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SOCIAL NETWORKS AND TECHNOLOGY ADOPTION IN NORTHERN MOZAMBIQUE*

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We present evidence on how farmers' decisions to adopt a new crop relate to the adoption choices of their network of family and friends. We find the relationship to be inverse-U shaped, suggesting social effects are positive when there are few adopters in the network, and negative when there are many. We also find the adoption decisions of farmers who have better information about the new crop are less sensitive to the adoption choices of others. Finally, we find that adoption decisions are more correlated within family and friends than religion-based networks, and uncorrelated among individuals of different religions.

The adoption of new agricultural technologies is an important route out of poverty for many in the developing world. Yet agricultural innovations are often adopted slowly and some aspects of the adoption process remain poorly understood.[1] This article analyses how social learning may lead a farmer's initial decision to adopt a new technology to be related to the decisions of others in his social network.[2]

Our motivation derives from empirical evidence that farmers learn how to cultivate a new crop from the choices of others also cultivating the same crop (Besley and Case, 1997; Foster and Rosenzweig, 1995; Conley and Udry, 2003; Munshi, 2004). This literature shows the importance of social learning *after* a new technology has been adopted. In contrast, this article addresses the question of whether social learning leads *initial* adoption decisions to be correlated within social networks. This sheds light on which individuals are the first to adopt a new technology, which in turn, affects its diffusion.

The analysis of social learning in the specific context of rural technologies also yields useful insights to help understand the adoption and diffusion of new technologies in other economic environments. Indeed, the insights apply to any situation in which lack of information is a barrier to adoption and potential adopters can communicate with each other.

In this article we analyse the decision to adopt a new crop, sunflower, by farmers in the Zambezia province of Northern Mozambique. The data covers the first season

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[1] There is a long history in economics of studying the diffusion of new agricultural technologies beginning with Griliches (1957). Much of the earlier literature recognised the importance of social learning in agriculture, although it did not attempt to identify the effects of learning separately from other determinants of adoption. Rogers (1995), Evenson and Westphal (1994) and Feder *et al.* (1985) provide overviews of this literature.

[2] We refer to farmers using the male pronoun as they constitute 85% of our sample.

farmers have access to sunflower, and was collected in conjunction with the NGO *Movimondo,* the sole regional provider of sunflower.

Key to the analysis is measuring the information on sunflower cultivation actually available to each farmer from his social network. We define this to be the number of adopters among his self-reported network of *family and friends.* These consist of individuals with whom the farmer has strong social ties, and is therefore more likely to exchange information and to learn from.[3] We later contrast this measure of networks to those based on the geographical or cultural proximity of individuals.[4]

To shed light on the effect of social learning on sunflower adoption, we estimate farmers' propensity to adopt sunflower as a function of the number of adopters among their family and friends.

While intuition suggests that adoption choices should be positively related within networks, theories of social learning indicate that the sign of the relationship is actually ambiguous. On the one hand, the benefit of adopting in the current period is higher when there are many adopters in the network because of the information they provide. On the other hand, having many adopters in the network increases incentives to delay adoption strategically and free ride on the knowledge accumulated by others. If strategic delay considerations prevail, a farmers' propensity to adopt decreases as the number of adopters among his network increase.[5]

Our estimation strategy allows for a nonlinear relationship between the probability of adoption and the number of adopters in the network. We find that the relationship is shaped as an inverse-U. The *marginal* effect of having one more adopter among friends and family is positive when there are few other adopters in the network and negative when there are many.[6]

The results also show that, in line with the literature, literate, older and less vulnerable farmers are more likely to cultivate the new crop, all else equal. However, evaluated at the mean network size, the marginal effect of having one more adopter in the network is quantitatively larger than these other determinants of adoption.

We then allow the effect of the network to vary according to farmer characteristics that proxy for the precision of his initial information on how to cultivate sunflower. We

[3] Following Granovetter (1985), social ties between farmers and their family and friends are considered strong in the sense they are long term, embody mutual trust and reciprocity, and are not easily undone. Foster and Rosenzweig (1995) and Conley and Udry (2003) provide evidence from similar economic environments that this set of close contacts are the most important for providing information on agriculture.

[4] The empirical literature on social learning has typically defined networks based on geographical or cultural proximity (Munshi and Myaux, 2002; Bertrand *et al.*, 2000). In the context of agriculture, Foster and Rosenzweig (1995), Besley and Case (1997), and Munshi (2004) assume social learning occurs at the village level. Similar to this paper, Conley and Udry (2003) use individual measures of information neighbourhoods, as do Kremer and Miguel (2004*a*) in the context of adopting a new health technology.

[5] That information externalities can lead to strategic delay is widely recognised in the theoretical literature. Bardhan and Udry (1999) apply this idea to technology adoption in agriculture, while other applications are found in Caplin and Leahy (1998), Chamley and Gale (1994), Kapur (1995), McFadden and Train (1996) and Vives (1997). Hausman and Rodrik (2003) show the failure to internalise information externalities might yield suboptimal specialisation patterns and hence slower growth.

[6] Most previous studies take social effects to be linear, and find behaviour to be positively related within the network. Exceptions to the assumption of linearity include Behrman *et al.* (2001), who find that for family planning decisions in Kenya, the marginal effect of knowing one adopter is larger than the effect of knowing two or more. Conley and Topa (2002) use census tract employment data for Los Angeles County and find that informational spillovers in job search exhibit decreasing returns.

find that the relationship between the propensity to adopt and the number of adopters in the network is weaker, but still significant and inverse-U shaped, for more informed farmers.

Finally, we compare our measure of social networks to one based on the number of adopters of the same religion and village as the farmer. We find that while adoption choices are correlated within religion networks, the marginal effect of having an additional adopter among family and friends is larger than having one among those of the same religion. We also find that the two types of networks provide independent sources of information, and that adoption choices are uncorrelated across religions.

The analysis yields three key insights. First, the probability that a farmer adopts the new technology is increasing in the number of adopters in his network when there are few, and decreasing when there are many. In contrast to most studies that assume linearity and find a positive correlation, we show that social effects can be negative, perhaps due to strategic delays.[7]

Second, social effects are *heterogeneous*, namely the effect of the number of adopters among the network on the propensity to adopt depends on the characteristics of the farmer himself. In particular, more informed farmers are less sensitive to the adoption choices of their network.

Third, the choice of the reference group matters. Farmers' adoption decisions are correlated both to the choices of their network of family and friends and to those among their religion, but *not* to those in other religions.

The identification of social effects is confounded by the presence of omitted variables. If networks are formed by people with similar unobservable characteristics, finding their decisions to be positively correlated may just reflect their similarity. Alternatively, farmers may simply imitate one another. Finally, spuriously correlated behaviour could also be generated by unobserved heterogeneity that drives adoption and is correlated to the number of adopters among family and friends.

While we do not rule out that there is similarity between network members, unobserved heterogeneity, or some imitation, it is important to note that all such concerns generate a spurious relation among adoption decisions that is either *only* positive or *only* negative. They do not explain the robust inverse-U shaped relationship we find in the data.

Throughout, we focus the discussion around social learning as the underlying mechanism connecting decisions within a network. We do this because lack of information is a key barrier to adoption in our setting and because previous work has shown farmers learn from each other about the parameters of a new technology.

There are, however, other plausible causal explanations of why adoption choices are related in social networks. For instance, farmers' decisions are positively correlated if there are economies of scale in the commercialisation of the new crop.[8] Alternatively,

[7] Kremer and Miguel (2004*b*) also find evidence of negative social effects. They find the probability of an individual taking deworming drugs is decreasing in the number of those who have taken the drug earlier.

[8] Given that farmers in the region commercialise their produce via traders that travel to the village, economies of scale might arise if traders of sunflower require a guaranteed a minimum level of output to travel to the village. Farmers' ability to commercialise sunflower would then depend on all other farmers' adoption choices.

decisions are negatively related if there is risk sharing within the network, because the ability to provide insurance within the group is reduced as more farmers in the network adopt the new crop.[9] While we make no attempt to distinguish between the various hypothesis on why social effects may exist in this context, we note that no one of these alternative explanations can by itself, generate both the positive and negative social effects we find in the data.

While our analysis is tailored to the specific context of rural Mozambique, the findings have broader applicability. First, similar patterns of initial adoption decisions within and across social networks may occur in other economic environments in which a new technology is introduced, information is a key barrier to adoption, and individuals can be expected to learn about the new technology from others. In particular, the possibility of nonlinearity in the relationship between the adoption decision and the number of adopters in the network should always be taken into account in contexts where social learning plays a key role.

Second, our two findings on the heterogeneity of network effects and on the boundaries of the reference groups apply more in general to all situations where individuals are thought to affected by the choices of others in their social network, for instance in schools and in labour markets.

Finally, obtaining a precise estimate of the magnitude of network effects is key to making informed policy decisions on targeting and subsidised adoption, for instance. To this purpose it is then most important to take into account nonlinearities, to allow for heterogeneous effects and to identify the precise boundaries of the reference group.

The rest of the article is in six sections. Section 1 describes the intervention. Section 2 presents a model of social learning about the parameters of a new crop, and makes precise how the number of adopters among the network influence the initial adoption choice. Section 3 describes the data and empirical method. Section 4 presents the empirical analysis. Section 5 interprets the results and discusses whether they may be driven by spurious correlations. Section 6 concludes. Further robustness checks are presented in the Appendix.

1. Context

We study the adoption of sunflower by farmers in the Zambezia region of Northern Mozambique. Sunflower is not indigenous to Mozambique and was introduced to the region by the NGO *Movimondo* in early 2000. As in most of Mozambique, agricultural practices in the Zambezia region are rudimentary. Chemical inputs are generally unavailable, irrigation systems, machinery, and fixed installations are equally rare. Hence, there is little scope for economies of scale.

Farmers produce a large number of crops, mostly for home consumption. Trade across villages is limited by the inadequate road infrastructure, and except in response to shocks, food exchange within the village is rare. The staple crops in the region are

[9] Social networks can be a mechanism through which individuals insure against idiosyncratic shocks (Fafchamps and Lund, 2000; Townsend, 1994; Udry, 1994 and Goldstein, 1999).

cassava and maize while cashew is the only cash crop. Cashew production is sold to traders from the regional capital who then sell it for export.[10]

Movimondo introduced sunflower for three reasons. First, and most importantly, seeds can be pressed into oil which has strong nutritional benefits as farmers have no other source of fat in their diets.[11] Second, sunflower can be commercialised if the scale of production is large enough to attract traders to the village. Third, the techniques, soil type, and other inputs required to cultivate sunflower are similar to those for the existing crops.[12]

The project operates as follows. *Movimondo* initially organises a village meeting, where the potential benefits of adoption are explained. The village meeting is open to all and well publicised. Over 95% of our sample farmers became informed on the project through this channel, suggesting little self selection into adoption at this stage.

