, also here for an unrelated study, but offering an opportunity to save time on creating a panel. This means there exists a large data set about the same households that complements the data collected specifically for this study. Data from the BASIS study that have been used in analyses presented here were collected in 2002, and they contain information about the

[1] The concept of a tribe is rather politicized in Kenya, and sometimes disregards basic identifiers of ethnicity, such as language. Members of the Embu tribe speak a dialect of the Kikuyu language, but they insist they are not Kikuyus, while the Luhya tribe is rather a cluster of tribes speaking languages that are related but not mutually intelligible. Yet, they are referred to as one tribe. Thus, one may question what the term "tribe" means in this context.

[2] This study started as a socioeconomic study with funding from BASIS CRSP, but was later incorporated into an interdisciplinary study with additional funding from NSF.

households' assets, including farm size and areas under various crops, as well as detailed input and output data for the farm operations, a household census, and data on access to credit and how households cope with adverse shocks. Moreover, these data include information about all the natural resource management techniques the sample households have adopted, (but as mentioned above, only *if* the household has adopted a practice, not how large proportion of the farm it is applied to).

The data collected specifically for this study are a network data set, where the respondents (egos) were asked to identify the people they engage in borrowing and lending with (the "exchange" or "transfer" network), the people they like to discuss issues of farming with (the "communication" or "friends" network), and their geographically proximate neighbors. Then they were asked a set of questions about each of these network contacts (alters). The questionnaire uses a 12-month recall period. A subset of the sample was selected for a follow-up round ("snowballing"), where the alters identified in the first round were tracked down and interviewed, using the same questionnaire as in the first round. Within each household, the person who had the main responsibility for day-to-day farm management decisions was selected for interviews. This person was not necessarily the household head. In many households both spouses were farm managers, either working together, or having separate enterprises. Therefore, about one tenth of the sampled households were selected for interviews with both spouses, selected among those where both spouses were farm managers.

The respondents were not asked all the same questions about themselves as about the network members, so the data about respondents and their network members do not mirror each other. Moreover, the rich complementary data set about the sample households that has been collected for the BASIS study does not include the network members. Data on technology adoption by network members is cruder than the data that is available for the BASIS respondents, and generally refers to aggregates of technologies, as described in the next section.

For the subset that was used in the “snowballing” round, it is possible to apply network analysis techniques, such as calculation of various quantitative network measures developed by networks researchers. The network measure used here is known as Freeman Degrees, after Freeman (1978). For further details about how Freeman Degrees are calculated, one may consult Wasserman and Faust (1994). This is a measure that captures the level of social closure among first-order network links in egocentric networks.

Variables used here to control for the correlated effects described by Manski include village dummies and the variable for having one of the three extension officers who appear most frequently in networks as a network member. Where too few degrees of freedom became a problem, a site variable substituted for the village dummies, distinguishing the two main districts from each other but not the villages.

Summary of Variables and Descriptive Statistics

This study suffers from the luxury of having too much data about the respondents. Using all interesting or relevant variables in the same regressions would generate results that would suffer from insufficient degrees of freedom and therefore poor power of testing. A procedure for data reduction has therefore been necessary. The main interest of this study is social network effects, but variables controlling for non-network effects were still needed. Variables representing exogenous effects were substituted by index variables generated through the use of factor analysis, following the procedure used by Sahn and Stifel (2000) when they generated a welfare or wealth measure. Summary statistics for all variables that are not restricted to be equal to zero or one, or to be within the range from zero to one, are presented in Table 1. A table with summary statistics for all variables that have been used in regressions here would be too long for this publication.

Regressions will not reveal all interesting interactions between variables unless interaction terms are included, which has been avoided in this study in order to limit the number of regressors. To make up for this deficiency, I will first discuss basic statistics for some of the variables, including some interactions, and provide background information about component parts of the study, before venturing into a discussion of regression results, which will follow in the next section.

All of the technologies considered in this study are known and adopted by at least some respondents in both study sites, but there are villages where adoption or non-adoption is universal for some of the technologies. Adoption rates of both terracing and drainage structures are higher in Vihiga than in Embu despite much steeper sloping farmland in the latter site. About 78% of the respondents in Vihiga have terraces, and 24% have drainage structures, while in Embu these adoption rates are 58% and 17%, respectively. In 3 of the 11 villages used in the Vihiga sample, all respondents had terraced. In Vihiga mulching is also widely practiced (61% against 19% in Embu), but application of chemical fertilizers and *tumbukiza* are much more common in Embu (78% and 50%, respectively, compared to 52% and 6% in Vihiga). In 6 of the villages in Vihiga, nobody practiced *tumbukiza*. All of the tree technologies (tree crops, agroforestry trees, windbreak) are more common in Embu, with adoption rates about 20-25% higher in Embu.

<u>The relationship between technologies - are they substitutes or complements?</u>

The clustering of technologies in this study is based on the assumption that technologies within clusters are complementary to each other, and will tend to be adopted together. And indeed, adoption is positively correlated for terracing and drainage structures (Pearson correlation coefficient 18%), and for the tree technologies (correlation coefficients around 33-34% except between tree crops and windbreak, where it is insignificant). But the soil nutrient management techniques do not follow this pattern. The only significant correlation between them is between mulching and *tumbukiza*, and this correlation is negative (-29%), reflecting their contrasting adoption rates in the two sites. But there is a positive correlation (19%) between mulching and drainage structures, suggesting that mulching may be chosen as much for its protection against soil erosion as for its organic fertilizer effects.

<u>Accuracy of information about network members</u>

Information about what practices alters have adopted are provided only by respondents unless alter is also a respondent. The accuracy of this information can be checked for alters who are themselves respondents by comparing the answers of ego with alter's own answers. It happened occasionally that primary respondents chose other primary respondents as alters, but it is for the snowballing subset that data from interviews with alters as secondary respondents are available. A direct inspection of the data suggested that egos did not know what alters were practicing, and that the answers were no more than guesses. Table 2 provides a simple check of the hypothesis that respondents are guessing, and that they base their guesses on a hunch about what overall adoption rate is. That means, if ego knows the adoption rate is α then she will guess alter is an adopter with frequency α. If respondents actually know who are adopters they should be able to answer correctly more often than they would if this hypothesis is right. If the hypothesis is right, respondents should guess correctly that alter is an adopter with expectancy α^2 and that alter is a non-adopter with expectancy $(1-\alpha)^2$.

In the aggregate this turned out to fit the data. This result is not reported here. But interesting patterns emerged when guesses were sorted by whether alter is a family member, whether ego is an adopter, and whether the two have discussed the technology in question. These results are reported in Table 2. The table reports percentage of guesses that correctly state alter is or is not an adopter, and percentage of guesses that incorrectly make the same statements. Then the actual adoption rate (α) for the sample is reported, the sum of correct guesses, and the expected sum if one were to guess freely, knowing α. The error is the difference between observed and expected rate of correct guesses under the hypothesis. In general, these errors suggest that respondents do somewhat poorer than they should under the hypothesis. But a closer inspection reveals biases in the answers.

The guessing is about as expected when the data is sorted by whether alters are family members, with only two aggregate errors exceeding 5% (an arbitrary threshold chosen for error tolerance). Those are the figures for terracing and *tumbukiza* when alter is a family member. The answers are better than expected for *tumbukiza* (both negative and positive answers more often correct), but poorer than expected for terracing (vice versa), the former perhaps suggesting that respondents are better informed about what is happening about this new and still uncommon practice, while they are not paying attention to the other, older technology. When data are sorted by whether ego is an adopter, all but two aggregate errors exceed 5%. The answers are better than expected (both negative and positive answers more often correct) for non-adopters guessing about adoption of fallows, possibly just a coincidence. For non-adopters errors are otherwise driven by a negative bias - assuming a lower than correct adoption rate, while for adopters errors are driven by a positive bias - assuming a higher than correct adoption rate.

When errors are positive, i.e., more correct answers than expected, the data generally do not support the assumption that respondents are better informed - errors are still driven by biases in their answers. Whether a bias will lead to a positive or negative error under the hypothesis depends on the magnitude and direction of the bias and the magnitude of the true α. For example, if $\alpha = 90\%$, then guessing "yes" 90% of the time will result in on average 81% correct "yes" and 1% correct "no", while guessing "yes" 100% of the time will result in 90% correct "yes" and 10% incorrect "yes" - a better result based on poorer information.