If subsequent to this meeting, at least 10% of all farmers express willingness to adopt, sunflower seeds are distributed in the village. Distribution takes place some weeks after the initial meeting and each adopting farmer receives the quantity of seeds he desires.[13]

A number of project details are relevant. First, seeds are distributed free and no complementary inputs are required to grow sunflower. Second, *Movimondo* appoints a *contact farmer* in each village to ensure that farmers who take the seeds actually plant them. Third, receiving sunflower seeds is not conditional on participation in other *Movimondo* projects. Fourth, farmers have free access to an oil press provided by *Movimondo*. Finally, *Movimondo* provides two on-going sources of information on sunflower cultivation – extension workers visit the villages after seeds are distributed and demonstration plots are set up.[14]

Given the characteristics of the intervention, farmers do not face all of the usual barriers to adoption. In particular they do not need to finance the initial purchase of seeds, nor do they need to purchase any complementary inputs. The cost of adoption is therefore only the opportunity cost in terms of labour and land that can no longer be devoted to the cultivation of other crops.[15] In our sample, farmers who adopt sunflower are more likely to reduce cashew production compared to non-adopters, indicating some labour substitution from cashew to sunflower.[16] There are no significant differences in the production of other crops across adopters and non-adopters.

[10] Liberalisation of the cashew sector began in the early 1990s. McMillan *et al.* (2002) estimate this led to an increase in annual income of only $5.30 for the average cashew growing household, partially because they had to market their output through regional traders. This suggests the returns to cashew production are relatively stable around the sample period.

[11] None of the other cultivated crops yield oil fit for human consumption, and there is little animal husbandry.

[12] Our time in the field suggests an additional benefit of adoption is that oil consumption, being quite rare in the region, is a source of social prestige.

[13] Farmers are constrained to receive no more than 5 kg, but this is not a binding constraint for the majority. This amount of seeds can be planted on less than one hectare of land, yielding approximately one litre of oil. The yield of sunflower seeds per kilogram of planted seed varies between 50 and 75 kg depending on the cultivation technique and agroclimatic conditions.

[14] These potentially create variation across villages in exposure to information on sunflower cultivation. Such permanent differences across villages are controlled for in the empirical analysis using village fixed effects.

[15] Land is abundant but the agreement of village elders is required before new land can be acquired.

[16] Among adopters, 71% reported producing less cashew than the previous year while only 50% of non-adopters reported producing less. McMillan *et al.* (2002) report labour is the main input into cashew production and that 50% of labour time is spent caring for cashew trees before harvest.

Table 1 sheds light on farmers' subjective perceptions of the costs and benefits of adoption. Panel (*a*) lists the main reasons why farmers chose to adopt. The most frequent reason reported is they wanted to consume the sunflower oil. Indeed, at the end of the first harvest, 90% of adopting farmers reported consuming all of their production, suggesting both that oil consumption rose for adopters, and that little oil was traded to non-adopters. The second most frequent reason is farmers thought the crop would be profitable. Both reasons are in line with *Movimondo*'s expectation of why the adoption of sunflower leads farmers to become better off – through the consumption and commercialisation of sunflower seed.

Panel (*b*) in Table 1 lists the main reasons why non-adopters did not adopt. Lack of information about the production technique is the main barrier to adoption for half of these farmers. Just under 20% of the farmers reported not adopting because of land constraints or because they believed sunflower cultivation would not be remunerative.

Panel (*b*) indicates that despite the fact that *Movimondo* provides information on cultivation – through extension workers and demonstration plots – to all farmers in the villages, non-adopting farmers appear to lack the information, or have different information and beliefs compared to adopting farmers.

The existing empirical literature has shown that farmers share information and learn from each other on how to cultivate new crops. Farmers that have social ties to adopters are therefore more likely to overcome informational constraints to adoption, all else equal. The theoretical framework in the next Section makes precise the relationship such social learning creates between a farmer's adoption decision and those of his network.

2. A Simple Model of Social Learning

We present a standard target input model in which forward looking farmers use Bayesian updating to learn about the parameters of a new crop technology. The presentation of the model follows that in Bardhan and Udry (1999).[17] The parameters of the new crop vary across farmers, because of varying soil conditions say. While the form of the underlying production technology is known with certainty, one parameter – the target – is unknown. More precisely, for farmer i in period t, output, q_{it}, declines in the square of the distance between the input used, k_{it}, and the uncertain target, κ_{it};

$$q_{it} = 1 - (k_{it} - \kappa_{it})^2. \tag{1}$$

The target input level, κ_{it}, is not known at the time the input is chosen. After the input has been applied and output realised, the farmer updates his beliefs on what the target input level is. Each period the farmer uses the input can be thought of as a trial that yields information on the distribution of the target parameter. Each period is the length of time over which the input choice affects output, which we take to be far

[17] The target input model has been developed by Prescott (1972), Wilson (1975), Jovanovic and Nyarko (1994) and applied to learning in agriculture by Foster and Rosenzweig (1995). Alternative models of learning from networks include those based on informational cascades (Banerjee, 1992; Bikhchandani *et al.*, 1992), or rule-of-thumb learning (Ellison and Fudenberg, 1995). Distinguishing between these goes beyond the scope of this article.

Table 1

Main Reasons for Adoption or Non Adoption

(*a*) Why Adopters Adopted	
I want to consume the new crop	72%
I thought it would be remunerative	66%
The NGO convinced me it would be remunerative	35%
Number of respondents	102
(*b*) Why Non Adopters Did Not Adopt	
I did not know the production techniques	48%
I thought it would not be remunerative	18%
No land available	17%
Number of respondents	96

Notes: Each cell reports the percentage of farmers who reported each of the stated reasons for adoption/non adoption. The sample is respondents in villages where sunflower seeds have been distributed. This is the same sample used for the regression analysis. There are 102 adopters and 96 non-adopters in the sample. The responses of village leaders and contact farmers are not included. Respondents were asked to list two reasons why they chose to adopt, or not to adopt. Other reasons for non adoption were 'no market for this crop' (14%) and 'existing crops are remunerative', (3%).

shorter than one growing season. For example this can be as short as a week if the input is the amount the new crop has to be watered and the output is plant height.

Learning is the process of gathering information to better estimate what, on average, is the optimal target, κ^*. Farmers learn by doing, gaining information about the optimal target from their own past trials. They may also learn from others, by observing the trials of their network.

The optimal target fluctuates around κ^* as follows;

$$\kappa_{it} = \kappa^* + \mu_{it}, \tag{2}$$

where $\mu_{it} \sim$ i.i.d. $N(0, \sigma_u^2)$. These μ_{it} are transitory shocks to the optimal target input. While κ^* is, on average, the optimal input level, this fluctuates due to farmer-period specific factors.

In period t farmer i has beliefs about κ^* which are distributed as $N(\kappa_{it}^*, \sigma_{\kappa it}^2)$. We make two simplifying assumptions – that σ_u^2 is known, and the input is costless so that farmer i's profit is his output multiplied by the constant price of output, p, normalised to one throughout. As $E_t(\mu_{it}) = 0$, to maximise expected output, farmer i uses as his input level his expected optimal target level, so $k_{it} = E_t(\kappa_{it}) = \kappa_t^*$. Hence expected output is;

$$E_t(q_{it}) = 1 - E_t[\kappa_{it} - E_t(\kappa_{it})]^2 = 1 - \sigma_{\kappa it}^2 - \sigma_u^2. \tag{3}$$

Intuitively, expected output rises as the farmer has less uncertain beliefs on the optimal target, and as the variance of transitory fluctuations in the optimal target falls.

2.1. *Learning*

2.1.1. *Learning by doing*

Suppose farmer i learns in isolation from others. Each period an input level is chosen, output observed, and an inference made on κ_{it} which is used to update beliefs about κ^*. In period $t-1$ the variance of i's prior belief about κ^* is $\sigma_{\kappa i,t-1}^2$. In period t, after observing κ_{it}, the farmer applies Bayes's rule to update his belief about the variance of κ^*. This yields a posterior belief;[18]

$$\sigma^2_{\kappa it} = \frac{1}{\dfrac{1}{\sigma^2_{\kappa i,t-1}} + \dfrac{1}{\sigma^2_u}}. \tag{4}$$

Define $\rho_o = 1/\sigma^2_u$ as the precision of the information generated by i's own trial, and $\rho_{i0} = 1/\sigma^2_{\kappa i0}$ as the precision of i's initial beliefs about the true value of κ^*. After repeated backwards substitution, (1) can be rewritten as;

$$\sigma^2_{\kappa it} = \frac{1}{\rho_{i0} + I_{t-1}\rho_o}, \tag{4$'$}$$

where I_{t-1} is the number of trials i has with the new crop on his own farm between periods 0 and $t-1$.[19] Substituting (4′) into (3), expected output is;[20]

$$\mathrm{E}_t(q_{it}) = 1 - \frac{1}{\rho_{i0} + I_{t-1}\rho_o} - \sigma^2_u. \tag{3$'$}$$

Hence as expected, learning by doing increases expected output;

$$\frac{\partial \mathrm{E}_t(q_{it})}{\partial I_{t-1}} = \frac{\rho_o}{(\rho_{i0} + I_{t-1}\rho_o)^2} > 0. \tag{5}$$

2.1.2. *Learning from others*

If farmers share the same distribution of the input target, they can potentially learn from each others' trials. Define the network of farmers that share information with i as $n(i)$. Suppose farmer i can costlessly observe the input choice of $j \in n(i)$, κ_{jt}.[21] In period t, farmer i uses Bayes's rule to update his prior belief on the variance of κ^* using

[18] Note that the information generated by a trial is independent of the amount of the input used, so there are no returns to experimentation.

[19] The results that follow are robust to fluctuations in the optimal target input being persistent and not transitory i.i.d. shocks. Suppose $\mu_{it} = \lambda\mu_{it-1} + u_{it}$, $u_{it} \sim$ i.i.d. $\mathrm{N}(0, \sigma^2_u)$. In period t the posterior belief about the variance of κ^* is;

$$\sigma^2_{\kappa it} = \left[\frac{(1-\lambda^2)\sigma^2_{\kappa i,t-1} + \sigma^2_u}{\sigma^2_{\kappa i,t-1}\sigma^2_u} + \frac{(1-\lambda^2)I_{t-2}}{\sigma^2_u}\right]^{-1}.$$

A higher λ implies it takes the farmer longer to learn κ^*, but crucially, the posterior belief remains inversely related to the number of own trials.

[20] Learning is bounded because in the limit, $\lim_{I_{t-1}\to\infty}\sigma^2_{\kappa it} = 0$, so expected output is $\lim_{I_{t-1}} \to \infty \mathrm{E}_t(q_{it}) = 1 - \sigma^2_u$.