The largest deviations from expectation under the hypothesis are found when data are sorted by whether people have discussed the technology. Again, all but two aggregate errors exceed 5%, but now nobody gets both positive and negative answers more often correct. All those who have not discussed the technology get aggregate errors exceeding 5%, and in all cases it is due to a negative bias - assuming a lower than correct adoption rate. When those who have discussed the technology get large aggregate errors, it is driven by a positive bias.

This simple analysis cannot determine whether people really are just guessing, but the hypothesis cannot be rejected either. It may appear like people in the aggregate guess as if they know the adoption rate, but not who the adopters are, but this masks systematic biases in the answers. These biases reflect the respondents' own behavior and subjective impressions based on (presumably) superficial communication about actual adoption, and confirm findings made by other studies (Valente 2005).

Weak ties

To measure respondents' ability to mobilize weak social ties to solve problems a specially designed experiment was conducted as a spin-off from this study, and two variables generated by it are included as regressors in the analyses that conclude this paper. In this experiment, respondents were given a set of questions they were not expected to be able to answer off the top of their heads, and then they were given three weeks to find the answers. We knew this information was available locally, as we had ourselves gathered it through mass media and selected local informants. To give respondents an incentive to put effort into the exercise, they were promised a cash reward for each correct answer. They were visited weekly, and rewards declined the longer time respondents needed to find the right answer.

The cash reward participants earned was a function of how many correct answers they found, and how quickly they found them, and this amount is one of the two variables later used in regressions to represent the ability to mobilize weak ties. The other variable is whether the respondent managed to answer correctly one of the questions that the exercise revealed to be the most difficult ones. It turned out to be the prices of farm inputs and outputs traded at the district or national level. About 45% never found these prices, even with three weeks and the promise of a cash reward as an incentive.

More than half of all correct answers produced were known to the respondents before being asked, or had been obtained from family members, but 20% of the correct answers were obtained by asking non-family members and 16% by contacting relevant institutions. To find the answer, respondents needed to travel to meet their informants in 25% of the cases, and they used an intermediary to assist them in 38% of the cases. Telephones are almost non-existent among these respondents, and only very few answers (2%) had been obtained by calling someone. Mass media were also not used much. Only 4% of correct answers had been obtained from radio, TV, or print media. Surprisingly, nobody discovered that tea and coffee prices obtained by local factories at auctions in Nairobi are announced weekly through newspapers. Those who found those answers had contacted the management of the local factory. In contrast, 76% managed to find currency exchange rates, and 19% of those who did, found the information in newspapers, so people are aware of newspapers as sources of some types of information. The exercise also included some questions about health recommendations promoted by the Government in campaigns that use radio and TV as important channels. About 85% of the participants got these answers right, although most of them had acquired the information from family and friends, not from media. But it means this information does reach rural villagers, a confirmation that the campaigns at least are successful in getting the information through.

A few were lucky and guessed one or two answers. After the three weeks were finished, respondents had succeeded in answering 83% of the questions correctly. There were 55 participants in this exercise.

Groups

Partnerships between government agencies and non-government organizations on one hand and community based organizations and local self-help groups on the other represent a cornerstone of Kenya's development strategy. The government encourages self-help groups to get registered with a government office, in order to establish channels of information. These groups are often referred to as farmers' groups, women's groups, and youth groups, according to their membership base. To get registered, groups need to have by-laws and an elected board, hold annual elections, and write minutes from their meetings.

Data about group membership was collected from the same 55 respondents who were participants in the weak ties experiment. These data are household and not respondent level data. This means that any household member may be the one who is member of a given group, not necessarily the respondent. In Vihiga there were no sample households (among the 23 sampled) who had members in either a farmers' or a youth group, a farmer's cooperative, or a savings and credit union (SACCO), while in Embu such groups were common. There, all households were active in a church and a farmers' cooperative, and 27 out of 32 were members of a SACCO. But in both places there were many women's groups, and a total of 60% of the sample households had active members of women's groups.

Results

As noted above, a data reduction procedure using factor analysis has been applied to reduce the number of variables used in regressions. Results of this factor analysis are not included here, but can be made available upon request. For what I refer to as exogenous factors here, following Manski, four factors were retained, representing 20 original variables. These variables include the farmer's gender, age, education level, a wealth proxy, farm assets, and access to formal finance, etc. An interpretation of the resulting factors is outside the topic of this paper, and will not be attempted. But their presence in the regressions hopefully controls for the exogenous factors.

The results of regressions are presented in tables 3 to 5 and 7 to 9. The first 3 tables present results of Probit estimations of adoption on correlated, exogenous and endogenous factors using the whole sample of respondents, while the final 3 present Probit estimations of adoption that bring exogenous and endogenous factors together with data on groups and weak ties to summarize it all. These final regressions are based on a subset of only 55 respondents for whom these additional data were collected. Each table presents one cluster of choice variables, where the clusters are "soil and water conservation techniques" (terraces and drainage structures), "soil nutrient management techniques" (inorganic fertilizers, mulching and *tumbukiza*), and "trees on farms" (tree crops, agroforestry treees and windbreaks).

Other candidate technologies were included in the data, but had to be discarded for this analysis because of lack of variation, either due to near universal adoption or near universal non-adoption. This includes improved fallows, a technique that has been developed and promoted by the World Agroforestry Center (WAC, formerly the International Center for Research on Agroforestry, ICRAF), a collaborator with this research project. Multivariate regressions for each cluster of selected technologies were attempted, but produced no significant results. Despite the data reduction procedure employed, regressions still suffered from too few degrees of freedom to allow such demanding estimations.

Testing H1

The first hypothesis is about the effect of informal credit and insurance on adoption. The relevant variables are network transfers variables, two variables representing access to cash, "Household receives remittances" and "Number of ROSCA memberships", and one variable representing how well informal insurance works for the household, "Not recovered from earlier shock". The network transfers variables are based on questions of the form: "How many times the last 12 months did you receive/provide ... from/to this person", referring to a named network contact. The questions identify three types of transfers, i.e., cash transfers, transfers in kind, and the exchange of unpaid labor. The variables used here are aggregates across network members per respondent. Amounts of transfers are not considered. Only the largest amount transacted each way within each dyad has been recorded, so aggregate amounts cannot be calculated. The recorded transfers include both borrowing and lending and the exchange of gifts that are not expected to be repaid. A deeper analysis of these network transfers as well as ROSCA memberships and informal insurance can be found in Hogset (2005).

Of course, whenever a technology was adopted more than a year ago, these transactions took place after adoption, and cannot be taken as causing them. But the assumption is that the activity level within transfer networks is a function of relatively stable characteristics of respondents, which were present also at the time when the adoption decision was made. However, when interpreting the results, one needs to consider the possibility that adoption itself may have interacted with a respondent's characteristics to change transfer patterns within the network.

Households that receive remittances have family members living outside the household who have good jobs and are able to send money home, providing a relatively reliable source of cash. ROSCA membership enables households to save cash for somewhat larger purchases, and can sometimes serve as a source of informal insurance. The poorest have difficulties meeting the requirements for ROSCA membership, and choose not to participate, or are excluded, while some who are better off are able to hold multiple ROSCA memberships. The households who had "Not recovered from earlier shock" had experienced a serious shock, like a major loss of livestock or crops or the death of a household member, during the last five years, and had not recovered socio-economically from this shock by the time of data collection. The inability to recover from a shock is here taken as an indicator of insufficient informal insurance.

For adoption of terraces the only one of these variables that has a significant coefficient estimate is the number of times respondent has provided cash transfers, and it is weak and negative. It means that those who are most active on the giving/lending side for cash transfers are slightly less likely to be adopters of terracing. But if they are able to provide cash frequently, they also ought to be able to invest in their own farms, so obviously, the absence of adoption is not driven by a cash constraint, nor has the absence of adoption caused a cash constraint. For adoption of drainage structures, the coefficient estimate on ROSCA memberships is significant and negative, suggesting the same reasoning as with terraces. But the relationships between ROSCA memberships, participation in cash transfers through networks, and wealth, are weak. It is those of intermediate wealth who participate in ROSCAs and network transfers, and neither the poorest nor the wealthiest (Hogset 2005). A positive effect of being a recipient of cash transfers on adoption of drainage structures is too weak to matter.

For adoption of inorganic fertilizers and mulching, there are no significant coefficient estimates among these variables. But the coefficient estimate on receiving remittances is strong and significant for adoption of *tumbukiza*. This is a weak support for H1, although remittances do not originate from what is normally termed “social networks”. There is also a positive relationship between adoption of *tumbukiza* and being a provider of transfers in kind, but the effect is weak, and cannot be interpreted as a direct support for H1.

For the “trees” technologies there are many transfers variables that are significant, but none has a magnitude that matters. For most respondents the number of transfers ranges from zero to maybe 20 for each of these variables. One might want to consider what difference 10 more transactions make, instead of 1 more, but still the effect is too small to matter. Moreover, the signs do not conform to the hypothesis. Receiving remittances has a positive coefficient estimate, which does conform to the hypothesis. Remittances may be a good source of cash for investments in tree crops. However, having inadequate informal insurance (“Not recovered from earlier shock”) also has a positive coefficient estimate for both tree crops and agroforestry trees, contrary to expectation.

Thus, the conclusion for the variables that are relevant for H1 is that the hypothesis is rejected. While having access to informal credit and insurance through social networks surely does not hurt technology adoption, it appears to be unimportant.

Testing H2

This hypothesis relates conservative behavior to the economic dependence on networks of a net borrower. Following the rejection of H1, I would expect a rejection of this hypothesis, too, as they are related and may be viewed as nested. H2 implies not necessarily that "conservative" farmers never adopt, only that they become adoption laggards, i.e., all else being equal, they adopted a lower number of years ago than alters, if they have adopted at all.

Some information is available about how long ago respondents adopted some natural resource management practices. Except for *tumbukiza*, these practices do not correspond directly to the practices included in the analysis here, but rather to aggregates of technologies. They are "terracing" (i.e., soil and water conservation measures, including grass strips, bunds, ridges, etc.), fallowing (incl. improved fallows), organic fertilizers, incl. mulching, green manuring, and *tumbukiza*. For all of the practices except *tumbukiza*, there is a positive and relatively strong correlation (19-42%) between respondent's age and how long ago the practice was adopted. This suggests that the respondent has known the practice since becoming a farmer, so that the sequence of adoption probably follows roughly the sequence by which the respondents became farmers.

But that is not the case for *tumbukiza*, which is a newer practice that is not as widely adopted as the others. The results of a count regression (using the Poisson distribution) of years since adoption on respondent's age, endogenous factors, and the predictor from a Probit regression of adoption on exogenous factors are presented in Table 6. Here we find that the strongest predictors for how long ago a farmer adopted are exogenous and correlated factors, and to some extent social learning. Those with many neighbors and friends who practice *tumbukiza* (according to the respondents' guesses) have adopted earlier, while those who know *tumbukiza* as something preachers and civil servants practice are later adopters. But recall from the previous section how biased the information about alters' adoption choices is. Those who are themselves adopters of *tumbukiza* have grossly overestimated the overall adoption rate in their guessing about the behavior of their network contacts. Thus, even the learning effect is not very reliable.

The results for network transfer variables in the adoption regressions in tables 3 to 5 can also serve as support for H2. But as noted above, coefficient estimates on these variables are rarely significant, and even if they are, their magnitudes are too low to matter. Moreover, the hypotheses to not relate being a provider of transfers to adoption, and many of the few significant coefficient estimates are indeed on variables for providing transfers. Participation in informal transfers through networks has negligible effects on how early someone became an adopter of *tumbukiza*. The conclusion is that the data do not support H2.

Discussion of H1 and H2 against each other

It is possible that these weak results for both hypotheses are a result of effects that cancel each other. Under H1, more transfers received lead to more adoption, while under H2 it leads to later, or less, adoption. The hypotheses make assumptions only about transfers received, not provided, but providers ought to be more resourceful than recipients, and thus not be among the disadvantaged ones. So providers of transfers should never be adoption laggards. Moreover, these effects should depend on features of the technologies, such as how capital intensive or risky they are. H1 should be expected to dominate for capital intensive technologies, H2 for risky technologies. But the patterns found in the regressions discussed here do not conform to either of the hypotheses, so neither is supported by the data.

Testing H3

This hypothesis states that the more adopters a farmer knows and interacts with through social networks, the more likely that farmer is to also adopt the new technology. There are two categories of variables here. All respondents have listed family members, neighbors and “friends” as network members. In this context, “friends” are people the respondent “likes to discuss issues of farming with”. A fourth category everybody has reported, is those they “engage in borrowing and lending with”, i.e., the transfers network. For these categories, variables have been generated that represent the proportion or fraction of members who (according to the respondent) are adopters. In addition, some few network members are persons of some significance in the community, such as school teachers, preachers, business owners and civil servants. For these four categories variables have been generated that represent the number of such persons a respondent has named as network members who are also adopters. These are count variables, not proportions. Also note that the technologies they represent, are the aggregates identified in the discussion of H2. These are included in the regressions presented in Tables 3 through 5.

In the regressions, the adoption choices of network members were included for technology clusters that the ones in question were thought to belong to. Thus, in the soil and water conservation regressions, network members' adoption variables for "terracing" are included. In the soil fertility management regressions, the adoption variables for "organic fertilizers" are included. And finally, for the trees regressions, the adoption variables for both of those aggregates are included, as trees are thought to address both soil conservation and soil fertility problems.

For the soil and water conservation technologies, the significant coefficient estimates on these variables are mostly negative (there are 6 significant, negative coefficients). The only exceptions are the positive estimates on the variables for the proportion of neighbors and "friends" who have adopted "terracing" in the terraces regression, but a positive relationship between terraces on own farm and neighbors' farms may be attributed as much to correlated factors (same topography) as to social learning.

For the soil nutrient management technologies there are very few significant coefficient estimates. For inorganic fertilizers there are no significant coefficient estimates, but for mulching there are three, two negative and one positive. For tumbukiza there are two significant estimates, both positive. The coefficient estimate on the number of civil servants who are network members and who have terraces is positive in all 3 tree regressions, while the estimate on the number of civil servants who use organic fertilizers is negative in two of the three regressions, for agroforestry trees and windbreak. Except for these results, there are only few significant coefficient estimates for trees (5 out of 42 possible), one negative and 4 positive.

The results may suggest that persons of some significance in the community, such as civil servants, who are the highest earners and often better educated than the average villager, do influence people's behavior, but the inconsistent signs on the coefficient estimates in question make the results hard to interpret. The lack of direct correspondence between the technologies on either side of the equality sign is a source of noise, and may contribute to weak results, but given the positive bias in reporting the alters' adoption choices, the sparsity of positive coefficient estimates is quite conspicuous. It does not look like the data support H3, at least not strongly. The existence of persons with influence on the behavior of network contacts cannot be rejected completely. But the relationship between overall adoption rates and adoption appears to be weak.

Testing H4

There are 4 variables representing exposure to the extension service in the regressions. One is a variable representing the number of extension officers, vets or representatives of agricultural cooperatives who are members of the respondents' networks. The other 3 are binary variables representing whether specific extension officers were listed as network members. These three are the designated extension officers in the extension units where the sample households in Embu are located. In Vihiga respondents had much less contact with the extension service, and there were no such designated extension officers in the area.

There is only one significant coefficient estimate on the number of extension officers, and that one is positive. That is the case for windbreaks. Most of the coefficient estimates on the specific extension officers are not significant, and of the 4 exceptions two are positive and two are negative. Apparently, the extension officer in Manyatta has a positive effect on the adoption of terraces, while the same extension officer has a negative effect on the adoption of agroforestry trees. These coefficients counterbalance the coefficients on the binary variables representing Manyatta, which for both technologies have the opposite sign. That means the coefficient estimate on the extension officer is positive when it is negative for the district, and vice versa. The same pattern is found for the extension officer in Mukangu and windbreaks. In Mukangu the adoption rate of windbreaks is higher than the control group, but less so for those who list the extension officer as a network contact. But in the regression for agroforestry trees, the coefficient estimates are positive for both the extension officer for Kianjuki and Kavutiri and for both of the corresponding village dummies, suggesting that agroforestry trees has been a priority of the extension service in these villages, with the particular extension officer playing an important role.