[21] Hence farmer i learns about the input choices of other farmers in his network without error. This assumption is not crucial for our empirical analysis but does allow us to simplify the model of Bayesian updating considerably. Another complicating issue when farmers learn from others is what occurs if networks are not self-contained. For example, suppose farmer k is in the same network as i and j but that i and j do not know each other. i will use k's input choice to infer the information generated by j. If i, j, and k are the entire network then k's choices may then be sufficient statistics for the whole history of information generated by the network, and all farmers would converge to the same beliefs. Hence there would be no relationship between the number of people in the network and adoption decisions. This argument however relies on higher order reasoning by each farmer, which is unlikely to be empirically relevant in this setting. We thank a referee for clarifying these features of Bayesian updating in this model of social learning.

information both from the number of his own past trials, I_{t-1}, and the trials made by people in his network, $n(i)_{t-1}$. Hence his posterior belief on the variance of κ^* is;

$$\sigma^2_{\kappa it} = \frac{1}{\rho_{i0} + I_{t-1}\rho_o + n(i)_{t-1}\rho_o}. \tag{6}$$

Expected output now also depends on the number of trials of the network;

$$\mathrm{E}_t\left[q_{it}, n(i)_{t-1}\right] = 1 - \frac{1}{\rho_{i0} + I_{t-1}\rho_o + n(i)_{t-1}\rho_o} - \sigma^2_u. \tag{7}$$

As one farmer uses the new technology, this creates an informational externality for all farmers within the network, increasing their expected output;

$$\frac{\partial \mathrm{E}_t\left[q_{it}, n(i)_{t-1}\right]}{\partial n(i)_{t-1}} = \frac{\rho_o}{\left[\rho_{i0} + I_{t-1}\rho_o + n(i)_{t-1}\rho_o\right]^2} > 0. \tag{8}$$

Three points are of note. First, information acquired by learning by doing and learning from others are substitutes for each other, $\partial^2 \mathrm{E}_t\left[q_{it}, n(i)_{t-1}\right] / \partial I_{t-1}\partial n(i)_{t-1} < 0$.

Second the learning externality is smaller for farmers that have more precise initial information on the true target level, $\partial^2 \mathrm{E}_t[q_{it}, n(i)_{t-1}]/\partial\rho_{i0}\partial n(i)_{t-1} < 0$. Hence farmers that are better informed of how to cultivate sunflower to begin with are less responsive to the choices of their network.

Third, farmers that obtain more precise information from their network need to observe fewer trials among their network to have the same change in expected output, $\partial^2 \mathrm{E}_t\left[q_{it}, n(i)_{t-1}\right]/\partial\rho_o\partial n(i)_{t-1} < 0$. Hence the learning externality varies across networks if in some networks, farmers are better able to observe the input choices of their network members. This may be because some networks are more geographically concentrated than others so that soil conditions are more similar for farmers within the network.

2.2. *The Adoption Decision*

We now consider each farmer's initial decision to adopt the new crop. Suppose farmers have access to some traditional crop with riskless return $\underline{q}$. Let $a_{it} = 1$ if farmer i uses the new crop in period t, and $a_{it} = 0$ otherwise.[22]

If farmers learn from others, a farmer's initial adoption decision depends on the adoption choices made by members of his social network. To see this note that the value of the future stream of profits to i from period t to T is;

$$\begin{aligned} V_t\left[I_{t-1}, n(i)_{t-1}\right] &= \max_{a_{is}\in\{0,1\}} \mathrm{E}_t \sum_{s=t}^{T} \delta^{s-t}\left\{(1-a_{is})\underline{q} + a_{is}q_s\left[I_{s-1}, n(i)_{s-1}\right]\right\} \\ &= \max_{a_{it}\in\{0,1\}} (1-a_{it})\underline{q} + a_{it}\mathrm{E}_t q_t\left[I_{t-1}, n(i)_{t-1}\right] + \delta V_{t+1}\left[I_t, n(i)_t\right], \end{aligned} \tag{9}$$

[22] The adoption decision is therefore a discrete choice for the farmer, namely we model the decision whether to adopt or not, rather than the choice over the acreage devoted to the new crop. This matches the empirical analysis in Section 3.

where $I_{s-1} = \sum_{t=0}^{s} a_{is}$ is the total number of trials i has conducted up to and including period s, $n(i)_{s-1}$ is the total number of trials of his social network over the same period, and δ is the discount rate.

Since expected output increases in the number of own trials, once a farmer switches to the new technology, he never switches out of it. Adoption is thus an absorbing state.[23]

The farmer adopts the new crop in period 0 if;

$$\mathrm{E}_0 q_0\big[0, n(i)_0\big] + \delta V_1\big[1, n(i)_0\big] \geq \underline{q} + \delta V_1\big[0, n(i)_0\big]. \tag{10}$$

Note that adoption of the new crop may occur even when the traditional crop is currently more profitable. To see this note that since adoption is an absorbing state;

$$\begin{aligned} V_1[1, n(i)_0] - V_1[0, n(i)_0] &= \mathrm{E}_0 \sum_{s=1}^{T} \delta^s \big\{q\big[s, n(i)_0\big] - q\big[s-1, n(i)_0\big]\big\} \\ &= \sum_{s=1}^{T} \delta^s \left[\frac{1}{\rho_{i0} + s\rho_o + n(i)_0\rho_o} - \frac{1}{\rho_{i0} + (s-1)\rho_o + n(i)_0\rho_o}\right] \\ &> 0. \end{aligned} \tag{11}$$

Hence the new technology may be adopted even if in the current period, the old technology is more profitable so that $\underline{q} \geq \mathrm{E}_0 q_0[0, n(i)_0]$.

Farmer i's adoption decision in period 0 depends on the information available from his network. The derivative of the net gains from adopting in period 0, (10), with respect to $n(i)_0$ is;

$$\begin{aligned} &\frac{\partial \mathrm{E}_0 q_0\big[0, n(i)_0\big]}{\partial n(i)_0} + \delta \frac{\partial\big\{V_1\big[1, n(i)_0\big] - V_1\big[0, n(i)_0\big]\big\}}{\partial n(i)_0} \\ &= \frac{\rho_o}{\big[\rho_{i0} + n(i)_{t-1}\rho_o\big]^2} + \delta \sum_{s=1}^{T} \delta^s \left\{\frac{\rho_o}{\big[\rho_{i0} + s\rho_o + n(i)_0\rho_o\big]^2} - \frac{\rho_o}{\big[\rho_{i0} + (s-1)\rho_o + n(i)_0\rho_o\big]^2}\right\}. \end{aligned} \tag{12}$$

There are two opposing effects on i's incentive to adopt as the number of adopters among his network increases. First, his incentives increase because use of the new crop by network members creates a learning externality for i, which increases his current profitability if he adopts, as seen in (8).

Second, i has an incentive to delay adoption because the value of information he receives from his own adoption is lower as more network members adopt. Hence the gain in future profitability from one additional trial by i with the new technology is *decreasing* in the number of trials of the network. If more network members adopt, less additional information is gained by the farmer himself adopting the new crop, giving rise to incentives to *strategically delay* adoption.

[23] We asked farmers in our sample to report if they planned to continue sunflower cultivation the following year. 98% of adopters said they did.

The net gains from adopting in period 0 can therefore be increasing or decreasing in the number of adopters among the network. Intuitively, if a farmer is more myopic, he has less incentive to delay strategically, and (12) is more likely to be positive. This creates a positive correlation between the propensity of farmer i to adopt and the adoption choices of his network, $n(i)_0$. Other things equal, for more forward-looking farmers, the adoption choice is more likely to be negatively correlated to those of the network.

Two further implications of the model are relevant for the empirical analysis. First, the effect of $n(i)_0$ on the propensity of farmer i to adopt is nonlinear as both the informational externality effect and the strategic delay effect are concave in the number of adopters in the network.

Second, the marginal effect of $n(i)_0$ on the net present value of the benefit of adoption is decreasing in ρ_{i0}. That is, although both the informational externality effect and strategic delay effects are still present, the more precise information the farmer has to begin with, the less sensitive his adoption decision is to the number of adopters among his network.

3. Empirical Analysis

3.1. *The Data*

We administered a household survey during December 2000, the first year sunflower seeds were distributed. Nine villages were sampled and we interviewed 198 randomly selected household heads, defined as the primary household decision maker with regards to agriculture.[24] *Movimondo* extension workers administered the household questionnaire, as well as a further questionnaire to village leaders – a village elder, political leader and contact farmer. This provides information on village characteristics.

Table 2 provides summary statistics for the sample villages. The villages are small with typically less than 300 households in each. The villages are remote – the median travel time on foot is one hour to the nearest food market, and 50 minutes to the nearest paved road. The Table highlights the variation across villages in their proximity to markets and levels of infrastructure.

Movimondo records indicate that the aggregate adoption rate was 25% across the 22 villages where the project operated in 2000. After three years, the aggregate adoption rate in the original 22 villages remained below 50%. Adoption rates are higher in the 9 sample villages, compared to the other 13 villages in which *Movimondo* also operated in 2000. In the sample, 48% of households adopted in the first year.

The empirical strategy – detailed below – only exploits the variation between farmers in the same village. Factors at the village level that lead to correlated adoption choices among farmers, such as proximity to markets, land quality, village institutions, or information on cultivation that is commonly known, are all controlled for using village fixed effects.

[24] Household decision making over adoption is assumed to follow a unitary model. In support of this, in households in which the household head adopted and their spouse had a separate plot, none of their spouses adopted. For households in which the household head did not adopt only 5% of spouses with a separate plot adopted.

Table 2
Village Descriptives

	Sample Villages								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Households interviewed	20	19	34	18	32	20	27	27	14
Approximate number of households in the village	350	300	250	200	300	550	300	350	200
Male headed adopting households	105	179	80	46	112	242	106	200	54
Female headed adopting households	34	13	9	15	36	29	34	30	20
Village adoption rate	0.40	0.64	0.36	0.30	0.49	0.49	0.47	0.66	0.37
Travel time to nearest permanent market on foot (minutes)	40	5	120	60	30	10	60	180	90
Travel time to nearest paved road on foot (minutes)	50	2	60	30	30	10	60	180	60
Median oil consumption (days per month)	4	11	12	8	2	4	4	0	0
Other NGO operates in village	√	√	√		√	√		√	
Well		√							
School	√	√	√	√	√	√	√	√	
Health post	√	√		√					

Notes. The number of households in the village is an approximate figure based on Movimondo records. The village adoption rate is defined as the proportion of all households in the village that have adopted sunflower. At the time of the survey, one other NGO was operating in the region. They were involved in the rehabilitation of local infrastructure.

3.2. *Data Description*

3.2.1. *Sunflower adoption*

The analysis focuses on the determinants of sunflower adoption, defined as a discrete choice variable equal to one when the farmer has planted sunflower and zero otherwise. Among farmers in the sample 51% adopted sunflower, which is close to the village adoption rate of 48% from *Movimondo* records.[25]

3.2.2. *Social networks*

The key variable for the analysis is the measure of information on sunflower cultivation available to each farmer from his social network. To proxy for this we use the number of adopters in the farmer's network of family and friends.

Each farmer was asked, relative to when sunflower was introduced, 'how many of the people you know are planting the new crop?', and then, 'how many of these belong to your family?', and, 'how many of these are your neighbours and friends?' The sum of responses to the last two questions measures the information on sunflower cultivation available to each farmer from his social network.