A positive effect from exposure to the extension service is both possible and likely, but it is not clear whether the extension service is concertedly promoting the technologies under study here. Rather, it looks like the extension officers have their particular agendas, promoting some practices, and not others. But that does not contradict the hypothesis, only modify it a little. When the extension service is promoting a practice, then contact between farmers and extension officers apparently does have a positive effect on adoption. Thus, H4 is not rejected.

Testing H5

Data on weak ties were only collected for a small subset of respondents. They were used in the final regressions that are presented in Tables 7, 8 and 9. Here the number of variables has been cut down to the barest minimum to compensate for the low number of observations, only 45-49 after loss of observations due to missing variables. Most of the variables used here are index variables generated by means of factor analysis, and substitute for the ones that were used to generate them. As for the generated variables representing exogenous factors in the regressions already discussed, the results of factor analysis for the variables in question here are not reported, but can be made available upon request. Due to the low number of observations, regressions did not run well, and some playing around with different levels of aggregation of variables was employed to select models that generated results that could be interpreted. But due to the low number of observations involved, the results are not robust, and should not be given too much weight.

The variable representing success with finding the answer to the most difficult question (a regional farm input price) is not significant in any of the regressions. The coefficient on the weak ties score, i.e., the cash reward earned, is weakly significant in two regressions, and it is negative in both cases, contrary to expectation under the hypothesis. This variable has mean 494 (Kenya) Shillings, median 510 Shillings, and standard deviation 105 Shillings. Thus the strongest effect, the one for inorganic fertilizers, represents a difference of 1.68 per standard deviation, which is not entirely negligible. This may represent a real relationship, but it may also be just a spurious correlation. Given the low number of observations and the low power of these tests, it is tempting to reject the regressions as inconclusive. Better data is needed to reach a conclusion about the hypothesis. Thus, H5 remains unresolved.

Testing H6 and H7

For this study, data about conflicts over technological externalities were collected to serve as proxies for the presence of such effects. But conflicts arise when negative externalities are present, not where there are positive externalities. Thus, this information does not capture the effects of positive externalities. The most frequently occurring conflicts between neighbors reported by the respondents are due to straying animals that cause damage, something 66% of respondents have experienced. But natural resource management techniques or their absence also generate conflicts, as 25% report having experienced conflicts over water run-off causing soil erosion, while 48% report having experienced conflicts due to detrimental effects of trees at or near boundaries. But although according to the extension service in Embu, acidification of soil due to run-off of chemical fertilizers from land planted in tea is known to be a problem there, only 15% of the respondents reported any experience with conflicts over fertilizer run-offs.

Conflicts over trees appear to be the ones that are most difficult to solve. Two-thirds (66%) of all respondents who had experienced such conflicts reported that they had not been solved, while 60% of conflicts over water run-off had been solved. When conflicts had been solved, the involved parties had usually solved it themselves through direct negotiations (82%), but in many cases a village chief or elder had been asked to mediate (16%).

Three questions about conflicts with neighbors are used here as regressors. They represent conflicts over water run-off causing soil erosion, fertilizer run-off causing pollution, and conflicts over trees at or near boundaries. Interaction terms between these variables and farm size are also used. Interaction terms between conflicts and the neighbors' adoption choices were tested, but did not generate any significant coefficients, so they were dropped. The problem here might be that the information available about the neighbors' adoption choices is both too imprecise (not specific enough about what technologies it refers to), and too noisy (respondents were only guessing about what neighbors do).

These variables have generated some significant coefficient estimates that are large enough to matter. Having experienced conflicts apparently leads to less adoption of drainage structures, and the coefficient estimate on conflicts is right on the edge of becoming significant for inorganic fertilizers as well. If a site variable (Vihiga/Embu) replaces the village variables in this regression, it becomes significant at the 5% level, taking the value -1.184.

For drainage structures conflicts can go both ways. If constructed well, they can be a solution to conflicts over water run-off, but if constructed poorly, they can make matters worse. Getting it right might be a problem the extension service can assist with. The data suggest that respondents are abstaining from building drainage structures to avoid conflicts they may lead to with neighbors. Conflicts over fertilizer run-offs are only relevant to inorganic fertilizers, and their effect is as expected under the hypothesis.

Having experienced conflicts also leads to less adoption of agroforestry trees and windbreaks, and more so the larger the farm. Windbreaks and agroforestry trees are often planted on boundaries, and may therefore be at the center of many conflicts over trees at or near boundaries. Thus, it is not surprising that conflicts over trees lead to less adoption of these two technologies. What is surprising is that the effect is stronger the larger the farm is. This is contrary to expectation. While a diminishing effect with larger farm sizes is not explicitly included in the hypothesis, it would make sense. Those who have larger farms have more freedom to plant trees at some distance from boundaries, whereby conflicts can be avoided.

In general, it looks like H6 and H7 are supported by the data, so these hypotheses are not rejected.

Social capital

The variable “Household head has always lived here” represents having a long history of continuous networking in the same environment, which one would expect increases the probability that an individual is well connected, an important component of “social capital”. Here, it is thought of as representing unmeasured social capital, complementing the groups and networks data collected for this study.

The coefficient estimate on “Household head has always lived here” is positive and strong for drainage structures, mulching and agroforestry trees. For drainage structures and agroforestry trees it is possible this is related to the fact that adoption of these technologies may be hampered by negative externalities leading to conflicts. The better connected may be in a better position to solve conflicts through mobilizing key contacts, or by initiating collective action. But an explanation for why households whose household head has always lived in the same place are more likely to practice mulching can only be purely speculative.

Groups

The group variables are only available for the small subset, and because of the small sample, the results of these regressions need to be taken with a grain of salt. The results of these regressions are found in Tables 7, 8 and 9. For the soil fertility management regressions and 2 of the 3 trees technologies regressions there are no significant coefficient estimates, except for a composite group membership index, derived through factor analysis using group membership variables, which is significant and positive for adoption of *tumbukiza*. In contrast, all the group membership variables are significant in the regression for adoption of windbreaks. Here, membership in a youth group is positive, while all the others are negative. For soil and water conservation techniques, membership in a youth group has a positive effect on adoption of terraces, while there are two significant coefficient estimates that are negative, one on membership in a village development committee for adoption of terraces, and the other on membership in a women's group for adoption of drainage structures.

Summary of All Factors

The final regressions in tables 7 to 9 represent a summary of all factors, (except correlated factors, but only two villages - one for each site - are represented in this subset, so the correlated factors should be basically the same, at least within site). In 6 out of 8 regressions at least one of the index variables representing exogenous factors is significant. In 3 of the regressions, the conflicts variable is significant, and it is negative in all cases.

The variable for network transfers, an index variable generated by factor analysis on Freeman Degrees for participation in network transfers, is significant and strong in the regression for terraces. Because of the aggregate nature of the variable, it is impossible to disentangle, e.g., enabling due to transfers received from a wealth effect that leads to more transfers provided, so interpretation of this variable is difficult. The variables for network influence - whether network contacts are adopters - are not significant in any of the regressions for soil and water conservation technologies. But in the regression for mulching, the Freeman Degrees for adoption of *tumbukiza* is included, mainly because in its presence, the best model fit was achieved, and the coefficient on it is significant and negative. This is basically a spurious result, due to the concentration of *tumbukiza* in Embu, and of mulching in Vihiga. The difference including it made reveals the difficulties I had with making these regressions run, due to the low number of observations and large number of variables. For agroforestry trees and windbreak, Freeman Degrees for adoption of terracing are significant, and in both regressions the coefficient estimates are positive. This suggests a positive relationship between soil and water conservation measures and the planting of trees for various purposes.

In 5 of the 8 regressions, the coefficient estimates on contact with extension officers are significant, and 3 of the significant estimates are negative, for drainage structures, inorganic fertilizers and agroforestry trees. Note that the included villages here are Manyatta and Kitulu. Contact with the extension service is much better in Manyatta (Embu) than in Kitulu (Vihiga), so these coefficients can be interpreted as a spurious relationship between site, extension service, and technologies. Drainage structures are much more common in Vihiga. In Manyatta the adoption rate for agroforestry trees is high, but within the village it is lower for those who have contact with the local extension officer, as revealed in table 5. The result for inorganic fertilizers in the summary regressions cannot be explained by appealing to the main regressions.

The summary regressions cannot determine what category of factors is most or least important for technology adoption. They appear to all be important, but not equally so for all technologies. Given the very low number of observations used in these regressions, these results need to be taken with a grain of salt, but they do suggest that group membership may be important, and that individual adoption behavior reflects the priorities of these groups.

Summary and Conclusions

Two hypotheses regarding the relationship between informal finance through social networks and technology adoption have been discussed here, one termed the “enabling model”, the other the “power model”. According to the former, a person is more likely to adopt the better access she has to informal finance through social networks, because it enables her to finance investments in technology adoption. This effect should be more pronounced the more capital intensive a technology is. The latter implies that a person will be more hesitant to adopt the more dependent she is on network transfers, so that more transfers received leads to more conservative behavior, and later adoption. This should be more pronounced the riskier adoption of the technology is.

Neither of these effects could be detected in the data. Coefficient estimates were either insignificant or were of too low magnitude to matter. Moreover, signs on the few significant estimates were inconsistent with the hypotheses. But being a recipient of remittances has a positive effect on the probability of being an adopter of several technologies considered here, consistent with the hypothesis that access to cash facilitates technology adoption. But network transfers do not appear to be important contributions to investments in new technologies. If such effects had been found, one might have wanted to avoid crowding out network transfers with interventions intended to improve access to finance for the purpose of technology adoption. The results presented here suggest such a concern is unwarranted. However, social networks may be important as a source of informal insurance, so policies aimed at improving social security need to take into consideration their effect on social networks and transfers within them.

This study finds that direct contact with the extension service has a strong effect on technology adoption in some cases. Of course, it matters whether the technology under consideration is being actively promoted by the local extension officers. But where this service is established, it is well worth including in future policies aimed at improving agricultural productivity.

Technological spill-over effects, or externalities, were found to have strong effects on adoption, and interestingly, adoption of agroforestry, a technology promoted as an important component in a technology package intended to improve soil nutrient management and prevent soil degradation, appears to suffer negative consequences of conflicts between neighbors over boundary trees. Agroforestry trees are typically planted on boundaries. Here, the extension service may play an important role with teaching farmers how to reap the benefits of agroforestry without generating the negative externalities associated with it. This can be achieved through, e.g., pruning of trees both above and below ground, techniques that have been promoted by Kenya Forestry Research Institute, KEFRI. These techniques require skills that the extension service can help farmers acquire.

An experiment designed to measure rural villagers' ability to access information by means of weak social ties has been discussed here. A high ability according to this experiment has not been shown to be important for adoption of the technologies considered in this paper. But more interesting is the direct findings about how people access information. In general, rural villagers appear to have poor access to information that is disseminated through mass media, in particular printed media. The sample respondents lived in coffee and tea districts, but even with three weeks to work on it, and the promise of a cash reward if they found the answer, they were not able to find out the prices the local tea and coffee factories had achieved at recent auctions in Nairobi, although these prices are announced weekly in national newspapers. However, information about health issues that is being disseminated through radio and TV was well-known. Most respondents got this information from family or friends if they did not have a radio or TV themselves. This means dissemination of information to farmers is not effective if print media are chosen as a main channel. But penetration of radio and TV has reached a level that means they can be effective channels of information to farmers.

Finally, this study has found that local groups, such as women's groups and youth groups, probably are important instruments for dissemination of information and social learning, although the data the analysis is based on here come from a sample that is too small to be representative. Such groups are an important component of the development strategy adopted by Kenya's government, and the findings of this study suggest that groups should continue to be a component of this strategy packet.

Table 1. Summary statistics of variables that are not restricted to equal zero or one or be within the range from zero to one.

Label	N	Mean	Std Dev	Minimum	Maximum
Respondent's age	230	51.90	15.44	14	88
Number of ROSCA memberships	241	0.79	1.00	0	5
Density of respondent's network	241	9.90	3.45	3	18
Highest education level in household	238	2.79	0.86	1	5
Area under cultivation in acres	237	1.96	2.06	0.2	15
Household labor days per month	235	40.70	25.59	0	140
Slope of steepest plot (%)	226	26.22	21.47	0	100
Mean slope (%)	226	13.12	10.63	0	70
Number of extension officers in network	240	0.48	0.83	0	5
Number of teachers who have terraces etc.	240	0.39	0.74	0	4
Number of teachers who use organic fertilizers	240	0.41	0.74	0	4
Number of preachers who have terraces etc.	240	0.10	0.34	0	2
Number of preachers who use organic fertilizers	240	0.13	0.41	0	3
Number of civil servants who have terraces etc.	240	0.44	0.84	0	5
Number of civil servants who use organic fertilizers	240	0.49	0.86	0	5
Number of business owners who have terraces etc.	240	0.79	1.09	0	5
Number of business owners who use organic fertilizers	240	0.86	1.12	0	6
Aggregate number of times receiving cash	240	6.93	10.06	0	93
Aggregate number of times providing cash	240	5.47	7.90	0	82
Aggregate number of times receiving in kind	240	15.05	23.17	0	256
Aggregate number of times providing in kind	240	16.89	36.22	0	500
Aggregate number of times receiving labor	240	5.75	12.36	0	110
Aggregate number of times providing labor	240	6.22	20.25	0	270
Freeman Degrees for discussing terracing	327	2.68	2.06	0	15.72
Freeman Degrees of adopting terracing	327	2.81	2.03	0	12.23
Freeman Degrees for discussing organic fertilizers	327	2.79	2.08	0	16.16
Freeman Degrees for adopting organic fertilizers	327	3.00	2.16	0	14.41
Fr. Deg. for frequency of cash transfers received	327	6.06	11.19	0	93
Fr. Deg. for amounts of cash transfers received	327	1231.62	4906.69	0	66000
Fr. Deg. for frequency of cash transfers provided	327	5.84	9.78	0	68
Fr. Deg. for amounts of cash transfers provided	327	1013.12	4492.99	0	66200
Fr. Deg. for frequency of transfers in kind received	327	31.33	56.03	0	437
Fr. Deg. for value of transfers in kind received	327	477.90	1287.55	0	19500
Fr. Deg. for frequency of transfers in kind provided	327	31.94	70.69	0	775
Fr. Deg. for value of transfers in kind provided	327	629.43	2024.98	0	24000
Fr. Deg. for labor days received	327	18.14	43.20	0	319
Fr. Deg. for labor days provided	327	13.02	28.07	0	200
Freeman Degrees Index for network transfers	228	0.00	0.92	-0.97	9.02
Interaction Farm Size x Conflicts (water run-off)	228	0.37	0.91	0	6
Interaction Farm Size x Conflicts (fertilizer run-off)	229	0.17	0.61	0	6
Interaction Farm Size x Conflicts (boundary trees)	229	0.81	1.43	0	8

Table2. Checking correspondence between respondents' answers about the adoption choices of alters, and alters' own answers. α is the adoption rate among alters.(%)