This measure is appropriate because –

(*i*) it relates to the *number* of different sources of information on sunflower cultivation the farmer has access to from within the set of all people the farmer knows, corresponding to $n(i)_0$ in the model of social learning;

[25] Recall that as part of the design of the project, a contact farmer within each village ensures that the distributed sunflower seed is actually planted and not consumed nor traded in a secondary market.

(*ii*) it relates to close contacts from whom information can be more easily obtained relative to those outside of this reference group;
(*iii*) it is measured at the time of the project implementation.[26]

Table 3 gives means, standard deviations and percentiles on the number of adopters among family and friends, by adoption status and network type. The average farmer has 4.9 adopters among his close contacts. Compared to non-adopters, adopting farmers have significantly *more* adopters among their family and friends. This is driven by adopters having significantly more adopters among their friends. Adopting and non-adopting farmers have the same number of adopters among their family.

There is variation in the network size for both adopters and non-adopters. The dispersion in the number of adopters among family and friends, measured by the coefficient of variation, is actually greater for non-adopters for each type of network.

Finally, around 70% of farmers have at least one adopter among their close contacts. Non adopters are however significantly more likely to have no adopters among their close contacts.

Table 3 highlights the fact that the number of adopters in each farmer's network is orders of magnitude smaller than the total number of adopters in the village. The average number of adopters among family and friends is 4.9, that is 3.4% of the average number of adopters in the village. This makes clear that networks of family and friends are much smaller than the village. It is not the case that an equal amount of information on sunflower cultivation is available to all farmers in the village.

3.2.3. *Other observable characteristics*

Table 4 provides information on other characteristics by adoption status. The first two rows show that adopting and non-adopting farmers are equally likely to be literate or numerate. In terms of physical capital, the next row shows that adopters and non-adopters do not differ in the ownership of agricultural tools. Moreover, adopters and non-adopters have similar availability of adult labour in the household.

We measure households' exposure to risk by the number of months of food security they have, defined as the number of months of the year in which the household has stocks of food available for consumption. The average household has insufficient food stocks for three months each year. This again does not differ by adoption status. Adopting and non-adopting households also do not differ on a measure of relative poverty, based on asset ownership.[27]

[26] Family refers to extended family, and friends only includes friends within the village. If correctly interpreted, this gives the number of sources of information on sunflower cultivation to each farmer at the time of his own adoption choice. The measure does not then pick up the endogenous formation of networks *ex post*. This issue is discussed further in Section 5.

[27] This measure of relative poverty is based on the weighted value of owned assets. The assets and their associated weights are – radio (1), chair (0.5), bed (1), water pot (0.5), bicycle (2), and jewellery (1). These weights reflect local market prices. Households with a weighted value of assets less than 75% of the sample average, are classified as 'very poor'. Those with a weighted value of assets above 125% of the sample average are classified as 'not poor'. All remaining households are classified as 'poor'. This relative poverty measure is positively correlated with relative poverty measures based on livestock ownership, income, food consumption, and enumerator's own evaluations.

Table 3

Social Networks by Adoption Status and Network Type

Mean network size (standard deviations in parentheses, 25th, 50th and 75th percentiles in brackets)	Total	Adopters	Non adopters
Number of adopters among family and friends	4.92	5.87	3.91
	(5.18)	(4.92)	(5.28)
	[0, 4, 7]	[3, 5, 8]	[0, 3, 5]
Number of adopters among family	2.46	2.69	2.22
	(3.36)	(3.01)	(3.70)
	[0, 1, 4]	[0, 2, 4]	[0, 0, 3]
Number of adopters among friends	2.46	3.19	1.69
	(2.86)	(3.02)	(2.46)
	[0, 2, 4]	[1, 3, 4]	[0, 0, 3]
Have no adopters among family and friends	0.278	0.167	0.396
	(0.449)	(0.374)	(0.491)

Notes. The sample is respondents in villages where sunflower has been distributed. This is the same sample used for the regression analysis. There are 102 adopters and 96 non adopters in the sample. The responses of village leaders and contact farmers are not included.

Table 4 sheds light on the organisation of production. Consistent with subsistence agriculture, farmers grow an average of 7 crops, so production is not specialised. Crops grown typically include maize, cassava, groundnuts, peas, beans and vegetables. Adopters and non-adopters grow the same crop mix (result not reported).

The next row in Table 4 reports information on cashew cultivation. This is particularly relevant because farmers who produce cashew are more likely to have contact with local traders, and have price information for agricultural produce. Importantly the ownership of cashew is determined before sunflower seeds became available since cashew is a tree crop which takes 3 to 5 years to bear its first fruit. Hence cashew cultivation provides an exogenous source of variation in a farmer's ability to exploit any gains from sunflower commercialisation. Adopters and non-adopters are equally likely to cultivate cashew at the time when sunflower is introduced.

To measure farmer attitudes towards innovations and NGO projects in general, we recorded whether farmers had participated in non *Movimondo* agricultural projects in the past.[28] Like cashew cultivation, this also pre-dates the decision to adopt sunflower. Adopters are twice as likely to have participated in NGO projects in the past, in line with the intuition that some farmers are more inclined to participate in NGO projects.

The final rows present demographic data. Female headed households, which constitute 15% of the sample, are significantly more likely to adopt. Adopters and non-adopters however do not differ by age or household size. Protestants and non religious farmers are slightly more likely to adopt than Catholics. Adopting and non-adopting households are equally likely to have migrated to the village.[29]

Oil consumption – measured prior to the first sunflower harvest – does not differ across adopters and non-adopters. It is uniformly low across all households, with the

[28] This was the first agricultural project implemented by *Movimondo*. Previously *Movimondo* had rehabilitated local infrastructure.

[29] Some 15% of the sample are migrants – these households were displaced by the civil war between 1982–92.

Table 4

Descriptive Statistics by Adoption Status (Standard Deviations in Parentheses)

Basic Characteristics	Adopters	Non Adopters	Test of Equality (p-value)
Literate (yes = 1)	0.65	0.56	0.23
	(0.48)	(0.50)	
Numerate (yes = 1)	0.81	0.81	0.98
	(0.39)	(0.39)	
Number of Tools	4.21	4.25	0.90
	(2.79)	(2.30)	
Number of adults in the household	2.19	2.18	0.94
	(0.90)	(0.70)	
Months of food security	9.18	8.93	0.28
	(1.69)	(1.50)	
Number of crops cultivated (not including sunflower)	6.92	6.86	0.86
	(2.29)	(2.17)	
Cultivating cashew (yes = 1)	0.59	0.55	0.61
	(0.49)	(0.50)	
Participated in NGO projects in the past	0.22	0.11	0.06
	(0.41)	(0.32)	
Female headed households	0.22	0.09	0.01
	(0.41)	(0.29)	
Age of household Head	41.9	39.2	0.15
	(12.5)	(13.3)	
Migrated to village (yes = 1)	0.12	0.19	0.17
	(0.32)	(0.39)	
Oil consumption (days per month)	7.27	7.97	0.62
	(0.98)	(1.02)	
Asset Poverty (proportion in each group)			
Very Poor	23.5	20.8	
Poor	49.0	50.0	
Not poor	27.5	29.2	
Religion (proportion in each group)			
Catholic	43.1	54.2	
Protestant	38.2	30.2	
Other	3.9	5.2	
Not religious	14.7	10.4	

Notes. For all tests of means or proportions, the null hypothesis is that the proportion/means are equal, against a two-sided alternative. Village leaders and contact farmers are not included. The number of tools is the sum of hoes, machetes, axes, spades, forks, saws and scythes owned. Adults are defined to be those aged 14 or older. Months of food security measures the number of months per year the household has stocks of food available for consumption. There are 35 female headed households in the sample. Migrated to village refers to households which moved to the village during the civil war during 1982–92. Asset poverty is a relative poverty measure.

average household consuming oil seven days per month. Over a third of households never consume oil, hence the median household consumes oil only once per week. In line with the reasons adopters gave for choosing to adopt (Table 1*a*), consuming sunflower oil can improve the household's nutritional status.

To summarise, prior to the introduction of sunflower, adopters and non-adopters consume oil to the same extent, have the same vulnerability to shocks, have the same levels of human and physical capital, and cultivate the same crop mix. The key distinctions between adopters and non-adopters is that adopters have more other adopters among their family and friends, and are more likely to have participated to other NGO projects in the past.

3.3. *Methodology*

We analyse data from period 0, namely the year in which sunflower seeds were first introduced to the region. As discussed in Section 2, farmer i adopts sunflower if the present value of profits from adopting in period 0 is higher than the present value of leaving the crop mix unchanged, as given in (10);

$$\mathrm{E}_0 q_0\left[0, n(i)_0\right] + \delta V_1\left[1, n(i)_0\right] \geq \underline{q} + \delta V_1\left[0, n(i)_0\right], \tag{10}$$

where $n(i)_0$ measures the information available to i on sunflower cultivation from his network. As emphasised in Section 2, i's likelihood of adoption is also determined by the precision of his initial beliefs on the parameters of the new technology, and the precision with which he receives information from his network.

Denote the unobservable (to the econometrician) present value of net gains from adoption to farmer i in village v, a_{iv}^*. We measure the information available to i on sunflower cultivation from his social network, $n(i)_0$, as the number of adopters among his family and friends. As this network is individual specific and defined *within* the village, we control for village fixed effects, $\mathbf{Z}_v$. These control for village determinants of adoption such as the proximity to markets, land quality, and any component of information on sunflower cultivation that is commonly known to all farmers.

Finally, we control for i's individual characteristics ($\mathbf{X}_i$) to capture the precision of his initial beliefs about the parameters of the new technology and other characteristics that determine the costs and benefit of adoption in period 0. In general;

$$a_{iv}^* = a[n(i), \mathbf{X}_i, \mathbf{Z}_v, u_{iv}], \tag{13}$$

where dropping time subscripts, $n(i)$ refers to the number of adopters among i's network in period 0, and u_{iv} contains unobserved individual and network characteristics that determine the present value of net gains from adoption.

The net gains from adopting may be increasing or decreasing in $n(i)$, depending on whether the positive effect of the contemporaneous information externality prevails over the negative effect of the incentive to delay. In addition the effect of $n(i)$ on a_{iv}^* is nonlinear as both the information sharing (positive) effect and of the strategic delay (negative) effects are concave in $n(i)$. To account for this, we assume the present value of net gains to adoption to be nonlinear in the number of adopters among the network of friends and family and linear in all other variables;

$$a_{iv}^* = f[n(i)] + \gamma \mathbf{X}_i^o + \delta \mathbf{Z}_v + u_{iv}. \tag{14}$$

The actual adoption decision, a_{iv}, is a discrete choice. It is observed and defined as;

$$a_{iv} = 1 \text{ if } a_{iv}^* > 0$$
$$a_{iv} = 0 \text{ otherwise.}$$

Hence the probability that farmer i is adopts sunflower is;

$$\mathrm{prob}(a_{iv} = 1) = \mathrm{prob}\left(u_{iv} > -\left\{f[n(i)] + \gamma \mathbf{X}_i^o + \boldsymbol{\delta} \mathbf{Z}_v\right\}\right). \tag{15}$$

We experiment with a number of alternative specifications for $f(.)$. Section 5 reports results for linear, spline, quadratic and non parametric estimates. Throughout, (14) is estimated, with a_{iv} substituted for a^*_{iv}, using a linear probability model. To correct for heteroscedasticity, we report standard errors based on the Eicher-White robust estimator for the asymptotic covariance matrix.

The advantages of the linear model over discrete choice models such as logit and probit are twofold. First the linear model is more amenable to the estimation of alternative functional forms for $f(.)$ and the computation of the marginal effects when higher order polynomials are fitted onto $f(.)$ is more transparent. Second, the linear model allows us to control for village fixed effects $\mathbf{Z}_v$ without biasing the other coefficients.

The obvious drawback is that the linear model does not take into account that the dependent variable is either zero or one and can therefore yield predicted values outside the unit interval. This problem is particularly serious when the mean of the dependent variable is close to either zero or one (Maddala, 1983). In our sample the adoption rate is 51%, and throughout less than 5% of the predicted values lie outside the unit interval.

Moreover the linear probability model implies that a unit increase in any of the right hand side variables has the same effect on the probability of the positive outcome, regardless of the initial value of the variable. The model thus yield good estimates near the centre of the distribution of the right hand side variables (Wooldridge, 2002). Reassuringly, in our case the coefficients estimated with a logit (or probit) model, without the village fixed effects, are indistinguishable from those estimated by linear probability.[30]

Below we find the quadratic polynomial fits the data best, so in most of the analysis we estimate the following specification using a linear probability model;

$$a^*_{iv} = \beta_1 n(i) + \beta_2 n(i)^2 + \gamma \mathbf{X}^o_i + \boldsymbol{\delta} \mathbf{Z}_v + u_{iv}, \tag{16}$$

where again, a_{iv} is substituted for a^*_{iv}.

To be clear, the estimated (β_1, β_2) coefficients do not identify the causal effect of the adoption choices of the network on *i*'s adoption decision since they also capture the endogenous effect of *i*'s choice on the adoption choice of each network member. This is the well-known reflection problem as discussed in Manski (1993). Our method is informative of whether adoption decisions are correlated within social networks, and so follows an approach similar to Bertrand *et al.* (2000) and Goolsbee and Klenow (2002).[31]

The key empirical challenge is to identify whether adoption choices are correlated due to social effects or simply because of omitted variables. In Section 5 we discuss two standard types of omitted variable that lead to spuriously correlated behaviour in the network. First, unobserved characteristics of network members may cause their behaviour to be similar, creating a spurious correlation in their adoption decisions. In

[30] Fixed effects can be taken into account in a discrete choice framework using the conditional logit model. The structure of the sample (198 observations in 9 villages) and the non linear network effects make the conditional logit model less suitable for this application.

[31] A goal for future research is to identify the mechanism through which social effects occur. This in turn requires the collection of better data. Two approaches that have been used recently are collecting panel data (Besley and Case, 1997; Conley and Udry, 2003), or designing interventions with randomised treatments (Sacerdote, 2001; Duflo and Saez, 2003; Kremer and Miguel, 2004*a*).

Manski's (1993) terminology, these are contextual effects. Second, unobserved individual variables lead to inconsistent estimates of the parameters of interest (β_1, β_2) if they are –

(*i*) determinants of adoption; and
(*ii*) correlated with the number of adopters among friends and family, $n(i)$.

For instance, more entrepreneurial farmers might be more likely to adopt and also more likely to have a larger social network, hence know more adopters.

Section 5 also discusses two other types of econometric concern for estimating (16). There may be unobserved targeting of information to some networks by *Movimondo*, or there may be the endogenous formation of networks *ex post*.

4. Results

4.1. *Baseline Regressions*

Table 5 reports the baseline results. For ease of exposition, the Table is divided in two parts. Part (*a*) reports the coefficients on the network variables (β), part (*b*) reports the coefficients on all other characteristics (γ). In all specifications we control for village fixed effects, which are always jointly significant. Factors that cause adoption rates to differ across villages – such as soil quality, village institutions, proximity to markets – are therefore controlled for throughout.

Column 1 regresses the adoption decision of each farmer on the number of adopters among his family and friends. The two are positively and significantly related. A one standard deviation increase in the number of adopters in the network increases the propensity to adopt by 0.134.

This effect exists *over and above* village level determinants of adoption. Hence, the adoption choices of network members matter for individual adoption choices even if there is some component of information on sunflower cultivation that is commonly known to all villagers.

Column 2 additionally controls for individual determinants of adoption – literacy, the number of adults in the household, months of food security, relative asset poverty, whether cashew is cultivated, whether the farmer has participated to other NGO projects in the past, gender, age, migrant status and religion. The effect of each of these controls on the propensity to adopt is discussed in the next subsection. Here we note that including these controls, the coefficient on the number of adopters among friends and family remains unchanged, and is estimated with the same precision as in Column 1. This suggests the measure of social networks is uncorrelated to these other determinants of adoption.

Column 3 splits the number of adopters among family and friends into splines, the omitted category is having no adopters among family and friends. Moving from having no adopters in the network to having 1–5, increases the propensity to adopt by 0.27, while having between 6 and 10 increases the propensity by 0.58. In other words, a given farmer is more likely to adopt than not if he has between 6 and 10 adopters among his family and friends. However, having more than 10 adopters increases the propensity to adopt by only 0.30, relative to having no adopters in the network.

Table 5

Baseline Regressions

(*a*) *Social Networks and Adoption*
Dependent variable = 1 if household head adopts sunflower, 0 otherwise
Linear regression estimates
Robust standard errors reported in parentheses

	(1)	(2)	(3)	(4)
Number of adopters among family and friends	0.026***	0.024***		0.101***
	(0.007)	(0.007)		(0.018)
Number of adopters among family and friends, Squared				−0.005***
				(0.001)
1–5 Adopters among family and friends			0.271***	
			(0.075)	
6–10 Adopters among family and friends			0.577***	
			(0.092)	
10+ Adopters among family and friends			0.300**	
			(0.126)	
Marginal effect, evaluated at the mean				0.054***
				(0.009)
Implied maximum				10.57
Test 1: p-value on 1–5 = 6–10			0.001	
Test 2: p-value on 6–10 = 10+			0.031	
Test 3: p-value on 1–5 = 10+			0.815	
Individual Controls	No	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Observations	198	198	198	198
R-squared	0.10	0.27	0.34	0.34

(*b*) *Individual Determinants of Adoption*
Dependent Variable = 1 if household head adopts sunflower, 0 otherwise
Linear regression estimates
Robust standard errors reported in parentheses

	(2)	(3)	(4)
Literate (yes = 1)	0.264***	0.199**	0.207***
	(0.080)	(0.078)	(0.077)
Number of adults in the household	0.040	0.028	0.033
	(0.050)	(0.052)	(0.052)
Months of food security	0.071**	0.083***	0.077***
	(0.027)	(0.027)	(0.027)
Asset poverty (very poor)	−0.026	−0.052	−0.057
	(0.118)	(0.123)	(0.120)
Asset poverty (poor)	−0.011	−0.066	−0.047
	(0.089)	(0.084)	(0.085)
Cultivates cashew	0.014	0.014	0.004
	(0.083)	(0.080)	(0.079)
Participated in NGO projects in the past	0.283**	0.336***	0.333***
	(0.127)	(0.114)	(0.114)
Female headed household	0.357***	0.309***	0.324***
	(0.105)	(0.109)	(0.109)
Age	0.033**	0.034**	0.034**
	(0.017)	(0.016)	(0.015)
Age squared $\times 10^{-2}$	−0.029	−0.032*	−0.032*
	(0.018)	(0.017)	(0.017)
Migrant (yes = 1)	−0.146	−0.178*	−0.164*
	(0.097)	(0.095)	(0.095)
Protestant	0.124	0.122	0.126*
	(0.076)	(0.074)	(0.071)
Other religion	−0.014	−0.109	−0.039
	(0.137)	(0.140)	(0.137)

Table 5

Continued

	(2)	(3)	(4)
Non Religious	0.217*	0.250**	0.266**
	(0.129)	(0.115)	(0.116)
Network controls	Linear	Spline	Linear, Quadratic
Village fixed effects	Yes	Yes	Yes
Observations	198	198	198
R-squared	0.27	0.34	0.34

Notes. *** denotes significance at 1%, ** at 5%, and * at 10%. Village elders and contact farmers are not included in the sample. Individual controls are literacy, the number of adults in the household, months of food security, relative asset poverty, whether cashew is cultivated, whether past NGO projects have been participated in, gender, age, age squared, migrant status and religion. Omitted categories are Catholic, and not poor.

At the foot of the Table, p-values are reported on tests of equality of the coefficients on each spline. Having 6–10 adopters in the network significantly increases the propensity to adopt relative to having only 1–5 adopters (test 1). However, the effect of having more than 10 is significantly *smaller* than the effect of having between 6–10 (test 2) and not significantly different from having between 1 and 5 (test 3). The spline regression specification therefore suggests the relationship between the number of adopters among family and friends and the propensity to adopt is shaped as an inverse-U.

To shed further light on this relationship, Column 4 controls for the number of adopters in the network and its square. The estimates confirm that the relationship between the adoption choices within the social network and the propensity to adopt is non linear and inverse-U shaped ($\widehat{\beta}_1 > 0$, $\widehat{\beta}_2 < 0$). The propensity to adopt increases (at a decreasing rate) as the number of adopters among family and friends increases up to ten. After that the marginal effect of the network is negative.[32] The result is not driven by outliers. The same conclusion is reached if individuals that have more than 14 other adopters in their network are dropped from the sample.[33]

Having one more adopter among family and friends, evaluated at the network mean, increases the propensity to adopt of each of their social network by 0.054. These are the initial effects, and there will also be multiplier effects as information spreads through the social network. A one standard deviation increase in the number of adopters in the network increases the propensity to adopt by 0.27, which is double the magnitude estimated in the linear specification.

Finally, we estimate the relationship between the number of adopters among family and friends and the propensity to adopt using a non parametric kernel regression. The kernel estimate, shown in Figure 1, 'partials out' the linear part of the model, $\gamma \mathbf{X}_i^o + \boldsymbol{\delta} \mathbf{Z}_v$, following the method of Hausman and Newey (1995). In line with the

[32] In the sample, 16% of farmers know 11 or more adopters.

[33] Further evidence in support of the quadratic form can be obtained by plotting the 'residual adoption probability' (namely the adoption decision after partialling out all controls) agains the number of adopters known. Results, not reported in the interest of space, indicate that the relationship is indeed inverse-U shaped.