	Terracing		Fallows		Organic Fertilizers		Tumbukiza	
Family	No	Yes	No	Yes	No	Yes	No	Yes
Correct negative	2.93	0.37	54.15	51.66	0.65	0.37	53.85	57.25
Correct positive	73.97	77.78	9.52	10.70	89.02	89.59	9.62	9.54
False negative	13.45	14.81	17.72	14.39	6.74	7.81	18.33	17.56
False positive	9.65	7.04	18.60	23.25	3.59	2.23	18.21	15.65
Observed α	87.42	92.59	27.24	25.09	95.76	97.40	27.95	27.10
(1-α) squared	1.58	0.55	52.94	56.12	0.18	0.07	51.91	53.14
α-squared	76.42	85.73	7.42	6.30	91.70	94.87	7.81	7.34
Obs. Sum	76.90	78.15	63.67	62.36	89.67	89.96	63.47	66.79
Exp. Sum	78.01	86.28	60.36	62.41	91.88	94.94	59.72	60.49
Error	-1.11	-8.13	3.31	-0.05	-2.21	-4.98	3.75	6.30
Observations	922	270	903	271	920	269	884	262
Adopter	No	Yes	No	Yes	No	Yes	No	Yes
Correct negative	6.42	1.95	58.26	41.56	0.00	0.63	66.34	23.82
Correct positive	57.80	76.44	9.26	10.94	89.09	89.11	4.96	21.63
False negative	26.61	12.52	18.87	11.56	9.09	6.93	19.49	15.05
False positive	9.17	9.09	13.60	35.94	1.82	3.33	9.20	39.50
Observed α	84.41	88.96	28.13	22.50	98.18	96.04	24.45	36.68
(1-α) squared	2.43	1.22	51.65	60.06	0.03	0.16	57.08	40.09
α-squared	71.25	79.14	7.91	5.06	96.39	92.24	5.98	13.45
Obs. Sum	64.22	78.39	67.52	52.50	89.09	89.74	71.30	45.45
Exp. Sum	73.68	80.36	59.57	65.13	96.43	92.39	63.06	53.55
Error	-9.46	-1.97	7.95	-12.63	-7.34	-2.65	8.24	-8.10
Observations	109	1078	853	320	55	1111	826	319
Discuss	No	Yes	No	Yes	No	Yes	No	Yes
Correct negative	7.59	1.05	64.99	34.47	1.57	0.40	69.34	22.44
Correct positive	48.95	81.26	5.43	17.12	67.54	93.29	2.80	24.38
False negative	36.29	8.17	20.76	10.50	27.75	3.01	22.77	8.31
False positive	7.17	9.53	8.82	37.90	3.14	3.31	5.09	44.88
Observed α	85.24	89.43	26.19	27.62	95.29	96.30	25.57	32.69
(1-α) squared	2.18	1.12	54.48	52.39	0.22	0.14	55.40	45.31
α-squared	72.66	79.98	6.86	7.63	90.80	92.74	6.54	10.69
Obs. Sum	56.54	82.31	70.42	51.59	69.11	93.69	72.14	46.82
Exp. Sum	74.84	81.09	61.34	60.02	91.02	92.87	61.94	55.99
Error	-18.30	1.22	9.08	-8.43	-21.91	0.82	10.20	-9.17
Observations	237	955	737	438	191	998	786	361

Table 3. Adoption of soil and water conservation techniques. Probit estimations.

	Terraces	Drainage structures
Extension officer Manyatta	2.008	0.159
	(0.897)**	(0.875)
Extension officer Kianjuki and Kavutiri	0.602	0.813
	(0.580)	(0.692)
Extension officer Mukangu	0.165	1.824
	(0.809)	(1.129)
Manyatta	-1.621	1.635
	(0.854)*	(1.117)
Kianjuki	-1.817	1.715
	(0.823)**	(1.108)
Kavutiri	-1.778	1.213
	(0.859)**	(1.137)
Mukangu	-2.965	1.241
	(0.934)***	(1.216)
Ikuyu		1.004
		(1.333)
Ivona	-0.968	1.937
	(1.051)	(1.313)
Indulo		1.359
		(1.142)
Kedeta	-1.134	0.955
	(0.672)*	(0.981)
Kitulu	-0.868	1.252
	(0.531)	(0.870)
Kisienya	-0.415	2.236
	(0.704)	(0.970)**
Luvuka	-0.764	-0.177
	(0.644)	(0.994)
Madzuu		1.001
		(1.023)
Vigina	0.381	-0.296
	(0.746)	(1.003)
Exogenous factors 1	0.435	-1.132
	(0.287)	(0.348)***
Exogenous factors 2	0.288	-0.252
	(0.165)*	(0.185)
Exogenous factors 3	-0.069	-0.082
	(0.177)	(0.223)
Exogenous factors 4	-0.392	-0.195
	(0.189)**	(0.199)
Aggregate number of times receiving cash	0.003	0.024
	(0.014)	(0.013)*
Aggregate number of times providing cash	-0.069	0.005
	(0.025)***	(0.027)

	Terraces	Drainage
Aggregate number of times receiving in kind	-0.019	0.002
	(0.014)	(0.017)
Aggregate number of times providing in kind	0.004	-0.008
	(0.008)	(0.014)
Aggregate number of times receiving labor	0.035	-0.007
	(0.025)	(0.020)
Aggregate number of times providing labor	-0.008	0.014
	(0.010)	(0.021)
HH receives remittances	0.277	-0.117
	(0.322)	(0.349)
Number of ROSCA memberships	0.161	-0.366
	(0.157)	(0.181)**
Not recovered from earlier shock	-0.100	-0.276
	(0.321)	(0.331)
HH head has always lived here	-0.407	0.915
	(0.374)	(0.446)**
Number of extension officers in network	0.249	-0.213
	(0.220)	(0.314)
Prop. of family members who have terraces etc.	-0.649	-0.390
	(0.347)*	(0.368)
Prop. of transfer network who have terraces etc.	-2.268	0.161
	(0.850)***	(0.787)
Prop. of neighbors who have terraces etc.	1.136	-1.293
	(0.646)*	(0.669)*
Prop of friends who have terraces etc.	1.159	0.683
	(0.509)**	(0.572)
Number of teachers who have terraces etc.	-0.121	0.106
	(0.190)	(0.249)
Number of preachers who have terraces etc.	0.805	-0.092
	(0.533)	(0.450)
Number of civil servants who have terraces etc.	-0.291	0.029
	(0.166)*	(0.188)
Number of business owners who have terraces etc.	-0.343	0.130
	(0.143)**	(0.171)
Has experienced conflicts over water run-off	0.277	-1.111
	(0.495)	(0.641)*
Interaction between farm size and conflicts	0.215	0.222
	(0.225)	(0.266)
Constant	2.628	-1.915
	(0.790)***	(1.070)*
Observations	186	186
Pseudo R^2	0.3746	0.3479
P-value	0.0000	0.0072
Log likelihood	-73	-62

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Adoption of soil nutrient management techniques. Probit estimations.

	Inorganic fertilizers	Mulching	Tumbukiza
Extension officer Manyatta	-0.590	0.259	0.017
	(0.778)	(0.735)	(0.793)
Extension officer Kianjuki and Kavutiri	0.169	-0.432	-0.048
	(0.614)	(0.627)	(0.694)
Extension officer Mukangu	1.348	0.742	-0.200
	(0.941)	(0.993)	(0.939)
Manyatta		-2.187	1.767
		(1.231)*	(1.220)
Kianjuki	-0.539	-2.322	2.819
	(0.747)	(1.244)*	(1.198)**
Kavutiri	-0.640	-2.021	2.861
	(0.795)	(1.266)	(1.224)**
Mukangu	-1.304	-2.741	3.250
	(0.779)*	(1.282)**	(1.230)***
Ivona	-0.905	-1.245	1.908
	(1.264)	(1.443)	(1.745)
Isiagalo	-1.454	0.642	
	(0.978)	(1.225)	
Indulo	-0.554	0.920	
	(0.972)	(1.312)	
Kedeta	-2.343	-0.315	1.414
	(0.794)***	(1.002)	(0.962)
Kitulu	-0.942	-0.057	
	(0.757)	(0.978)	
Kisienya	-1.078	0.258	
	(0.770)	(1.111)	
Luvuka	-2.246	-0.184	
	(0.811)***	(1.020)	
Madzuu	-0.418	0.759	2.134
	(0.890)	(1.090)	(0.997)**
Makanya	-2.130	-1.409	
	(0.839)**	(1.103)	
Vigina	-1.682	-0.769	
	(0.740)**	(1.020)	
Exogenous factors1	-0.276	-0.134	0.219
	(0.255)	(0.321)	(0.289)
Exogenous factors2	0.168	0.000	-0.151
	(0.180)	(0.182)	(0.228)
Exogenous factors3	0.195	-0.339	0.041
	(0.170)	(0.187)*	(0.191)
Exogenous factors4	-0.187	-0.202	-0.200
	(0.168)	(0.195)	(0.191)
Aggregate number of times receiving cash	-0.019	0.011	-0.025
	(0.013)	(0.013)	(0.028)
Aggregate number of times providing cash	0.003	-0.017	0.029
	(0.017)	(0.023)	(0.019)

	Inorganic	Mulching	Tumbukiza
Aggregate number of times receiving in kind	0.006	0.009	0.008
	(0.013)	(0.015)	(0.015)
Aggregate number of times providing in kind	0.004	0.000	0.029
	(0.011)	(0.008)	(0.015)*
Aggregate number of times receiving labor	0.033	-0.039	0.023
	(0.028)	(0.034)	(0.015)
Aggregate number of times providing labor	0.009	0.019	0.004
	(0.030)	(0.014)	(0.010)
HH receives remittances	0.154	0.529	1.258
	(0.290)	(0.308)*	(0.471)***
Number of ROSCA memberships	0.116	0.072	-0.310
	(0.166)	(0.154)	(0.202)
Not recovered from earlier shock	-0.313	-0.403	0.034
	(0.294)	(0.318)	(0.377)
HH head has always lived here	-0.317	1.321	0.100
	(0.326)	(0.421)***	(0.478)
Number of extension officers in network	-0.207	-0.339	0.090
	(0.232)	(0.248)	(0.315)
Prop. of family members who use org. fertilizers	0.334	-0.242	-0.155
	(0.324)	(0.343)	(0.391)
Prop. of transfer network who use org. fertilizers	-1.225	-0.046	-0.015
	(0.835)	(0.804)	(1.154)
Prop. of neighbors who use org. fertilizers	0.041	-1.945	1.530
	(0.786)	(0.819)**	(0.903)*
Prop. of friends who use org. fertilizers	0.375	1.581	-1.004
	(0.570)	(0.632)**	(0.835)
Number of teachers who use org. fertilizers	0.091	-0.140	0.201
	(0.173)	(0.192)	(0.222)
Number of preachers who use org. fertilizers	-0.231	-0.643	0.961
	(0.297)	(0.373)*	(0.479)**
Number of civil servants who use org. fertilizers	0.096	-0.191	0.031
	(0.188)	(0.207)	(0.179)
Number of business owners who use org. fertilizers	-0.028	-0.030	0.016
	(0.120)	(0.123)	(0.191)
Has experienced conflicts over fert.run-off	-0.981	-0.359	-0.180
	(0.597)	(0.599)	(1.032)
Interaction between farm size and conflicts	0.012	-0.201	-0.094
	(0.436)	(0.431)	(0.472)
Constant	2.346	0.952	-4.716
	(1.000)**	(1.395)	(1.448)***
Observations	187	187	203
Pseudo R^2	0.2856	0.3698	0.5288
P-value	0.0052	0.0000	0.0000
Log likelihood	-85	-79	-53

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Adoption of trees on farms. Probit estimations.

	Tree crops	Agroforestry trees	Windbreak
Extension officer Manyatta	-0.973	-2.979	-1.112
	(0.770)	(1.069)***	(0.747)
Extension officer Kianjuki and Kavutiri	0.318	1.051	0.648
	(0.730)	(0.635)*	(0.700)
Extension officer Mukangu	-1.514	0.603	-1.506
	(1.057)	(0.923)	(0.890)*
Manyatta	2.602	6.490	4.354
	(1.673)	(1.833)***	(1.327)***
Kianjuki	0.713	3.064	2.231
	(1.739)	(1.631)*	(1.393)
Kavutiri	3.495	4.238	3.074
	(1.805)*	(1.674)**	(1.425)**
Mukangu	1.978	3.532	3.355
	(1.717)	(1.667)**	(1.383)**
Ikuyu		3.317	
		(1.716)*	
Ivona			4.182
			(1.876)**
Isiagalo	0.709	2.176	
	(1.685)	(1.643)	
Indulo	1.488	4.322	
	(1.953)	(1.832)**	
Kedeta	1.215		2.290
	(1.589)		(1.112)**
Kitulu	1.632	2.751	1.324
	(1.600)	(1.566)*	(1.002)
Kisienya	1.627		1.583
	(1.580)		(1.191)
Luvuka	0.238		1.935
	(1.689)		(1.078)*
Madzuu	1.796	2.912	2.513
	(1.627)	(1.571)*	(1.117)**
Makanya	0.871	2.865	
	(1.746)	(1.594)*	
Vigina	0.667	2.990	0.956
	(1.610)	(1.566)*	(1.091)
Exogenous factors1	0.824	0.176	-0.387
	(0.337)**	(0.294)	(0.315)
Exogenous factors2	0.889	0.129	-0.053
	(0.233)***	(0.193)	(0.206)
Exogenous factors3	0.231	0.170	-0.027
	(0.210)	(0.206)	(0.200)
Exogenous factors4	0.009	0.130	0.647
	(0.201)	(0.199)	(0.229)***

	Tree	Agroforestry	Windbreak
Aggregate number of times receiving cash	-0.007	0.024	0.036
	(0.016)	(0.013)*	(0.015)**
Aggregate number of times providing cash	-0.042	-0.010	0.040
	(0.028)	(0.017)	(0.018)**
Aggregate number of times receiving in kind	-0.043	-0.008	0.010
	(0.014)***	(0.015)	(0.013)
Aggregate number of times providing in kind	0.021	0.007	-0.010
	(0.008)***	(0.010)	(0.013)
Aggregate number of times receiving labor	-0.002	-0.036	-0.006
	(0.014)	(0.028)	(0.016)
Aggregate number of times providing labor	0.008	0.020	0.020
	(0.009)	(0.010)*	(0.021)
HH receives remittances	0.704	0.562	0.097
	(0.382)*	(0.363)	(0.346)
Number of ROSCA memberships	-0.318	-0.162	0.165
	(0.197)	(0.168)	(0.174)
Not recovered from earlier shock	0.740	1.356	-0.222
	(0.384)*	(0.393)***	(0.348)
HH head has always lived here	0.281	0.818	0.418
	(0.428)	(0.438)*	(0.417)
Number of extension officers in network	0.172	-0.014	0.507
	(0.292)	(0.259)	(0.232)**
Prop. of family members who have terraces etc.	-0.060	-0.867	0.936
	(0.791)	(0.852)	(0.809)
Prop. of transfer network who have terraces etc.	-0.871	1.578	-0.417
	(0.875)	(1.088)	(0.933)
Prop. of neighbors who have terraces etc.	0.832	-0.293	-0.996
	(0.752)	(0.775)	(0.790)
Prop of friends who have terraces etc.	-0.651	-1.078	1.431
	(0.629)	(0.749)	(0.750)*
Number of teachers who have terraces etc.	-0.938	-1.054	-0.418
	(0.650)	(0.753)	(0.670)
Number of preachers who have terraces etc.	-0.562	0.351	0.249
	(0.774)	(0.914)	(0.705)
Number of civil servants who have terraces etc.	0.937	1.330	1.276
	(0.513)*	(0.567)**	(0.570)**
Number of business owners who have terraces etc.	-0.253	-0.179	-0.517
	(0.431)	(0.487)	(0.442)
Prop. of family members who use org. fertilizers	-0.012	0.828	-0.421
	(0.761)	(0.836)	(0.770)
Prop. of transfer network who use org. fertilizers	-0.633	-3.462	-0.603
	(1.101)	(1.212)***	(1.132)
Prop. of neighbors who use org. fertilizers	0.775	0.260	0.482
	(1.052)	(1.013)	(0.975)
Prop. of friends who use org. fertilizers	0.789	2.362	0.486
	(0.793)	(0.954)**	(0.881)

	Tree	Agroforestry	Windbreak
Number of teachers who use org. fertilizers	1.065	0.977	0.751
	(0.646)*	(0.751)	(0.705)
Number of preachers who use org. fertilizers	-0.477	-0.999	0.019
	(0.518)	(0.751)	(0.620)
Number of civil servants who use org. fertilizers	-0.826	-1.223	-1.048
	(0.509)	(0.548)**	(0.582)*
Number of business owners who use org. fertilizers	0.031	0.308	0.810
	(0.401)	(0.480)	(0.409)**
Has experienced conflicts over boundary trees	-0.054	0.551	0.672
	(0.433)	(0.438)	(0.472)
Interaction between farm size and conflicts	-0.071	-0.331	-0.376
	(0.159)	(0.156)**	(0.166)**
Constant	-2.164	-4.851	-5.350
	(1.814)	(1.717)***	(1.621)***
Observations	187	187	187
Pseudo R^2	0.4593	0.4786	0.3908
P-value	0.0000	0.0000	0.0006
Log likelihood	-69	-65	-66

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Number of years ago respondent adopted *tumbukiza*. Poisson regression.