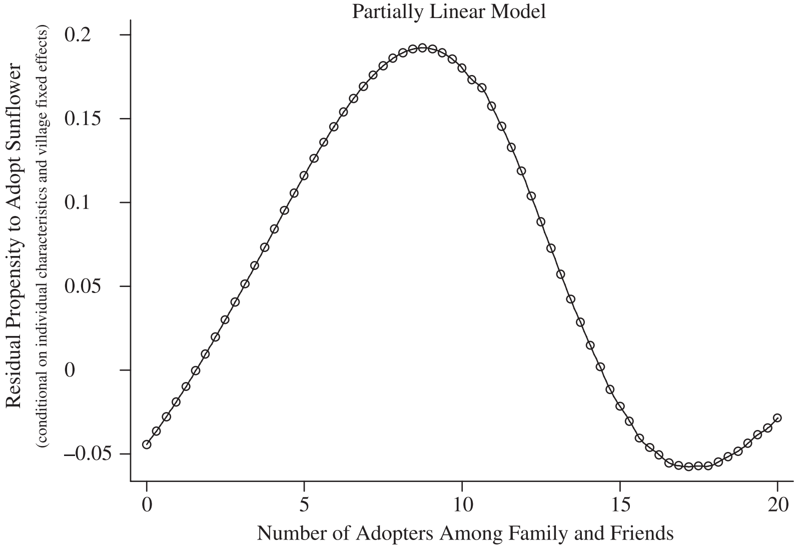

Fig. 1. *Non Parametric Estimate: Number of Adopters and the Propensity to Adopt*
Notes: A Gaussian kernel function is used a bandwidth of 3, and 65 grid points. Individual controls are literacy, the number of adults in the household, months of food security, relative asset poverty, whether cashew is cultivated, whether past NGO projects have been participated in, gender, age, age squared, migrant status and religion. Village elders and contact farmers are not included in the sample.

results in Table 5, the non parametric relationship between the adoption choices within the social network and the farmer's propensity to adopt is shaped as an inverse-U. This suggests the quadratic specification fits the data well, and so we retain this specification in the analysis that follows.

4.1.1. *Other determinants of adoption*

Table 5(*b*) reports the coefficients on the other individual controls in the baseline regression specifications. These are literacy, the number of adults in the household, months of food security, relative poverty status, whether cashew is cultivated, whether the farmer has participated in other NGO projects in the past, gender, age, migrant status and religion.[34]

Column 2 reports the coefficients on these controls when the number of adopters among family and friends is controlled for. As expected, literate farmers are significantly more likely to adopt. Being literate increases the probability of adoption by 26 percentage points. Households that are more food secure and therefore face lower

[34] We experimented with a number of other determinants of adoption. Throughout we found that total household size, roof materials, wall materials, and the existing crop mix were not significant determinants of adoption. Tribe is not controlled for as 99% of the sample belong to the Lomue tribe. There is also no variation in years of schooling. Literacy and numeracy are more relevant for agricultural decision making in this context. We only control for literacy as the two are highly correlated.

risks, are more likely to adopt, all else equal; a one standard deviation increase in food security raises the propensity to adopt by 13 percentage points.[35]

Asset poverty has no direct effect on the propensity to adopt. Although seeds are provided to farmers at no cost, land is abundant and no additional inputs are required for the cultivation of sunflower, credit constraints can still be important if labour constraints bind. The fact that neither poverty nor the availability of adult labour affect the adoption decision suggest that labour constraints do not bind in this context.[36]

The cultivation of cashew is not a significant predictor of sunflower adoption. Farmers who have participated in NGO projects in the past are more likely to adopt, which is consistent with this variable being correlated to farmers' entrepreneurship or openness to innovations. The probability of adoption is 28 percentage points higher for farmers who have participated to NGO projects in the past.

The remaining controls relate to demographic characteristics of the household head. Female household heads are significantly more likely to adopt (by 36 percentage points), as are older farmers. The first result is in contrast with earlier findings in the literature. To the extent that these previous results were due to female heads, mostly widows, being poorer than the average household, our result may be driven by the fact that credit constraints are less relevant in this context.[37]

Farmers who have migrated to the village are less likely to adopt by 16 percentage points. This may be due to migrants being allocated residual, hence worse quality, land. Protestant and in some specifications, non-religious farmers, are more likely to adopt than the omitted religious category – Catholics.[38]

The magnitude, precision, and significance of the coefficients are stable across specifications 2 to 4, where the number of adopters known is controlled for linearly, with splines, and with linear and quadratic terms.

To compare the magnitude of the effect of networks to those other determinants of adoption we refer to the specification in Column 3, where the number of adopters among family and friends is divided into splines. Relative to having no adopters in the network, having 1–5 adopters has a greater effect on the propensity to adopt than being literate, or having two more months of food security. The marginal effect of having 6–10 adopters in the network is at least twice as large as the effect of any other determinants. Similarly, the estimates in Column 4 imply a one standard deviation increase in network size raises the likelihood of adoption by 0.28, while a one standard deviation increase in food security raises the propensity to adopt by only 0.13.

[35] Suppose food security is a choice variable for farmers, and so measures discount rates rather than vulnerability. The results then suggest more impatient farmers do not adopt in the first year. Alternatively those with low food stocks may be insured in some other way, so that fewer months of food security actually implies less vulnerability. This is less plausible as food stocks are the primary means to insure against aggregate shocks. Moreover food security is the standard measure of vulnerability employed by *Movimondo*.

[36] This result is robust to alternative measures of relative poverty based on livestock holdings, income, food consumption, and survey enumerators' evaluations of poverty.

[37] In common with other studies, female headed households in the sample are twice as likely to be very poor.

[38] Relatedly, Gifford (1998) documents how the Catholic religion in Mozambique has become associated with conservatism in civil society, and may therefore be less open to new ideas.

In short, the effect of each farmer's social network on his adoption propensity is qualitatively significant, and quantitatively important relative to other determinants of adoption.

In the Appendix we show this baseline result to be robust to a number of concerns. These include redefining the adoption choice to exclude farmers who may be experimenting; measurement error in network sizes due to farmers being innumerate; distinguishing farmers that have zero other adopters in their network from those that have at least one adopter; and correcting standard errors if multiple sample farmers belong to the same network.

4.2. *Heterogeneity*

If social learning is important for adoption, the relation between the adoption choice of a farmer and his network depends on the precision of the farmer's own initial belief on the parameters of the new crop. The adoption decision of farmers that have more precise information to begin with (higher ρ_{i0}) are *less* sensitive to the adoption decisions of the network, $n(i)_0$. This follows from the fact that both current profits and the incentive to strategically delay are less sensitive to the adoption decisions of the network when the farmer's own information is more precise.

To see if this hypothesis finds support in the data, we allow the effect of the network to vary according to farmers' characteristics. These characteristics proxy for the precision of his own initial beliefs on sunflower cultivation, ρ_{i0}. The present value of net gains from adoption are;

$$a^*_{iv} = \beta_1 n(i) U_i + \beta_2 n(i)^2 U_i + \psi_1 [n(i) I_i] + \psi_2 \left[n(i)^2 I_i \right] + \gamma \mathbf{X}_i + \boldsymbol{\delta} \mathbf{Z}_v + u_{iv}, \qquad (17)$$

where I and U identify farmers that are 'informed' and 'uninformed' about sunflower cultivation, respectively. Namely $I = 1$ if the farmer is informed, 0 otherwise, and $U = 1 - I$.

We are interested in establishing whether, in the empirical specification above, the marginal effect of the network is lower for informed farmers, that is if $|\psi_1 + 2\psi_2 n(i)| < |\beta_1 + 2\beta_2 n(i)|$.

We use four criteria to sort farmers into informed and uninformed groups. We first use data on whether a given farmer has participated in other agricultural NGO projects and whether they produce cashew.[39] The rationale is that farmers who have participated in past agricultural NGO projects and who produce cashew have greater experience with different crops and technology, compared to farmers who have not participated in the projects and who only grow the basic staple crop mix. We classify farmers who have participated in NGO projects as informed ($I = 1$) and those who have not as uninformed ($U = 1$). Similarly farmers who produce cashew are classified as informed ($I = 1$) and those who do not as uninformed ($U = 1$).

The third criterion uses information on whether the farmer was born in the village or migrated there. The rationale is that, relative to natives, migrants know less about local

[39] Both measures are based on actions taken prior to the introduction of sunflower to the region. They are therefore not themselves endogenously determined by the adoption decision.

soil conditions and are therefore more likely to learn from others, all else equal. We classify natives as informed ($I = 1$) and migrants as uninformed ($U = 1$).

Finally, we use the measure of relative poverty and classify not poor farmers as informed ($I = 1$) and poor and very poor farmers as uninformed ($U = 1$). The underlying assumption is that since agriculture is the only source of livelihood for most individuals in these villages, the least poor individuals may also be the more talented and, hence, more informed farmers, relative to others.

Table 6 reports estimates of (17) for each of the four dimensions along which farmers are classified as informed and uninformed. For ease of exposition, only the coefficients (β_1, β_2, ψ_1, ψ_2) are reported but all individual characteristics in the baseline specification are controlled for. Two results are of note.

First, the marginal effect of having one more adopter among family and friends, evaluated at the mean, is positive and significant for all types of farmer and is indeed lower for more informed farmers. Informed farmers – as measured by whether they cultivate cashew, participated in NGO projects in the past, migrated to the village, and poverty status – are less sensitive to the adoption choices of their friends and family.[40]

For instance, having one more adopters in the network increases the farmers' propensity to adopt by 0.039 if they belong to the group of cashew cultivators and by 0.076 if they do not.

Second, there is an inverse-U relationship between the number of adopters in the network and the propensity to adopt for *both* informed and uninformed farmers. This is reassuring as it suggests that the previous finding in Table 5 was not spuriously generated by a composition effect. In particular, a concern would have been that the inverse-U result was due to pooling together farmers for whom the correlation is always positive and farmers for whom the correlation is always negative. The results in Table 6 indicate that, in contrast, the relationship between the number of adopters in the network and the propensity to adopt is inverse-U shaped for *all* types of farmers.

4.3. *Cohort-based Networks*

Throughout we have taken friends and family to be the relevant reference group among which farmers learn about sunflower cultivation. This group have frequent contacts with each other and the earlier literature has shown this to be an important source of information on agriculture in similar economic environments (Foster and Rosenzweig, 1995; Rogers, 1995; Conley and Udry, 2003). However there are others in the village, that can be considered *potential* rather than *actual* sources of information. Farmers' adoption decisions may also be correlated to the choices of these individuals, even though at the time of adoption the farmer has weaker social ties with them than with his friends and family. We explore this hypothesis in what follows.

We analyse whether the adoption decisions are correlated to the number of adopters in the village of the same religion. Religion-based networks are relevant in this context

[40] As highlighted in Section 2, we cannot identify whether this effect is because informed farmers are less sensitive to the adoption choices of their network, or because the precision of information received from the network (ρ_v) differs across the networks of informed and uninformed farmers. The results fit the second interpretation if disadvantaged farmers are in networks with more precise information, say because soil conditions are more similar across their land than for networks of informed farmers.