Label	Coef. Est.	Label	Coef. Est.
Probability of being an adopter	5.209	HH head has always lived here	-0.463
of *tumbukiza*	(1.038)***		(0.278)*
Respondent's age	-0.008	Number of extension officers	-0.443
	(0.009)	in network	(0.153)***
Extension officer Manyatta	-1.012	Prop. of family members	0.361
	(0.341)***	who use organic fertilizers	(0.395)
Extension officer Kianjuki	1.470	Prop. of transfer network	-2.642
and Kavutiri	(0.377)***	who use organic fertilizers	(0.680)***
Extension officer Mukangu	1.610	Proportion of neighbors	-0.641
	(0.587)***	who use organic fertilizers	(0.597)
Manyatta	3.857	Proportion of friends	-0.987
	(1.001)***	who use organic fertilizers	(0.374)***
Kianjuki	4.790	Number of teachers	-0.215
	(1.087)***	who use organic fertilizers	(0.295)
Kavutiri	2.051	Number of teachers	1.731
	(1.046)**	who use organic fertilizers	(0.471)***
Mukangu	4.053	Number of civil servants	0.347
	(1.140)***	who use organic fertilizers	(0.213)
Ivona	2.352	Number of business owners	-0.141
	(1.747)	who use organic fertilizers	(0.257)
Kedeta	4.520	Prop of family members who	-0.807
	(1.028)***	practice *tumbukiza*	(0.528)
Madzuu	3.048	Prop of transfer network	-0.066
	(1.187)**	who practice *tumbukiza*	(0.743)
Aggregate times receiving cash	-0.025	Prop of neighbors	0.959
	(0.019)	who practice *tumbukiza*	(0.579)*
Aggregate times providing cash	0.042	Prop of friends	1.233
	(0.012)***	who practice *tumbukiza*	(0.413)***
Aggregate times receiving in kind	0.037	Number of teachers	-0.064
	(0.009)***	who practice *tumbukiza*	(0.366)
Aggregate times providing in kind	-0.026	Number of preachers	-4.284
	(0.005)***	who practice *tumbukiza*	(1.051)***
Aggregate times receiving labor	0.010	Number of civil servants	-0.740
	(0.007)	who practice *tumbukiza*	(0.275)***
Aggregate times providing labor	-0.010	Number of business owners	-0.044
	(0.006)	who practice *tumbukiza*	(0.397)
HH receives remittances	1.001	Constant	-1.477
	(0.263)***		(1.084)
Number Of ROSCA memberships	-0.157	Observations	203
	(0.168)	Pseudo R^2	0.7882
Not recovered from earlier shock	0.950	P-value	0.0000
	(0.284)***	Log likelihood	-162
Density of respondent's network	-0.202		
	(0.060)***		

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. Adoption of soil and water conservation techniques, all factors. Using secondary and subset data. Probit estimation.

	Terraces	Drainage structures
Exogenous factors 2	2.168	-0.985
	(1.285)*	(0.646)
Exogenous factors 3	-2.066	-3.122
	(1.607)	(1.696)*
Has experienced conflicts over water run-off	-2.103	-3.137
	(1.843)	(1.832)*
Interaction farm size and conflicts	1.776	1.110
	(1.538)	(0.907)
Freeman Degrees Index for network transfers	11.958	0.754
	(6.454)*	(1.213)
Freeman Degrees for discussing terracing etc.	-1.776	0.219
	(1.103)	(0.587)
Freeman Degrees for adopting terracing etc.	1.057	-0.318
	(0.910)	(0.498)
HH head has always lived here	-9.685	
	(5.684)*	
Number of extension officers in network	6.165	-2.276
	(3.669)*	(1.099)**
Member of village development committee	-5.477	0.780
	(2.903)*	(1.445)
Member of farmers' group		-3.644
		(2.572)
Member of women's group	1.098	-4.853
	(1.499)	(2.377)**
Member of youth group	8.853	0.727
	(5.045)*	(1.236)
Amount rewarded in weak ties experiment	-0.011	0.008
	(0.010)	(0.009)
Found price of district input		3.026
		(1.968)
Constant	13.021	-3.468
	(7.178)*	(4.685)
Observations	45	45
Pseudo R^2	0.6311	0.5225
P-value	0.0028	0.0521
Log likelihood	-9	-11

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. Adoption of soil nutrient management techniques, all factors. Using secondary and subset data. Probit estimation.

	Inorganic fertilizers	Mulching	Tumbukiza
Exogenous factors 1	2.277		-0.295
	(1.384)*		(0.846)
Exogenous factors 2	0.509	0.263	1.578
	(0.642)	(0.413)	(0.885)*
Exogenous factors 3		-1.108	
		(0.651)*	
Has experienced conflicts over fertilizer run-off	-4.678		
	(2.423)*		
Interaction farm size and conflicts	1.967		
	(1.282)		
Freeman Degrees Index for network transfers	3.598	-1.378	-1.175
	(2.517)	(0.960)	(1.103)
Freeman Degrees for discussing organic fertilizers	1.601	0.561	
	(1.281)	(0.451)	
Freeman Degrees for adopting organic fertilizers	-1.933	-0.224	
	(1.478)	(0.401)	
Freeman Degrees for discussion tumbukiza		0.035	
		(0.203)	
Freeman Degrees for adopting tumbukiza		-0.798	
		(0.436)*	
Density of respondent's network	0.789		
	(0.547)		
HH head has always lived here		1.063	1.727
		(0.946)	(1.357)
Number of extension officers in network	-8.338	-0.532	1.727
	(4.623)*	(0.549)	(0.856)**
Member of village development committee	7.747	0.120	
	(18.944)	(0.728)	
Member of farmers' group	-2.403	-0.378	
	(2.060)	(0.813)	
Member of women's group	-0.066	-1.158	
	(0.826)	(0.774)	
Member of youth group		1.139	
		(1.012)	
Group Membership Index			2.572
			(1.329)*
Amount rewarded in weak ties experiment	-0.016	-0.006	0.007
	(0.009)*	(0.003)**	(0.009)
Found price of district input	1.285	1.978	-3.303
	(1.184)	(1.426)	(2.207)
Constant	7.996	1.301	-5.413
	(5.159)	(1.708)	(4.740)

	Inorganic	Mulching	Tumbukiza
Observations	45	47	49
Pseudo R^2	0.5176	0.4120	0.6816
P-value	0.0379	0.0455	0.0000
Log likelihood	-11	-18	-8

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. Adoption of trees on farms, all factors. Using secondary and subset data. Probit estimation.

	Tree crops	Agroforestry trees	Windbreak
Exogenous factors 1		0.458	0.519
		(0.573)	(0.799)
Exogenous factors 2	1.782	0.973	0.828
	(0.940)*	(0.495)**	(0.686)
Exogenous factors 3	1.640		
	(1.556)		
Has experienced conflicts over trees	-4.316	-0.745	2.145
	(1.792)**	(0.948)	(1.596)
Interaction farm size and conflicts	0.462	-0.080	-0.010
	(0.598)	(0.392)	(0.450)
Freeman Degrees Index for network transfers	-0.053	0.904	1.621
	(1.409)	(0.961)	(2.101)
Freeman Degrees discussing terraces, etc.	0.596	-0.295	-4.674
	(1.181)	(0.909)	(2.629)*
Freeman Degrees adoption of terraces, etc.	0.214	1.049	1.546
	(0.504)	(0.622)*	(0.804)*
Freeman Degrees discussing organic fertilizers	0.286	-0.149	1.784
	(1.205)	(0.746)	(1.813)
Freeman Degrees adopting organic fertilizers	-1.309	-0.675	0.939
	(1.151)	(0.596)	(1.160)
HH head has always lived here	1.134	1.462	2.778
	(1.192)	(0.899)	(1.587)*
Number of extension officers in network	-0.996	-2.590	-0.332
	(1.143)	(1.042)**	(1.093)
Member of village development committee	1.425	-0.410	-4.555
	(1.401)	(1.154)	(2.718)*
Member of farmers' group	1.165	-0.961	-3.728
	(2.020)	(1.040)	(2.162)*
Member of women's group	2.226	-0.227	-3.090
	(1.387)	(0.725)	(1.862)*
Member of youth group	2.059	1.993	5.275
	(1.814)	(1.341)	(2.579)**
Amount rewarded in weak ties experiment	-0.003	-0.003	0.000
	(0.006)	(0.004)	(0.005)
Found price of district input	-1.333	0.523	-1.295
	(1.752)	(0.987)	(1.860)
Constant	2.782	2.345	0.998
	(2.875)	(2.043)	(3.270)
Observations	45	45	45
Pseudo R^2	0.6653	0.4313	0.6196
P-value	0.0009	0.0632	0.0053
Log likelihood	-10	-18	-11

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

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