Table 6

Heterogeneity

Dependent Variable = 1 if household head adopts sunflower, 0 otherwise
Linear regression estimates
Robust standard errors reported in parentheses

	(1) Cashew Cultivation	(2) Past Participation in NGO Projects	(3) Migration status	(4) Poverty
Uninformed × Number of adopters among family and friends	0.114***	0.099***	0.218***	0.114***
	(0.028)	(0.020)	(0.047)	(0.021)
Uninformed × Number of adopters among family and friends, squared	−0.005**	−0.004***	−0.015***	−0.005***
	(0.002)	(0.001)	(0.003)	(0.001)
Informed × Number of adopters among family and friends	0.088***	0.120***	0.099***	0.092***
	(0.025)	(0.041)	(0.018)	(0.032)
Informed × Number of adopters among family and friends, squared	−0.004***	−0.007***	−0.004***	−0.006***
	(0.001)	(0.002)	(0.001)	(0.002)
Marginal Effect for UNINFORMED, evaluated at the mean	0.076***	0.057***	0.091***	0.072***
	(0.016)	(0.010)	(0.022)	(0.013)
Marginal Effect for INFORMED, evaluated at the mean	0.039***	0.052**	0.053***	0.025**
	(0.011)	(0.024)	(0.009)	(0.014)
Implied Maximum for UNINFORMED	11.21	11.67	7.14	120.4
Implied Maximum for INFORMED	10.36	8.23	11.01	7.98
Individual Controls	Yes	Yes	Yes	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes
Observations	198	198	198	198
R-squared	0.35	0.36	0.37	0.38

Notes. *** denotes significance at 1%, ** at 5%, and * at 10%. Robust standard errors are calculated throughout. Village elders and contact farmers are not included in the sample. Individual controls are literacy, the number of adults in the household, months of food security, relative asset poverty, whether cashew is cultivated, whether past NGO projects have been participated in, gender, age, age squared, migrant status and religion. The omitted categories are Catholic and not poor. Along the first three dimensions, informed households cultivate cashew, have participated in NGO projects in the past, or are permanent residents of the village. In terms of poverty status, informed farmers are defined to be those that are not poor, uninformed farmers are either poor or very poor.

for two reasons. First, religion-based cohorts have unambiguously and exogenously defined boundaries. Second, the majority of farmers report being religious, there are religious institutions in each village, and our fieldwork indicates this is an important dimension along which individuals interact.

Denote the number of adopting farmers in religion k and village v as n_{kv}. We allow the present value of net gains to adoption for farmer i in religion k in village v, a^*_{ikv}, to relate nonlinearly both to the number of adopters among family and friends, and among the same religion;[41]

$$a^*_{ikv} = \beta_1 n(i) + \beta_2 n(i)^2 + \theta_1 n_{kv} + \theta_2 n^2_{kv} + \gamma \mathbf{X}^o_i + \boldsymbol{\delta} \mathbf{Z}_v + u_{iv}. \tag{18}$$

The results are presented in Table 7. The first specification excludes the number of adopters among family and friends ($\beta_1 = \beta_2 = 0$). All the other determinants of

[41] The number of adopters in religion k in village v is $n_{kv} = (n^s_{kv}/Pop^s_v)Pop^p_v$ where n^s_{kv} is the sample based total number of adopters in religion k and village v, Pop^s_v is the total number of households in village v in the sample, and Pop^p_v is the actual number of households in the village.

Table 7

Cohort-level Networks

Dependent Variable = 1 if household head adopts sunflower, 0 otherwise
Linear regression estimates
Robust standard errors reported in parentheses

	(1)	(2)	(3)
Number of adopters among family and friends		0.097***	0.021***
		(0.019)	(0.007)
Number of adopters among family and friends, squared		−0.005***	
		(0.001)	
Number of adopters in the *same* religion	0.016***	0.014***	0.002**
	(0.005)	(0.005)	(0.001)
Number of Adopters in the *same* religion, squared $\times 10^{-2}$	−0.010***	−0.009***	
	(0.003)	(0.003)	
Number of Adopters in *other* religion			0.001
			(0.001)
Marginal effect - Same religion network	0.015***	0.013***	
	(0.004)	(0.009)	
Marginal effect – family and friends network		0.052***	
		(0.010)	
Test 1: p-value on Same religion = Other religion			0.016
Individual controls	Yes	Yes	Yes
Village fixed effects	Yes	Yes	No
Observations	184	184	184
R-squared	0.24	0.35	0.21

Notes. *** denotes significance at 1%, ** at 5%, and * at 10%. Robust standard errors are calculated throughout. Both marginal effects are evaluated at the mean number of adopters among family and friends (4.91). Village elders and contact farmers are not included in the sample. Individual controls are literacy, the number of adults in the household, months of food security, relative asset poverty, whether cashew is cultivated, whether past NGO projects have been participated in, gender, age, age squared, migrant status and religion. The omitted categories are Catholic and not poor. The number of adopters in the same cohort is computed by multiplying the sample share in the village by the village population and it does not include the farmer if he has himself adopted. The number of observations is less than in the previous specifications because in some villages all farmers of the same religion make the same adoption choice.

adoption as in the baseline regression are controlled for, including the farmers own religion.

The estimates in Column 1 indicate that the farmers' adoption decisions are related to the adoption decisions of other farmers in the village of the same religion. The relation is nonlinear. To ease comparison, we evaluate the marginal effect of the religion cohort at the mean size of the family and friends network. The marginal effect on the propensity to adopt is 0.013.

In Column 2 we additionally control for the number of adopters among family and friends. The magnitude and precision of $(\widehat{\theta}_1, \widehat{\theta}_2)$ are not significantly different from those in Column 1. Furthermore the magnitude and precision of $(\widehat{\beta}_1, \widehat{\beta}_2)$ are not significantly different from those in the baseline specification of Column 3 in Table 5. This implies the two types of network do not overlap, and indicates that both types of network are independent sources of information.

The comparison of the marginal effects, both evaluated at the mean number of adopters among family and friends, shows that the effect of the number of adopters among the family and friends network is four times larger and significantly different from the effect within the religion cohort.

While these results are in line with social learning being more important among close contacts than potential contacts, this is not the only explanation of why adoption choices are correlated among farmers. The present value of adopting sunflower may increase in the total number of adopters if this increases the likelihood of sunflower production being commercialised. If these types of marketing externality lead to correlated choices, the relevant reference group is the number of adopters *per se*, irrespective of the social ties between them.[42]

Column 3 explores this hypothesis by controlling for the number of adopters among the same religion as farmer *i*, and the number among other religions. To preserve degrees of freedom we control for all network measures linearly.

The number of adopters in the *same* religion significantly increase the adoption propensity, but those in *other* religions do not. Moreover the coefficients are significantly different (the p-value on the test of equality is 0.016). If adoption choices were correlated among farmers in a village due to some unobserved determinant of adoption, then we should find that adopters in other religions have a similarly (spurious) positive coefficient. This is not the case.

These result shows that the strength of social ties matter for adoption. The effect of close contacts is four times as large as those in the same religion, and those in other religions have no effect. Second, village level institutions do not exist that fully internalise the externalities in the adoption process, so that individual adoption choices are not sensitive to the adoption choices of *all* others in the village.

5. Interpreting the Results

5.1. *Social Learning and Other Sources of Social Effects*

Theory provides a number of reasons why a farmer's decision to adopt a new crop technology might depend on the adoption choices of his social network. We have focused on social learning because –

(*i*) farmers' subjective perceptions of the costs of adoption suggest that lack of information is the key barrier to adoption;
(*ii*) previous research has shown social learning to be relevant for agricultural decision making in similar economic environments.

Theories of social learning imply the sign of the relationship among adoption decisions is ambiguous. On the one hand, the benefit of adopting in the current period is higher when there are many adopters in the network because of the information they provide. On the other hand, having many adopters in the network increases incentives to strategically delay adoption and free ride on the knowledge accumulated by others. If strategic delay considerations prevail, a farmers' propensity to adopt decreases as the number of adopters among his network increase.

We find that the individual propensity to adopt is inverse-U shaped in the number of adopters among friends and family. This is consistent with social learning if the positive information externality provided by the network prevails in small networks, while the

[42] The same prediction arises if adoption choices are correlated because of peer pressure, social norms, or if all farmers imitate the same individual within the village.

incentive to delay prevails in larger networks. The downward sloping part of this relation is consistent with farmers being forward looking, as also found in Besley and Case (1997).

Second, we find heterogeneous effects of the network, as implied by a model of social learning. Farmers that are more informed on sunflower cultivation to begin with – as measured by whether they cultivate cashew, participated in NGO projects in the past, migrated to the village, and poverty status – are less sensitive to the adoption choices of their friends and family.

Third, the strength of social ties matters for adoption. The effect of the adoption choices among friends and family is four times larger than those in the same religion cohort. Furthermore, the adoption choices of those in other religions have no affect on the propensity to adopt.

Social learning is not the only mechanism that links adoption choices. Some explanations predict a *positive* relationship between adoption decisions in a network. This arises if for example there are marketing externalities in adoption. Other explanations predict a *negative* relation between adoption decisions within a network – for instance, if networks provide insurance against idiosyncratic shocks. While we do not attempt to distinguish between social learning and other causes of social effects, it is important to note that none of the other explanations by itself would predict an inverse-U pattern of adoption choices, heterogeneous social effects, and that the strength of social ties matters.

We do however want to distinguish between any causal relation between the adoption choices of farmers in the same network and spurious sources of correlated behaviour.

Distinguishing social effects from spurious correlations is important for two policy related questions. First, if we affect the adoption decision of a farmer's close contacts, will this change his adoption decision? This has implications for which farmers, if any, should be encouraged to adopt earlier. Second, can the adoption decision of farmer i have multiplier effects, namely indirectly influence the behaviour of others that are not affected by i's choice? If so, this raises the possibility of non market interactions leading to multiple equilibria in adoption rates, large differences in equilibrium outcomes arising from small differences in initial conditions, and welfare gains from policy interventions, as social and private gains from adoption do not coincide.

5.2. *Sources of Spurious Correlation*

5.2.1. *Contextual effects and mimicry*

The correlation among adoption decisions of farmers within the same social network might be spuriously correlated because of unobserved characteristics of each network member that causes their behaviour to be similar. For example, if farmers in the same network have similar ability, preferences for risk, soil quality, access to credit, or have been equally targeted by *Movimondo*, their behaviour will be correlated, but independent of each other's choices.[43] In addition, spurious correlation arises if farmers might merely imitate what others in their network do, without there being any information sharing or learning.

[43] In Manski's (1993) terminology, these are contextual effects.

We note that both contextual effects and mimicry generate a spurious *positive* correlation among adoption choices of farmers in the same network. In other words, the estimated relationship might be positive even if there is no causal relationship.

The fact that we find the relation between the individual propensity to adopt and the number of adopters among family and friends to be inverse-U shaped indicates that contextual effects and mimicry are not driving the results.

5.2.2. *Unobserved heterogeneity*

A third source of spurious correlation is unobserved heterogeneity across farmers that drives both the decision to adopt *and* the number of adopters among the network. Unobservable individual characteristics that are monotonically related to both the number of adopters in the network and the propensity to adopt would not drive the results. On the other hand, an inverse-U shaped relation may be spuriously generated if there are unobservables that are linearly correlated with the number of adopters in the network, and nonlinearly related with the propensity to adopt.[44]

There are potentially many such unobservables that may be driving the results. While we are unable to rule out all these possibilities, we can partially address a particular type of this concern arising from farmers' unobserved ability. Suppose the number of adopters among close contacts increases with ability, say because farmers that are most able also know more people, and hence have more adopters among their close contacts. This creates a linear relation between ability and network size, $n(i)$.

At the same time, both the least and most able farmers might have the weakest incentives to adopt sunflower, all else equal. Low ability farmers may face insurmountable barriers to adoption, and the most able farmers may have a valuable outside option to adopting. In these circumstances, unobserved ability would create an inverse-U relationship between the propensity to adopt and the number of adopters among the network, even in the absence of social effects.

To address this concern, we attempt to identify farmers who are more likely to have an higher outside option and see whether they drive the inverse-U pattern we find in the data.

From Section 4.2 we know the adoption decisions of both the wealthiest farmers and of the farmers who cultivate the only cash crop – cashew – display the same inverse-U shaped pattern as that of the average farmer. Among cashew cultivators, we identify the most productive farmers, where productivity is defined as the total kilograms of cashew production per active cashew tree owned. In addition, we examine farmers that list animal husbandry as an important source of income. As expected, both types of farmers are wealthier than average.

Reassuringly, we find that the inverse-U shaped relationship is not driven by either of these groups of farmers. Namely, dropping from the sample either the 25% most productive cashew cultivators, or those who report receiving any income from animal husbandry, and re-estimating the baseline specification (15), we continue to find a

[44] A spurious inverse-U shaped relation could of course also be generated if there are individual omitted variables that are nonlinearly related with the number of adopters in the network, and linearly related with the propensity to adopt.

significant and inverse-U shaped relation between the farmers' propensity to adopt sunflower and the number of adopters among their family and friends.

5.2.3. *Targeting and ex-post network formation*

Another concern relates to the implementation of the project. For example, *Movimondo* may target particular networks, providing information to some groups of closely connected farmers and none to others. In particular, suppose –

(*i*) the information provided by *Movimondo*, rather than from the network, is what drives adoption;
(*ii*) *Movimondo* prefer to target larger networks than smaller ones; and
(*iii*) *Movimondo* is less likely to be able to contact *all* the farmers in larger networks.

This creates a positive relation between the number of adopters among the network and the propensity to adopt when there are few other adopters, and a negative relation when the network is large, as we are more likely to sample a farmer not contacted by *Movimondo* in larger networks.

Three pieces of evidence suggest the behaviour of *Movimondo* is less likely to generate spurious network effects, although we cannot definitively rule out this hypothesis. First, the project is designed to be implemented in the same way across villages. Any differences in project implementation – say because of lobbying by village elders – that create differences in adoption rates across villages, are controlled for in the empirical analysis using village fixed effects.

Second, as discussed before, all farmers receive the same project details at an open village meeting, where the vast majority of farmers are in attendance. Third, direct persuasion by *Movimondo* workers was low on the list of reasons farmers' themselves gave for their adoption (see Table 1*a*).

Estimates of (β_1, β_2) in the baseline specification (8) are inconsistent if farmers befriend other adopters *after* having themselves adopted. This leads to reverse causality from the adoption decision to the number of adopters among friends and family. The standard argument for this type of *ex post* network formation is that adopters seek out other adopters, leading to an overestimate of the effect of the number of adopters in the network on individual adoption propensities. Clearly, the simplest story where all adopters seek out other adopters only generates a positive relationship between the propensity to adopt and the number of adopters in the network. However if social networks form in more complicated ways, in particular if there are heterogeneous incentives across farmers to form friendships with adopting farmers, this may lead to the pattern of coefficients we observe in our data. Understanding the process of network formation remains an open area for future research.

6. Conclusion

This article uses individual data from an NGO project to assess whether and how a farmer's decisions to adopt a new crop relates to the adoption decisions of his family and friends.

We find that the relation between the propensity to adopt and the number of adopters among family and friends is shaped as an inverse-U. Namely farmers are more likely to adopt when some farmers in their network also adopt but are less likely to adopt when many others do so.

We also find that the effect of choices among the network are heterogeneous, in particular they are stronger for farmers who are likely to have less information about the new crop to begin with. Moreover, the comparison between the effects of networks based on family and friends to those based on religion, suggest social effects are larger among individuals with stronger social ties.

It is now well recognised that the diffusion of new technologies can be slower than is socially optimal. To the extent that inefficiencies arise because of informational externalities, subsidising early adopters is commonly advocated as a socially optimal policy measure. Our finding of an inverse-U shaped relation between individual and network choices provides a note of caution to this debate. In contexts as the one studied here, giving incentives to adopt early to too many farmers can actually reduce the incentives to adopt for other farmers around them.

The result that networks matter differentially across farmer types has both methodological and policy implications that extend past the specific application of technology adoption in rural settings. First, the result suggests that network effects are not symmetric across pairs of individuals and this can aid identification of the causal effect of social networks on individual adoption decisions in a structural model of adoption (Brock and Durlauf, 2000).

Second, it raises the possibility that a given individual may respond heterogeneously to the choices of *different* members of his social network. Thus, the *identity* of network members may also be important for social learning and, as a consequence, for optimal policy targeting.[45]

Finally, our results highlight the importance of identifying the precise boundaries of the reference group when analysing social learning or, more in general, any type of peer effects. For example we find no relation among the adoption choices of farmers in different religious groups. In line with other papers that also exploit precise data on self-reported network measures from which individuals actually obtain information (Conley and Udry, 2003; Kremer and Miguel, 2004*a*; Woittiez and Kapteyn, 1998), we find that defining reference groups more broadly, leads to very different estimates of the qualitative impact of social effects.

Appendix: Robustness Checks

Table A1 reports robustness checks on the finding that the relationship between each farmer's adoption propensity and the adoption choices of his social network is inverse-U shaped.

First, we redefine the dependent variable to exclude farmers who have not 'adopted' in any meaningful way. This can be either because they planted a negligible quantity of sunflower, or because they stopped cultivating it during the season. We use information on sunflower pro-

[45] We cannot explore this issue in much detail in our data. We find no evidence that farmers in the same age group or religion as either the traditional leader or contact farmer, are more likely to adopt sunflower, all else equal. This suggests that those individuals are not more influential than others. Evidence along these lines is found by Conley and Udry (2003), who have information on the number and identity of network members. They show farmers respond more to the input choices of other farmers that have surprisingly good outcomes.

Table A1

Robustness Checks

Dependent Variable = 1 if household head adopts sunflower, 0 otherwise
Linear regression estimates
Robust standard errors reported in parentheses

	(1) Reclassify Adopters	(2) Numerate Farmers Only	(3) Know At Least One Adopter Among Friends and Family	(4) Clustering at Village Level
Number of adopters among family and friends	0.098***	0.106***	0.091***	0.101***
	(0.019)	(0.033)	(0.020)	(0.012)
Number of Adopters among Family and Friends, Squared	−0.004***	−0.005***	−0.004***	−0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
Marginal effect, evaluated at the mean	0.055***	0.049***	0.057**	0.054***
	(0.009)	(0.010)	(0.018)	(0.009)
Implied Maximum	11.14	11.55	10.76	10.57
Village Fixed Effects	Yes	Yes	Yes	Yes
Observations	198	161	143	198
R-squared	0.31	0.34	0.31	0.34

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Village elders and contact farmers are not included in the sample. Individual controls are literacy, the number of adults in the household, months of food security, relative asset poverty, whether cashew is cultivated, whether past NGO projects have been participated in, gender, age, age squared, migrant status and religion. Omitted categories are Catholic, and not poor. In column 1 farmers that produced in the bottom 10% of the distribution of production of sunflower seeds at the end of the first year of the project are reclassified as non adopters. Column 2 drops innumerate farmers. Column 3 drops farmers that know no other adopters among family and friends. In column 4 standard errors are clustered at the village level.

duction at the end of the first year to reclassify as non-adopters farmers that produce in the bottom 10% of the distribution of production. Column 1 shows that the results are unchanged when this alternative definition of adoption is used.[46]

A second concern is that the reported number of adopters among friends and family may be measured with error. Under the assumption that both the true network variable and the error are symmetrically distributed with mean zero, both the coefficient on the number of adopters and on its square will be biased towards zero. In particular, $\widehat{\beta}_1$ (the coefficient on the level term) will be biased towards zero by a factor of one minus the fraction of error variance in the total variance of the observed variable while $\widehat{\beta}_2$ (the coefficient on the square term) will be biased towards zero by the square of the same factor (Griliches and Ringstad, 1970). Column 2 explores the idea that measurement error might be more serious for innumerate farmers and drops these from the sample. The relation between the propensity to adopt and the number of adopters among the network is not significantly different from the baseline specification. Nor is the marginal effect of the network, evaluated at the mean.[47]

Another type of measurement error arises if farmers report the number of adopters to confirm their own adoption choices. For example those that are more likely to adopt report having more other adopters in their network, and those that have a low propensity to adopt report having fewer adopters. This type of measurement error can lead to a positive correlation being found among adoption choices within a network, when these choices are actually uncorrelated.

[46] As mentioned in Section 1, as part of the project design a contact farmer is appointed in each village to ensure the distributed seeds are actually planted.

[47] As a check farmers were asked to report the number of adopters among family and friends in specific ranges (none, 1–5, 5–10, 11–20, 21–30). The correlation between the two network measures was 0.91. This correlation was not significantly different between numerate an innumerate respondents.

Two pieces of evidence suggest this type of measurement error is not driving the results. First, as shown in Table 3, adopters and non-adopters report having almost identical numbers of adopters among their family. If farmers have a tendency to bias their reports in favour of their own actions, we would expect adopters to report more adopters among their friends *and* family. Second, while this pattern of misreporting can generate a positive correlation among the adoption decisions of farmers in the same network, it cannot generate the inverse-U relationship reported in Table 5.

The analysis has pooled together farmers that have zero other adopters in their network and those that have at least one adopter. This may not be a valid restriction to place on the data. As a check, Column 3 drops those farmers that report having no adopters among their friends and family. The resulting estimate of the effect of the network on the propensity to adopt is unchanged from the baseline regression.

A final concern is that if more than one sample farmer belongs to the same network, the observations are not independent and the estimated standard errors are downward biased. Given that the average number of adopters in a network (4.9) is much smaller that the average number of adopters in the village (148) this is unlikely to be the case. As a check, we take the worse case scenario and assume everyone in each village belongs to the same network and cluster the standard errors at the village level. Column 4 shows that standard errors rise as expected but the network variables are still significant at the 1% level, and the effect remains inverse-U shaped.[48]

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[48] In all the robustness checks, the significance of the coefficients on individual characteristics remains similar to the baseline regression.

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