Love thy neighbour? Evidence from ethnic discrimination in information sharing within villages in Côte d'Ivoire

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Abstract

There is an increasing amount of evidence that suggests that a fundamental source of information for farmers on how to access and use new agricultural technologies comes from observing their neighbours. Economic research on adoption of innovations in a rural context has only partially addressed the issue of how the social structure of a village can affect adoption and the final impact on productivity of farmers. This paper investigates the role of proximity interpreted not only in geographical terms but also along the line of ethnic similarities among neighbours (what we define as "social proximity"). We use a panel dataset collected in Côte d'Ivoire to define the probability to have access to the knowledge network. The main results indicate that farmers from ethnic minorities are less likely to access, and benefit less from, extension services. But they seem to try to re-equalize their condition by putting more effort than dominant ethnic group neighbours in sharing information among themselves.

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1 Introduction

In the context of the adoption of innovations in production it is important to distinguish between learning from an external source, such as an extension agent, and learning from other farmers in the village - from the interactions with neighbours and members of the same social groups. There is an increasing amount of evidence that suggests that a fundamental source of information on how to access and use new technologies comes from other farmers (Pomp and Burger 1995; Bevan et al 1989). Economic research on adoption of innovations in a rural context has partially addressed the issue of how the social structure of a village can affect adoption and the final impact on the productivity of farmers (Feder and Slade 1984; Case 1992; Foster and Rosenzweig 1995, Conley and Udry 2002). Evidence on the impact of extension in Côte d'Ivoire seems to indicate a divide in the access to extension services that moves along ethnic lines. This finding relates to the "ethnic sequence" in the history of integration of non-indigenous communities in cocoa growing areas of the counttry (see Leonard and Oswald, in Ruf, F. and Siswoputranto, P.S. (eds) 1995). This paper investigates to what extent information flows wuthin and between different ethnic groups in the village. Greater similarity between the farmer who is directly exposed to the innovation and his neighbours makes it more likely for the innovation to be replicated; similarly there is evicence that people belonging to minorities tend to create strong and efficient networks to safeguard their diversity (Feder and O'Mara 1982, Fafchamps 2000, Ruf, 1995). Such similarities have been more recently reinterpreted in the context of social capital: the stock of social capital is increasing in the density of the network and in the quantity and quality of relationships among its components (Barr 2000; Isham forthcoming). We will therefore try to understand whether the presence of neighbourhood networks associated with the ethnic affiliation of households help us understand the role of the quality of the relationships among members.

Section 2 will investigate the relationship between social structure and formation of networks, while section 3 will describe the simple model used to test the theory. Section 4 will describe the data available to test the hypothesis and section 5 will introduce some preliminary results on the ethnic component. Section 6 will set up the empirical formulation, Section 7 will illustrate the main results and section 8 will conclude.

2 Technology adoption and social structure

Being member of a community gives the farmers the advantage of sharing information on production techniques and innovations: this simple but sensible idea has produced interesting theoretical developments that have led to important empirical findings. In the last 20 years, evidence suggested that the way in which societies are organized and social groups interact can have an impact on the diffusion of knowledge and its consequent impact on the productivity of crops (Banerjee, 1992; Case, 1992; Besley and Case, 1994; Foster and Rosenzweig 1995, Conley and Udry, 2001). While these studies provided an invaluable theoretical platform to better understand the role of networks, there is still a lack of clarity on the role of social structures in determining the amount and the quality of the exchange of information among neighbours. This aspect remains difficult to model, as it is deeply rooted into the social characteristics of the environment where the empirical analysis is carried out. It is important and often difficult to distinguish between the effect linked to the characteristics of the individual and the social capital effect, which concerns the entire community attitude towards sharing knowledge and is not conclusive on the role of social differences in the dynamic of networking. Rogers (1995) uses well-established theories in sociology, psychology, and communications to develop a concise approach to the diffusion of innovations: diffusion takes place within the context of structures of social relationships based on power, norms and public acceptability. Communication networks (who you know), structure (what is your place in the chain of communication) and proximity (degree of overlapping personal communication between members) are all key elements in predicting adoption and, finally, the impact on productivity of farmers. While the literature on empirical testing of these theories is rather limited, some interesting results have developed in the context of ethnic homogeneity and efficiency (Kanbur 1992; Baland and Plateau 1995; Fafchamps 2000). In the more specific context of peer effects and ethnic homogeneity recent papers by Munshi and Myaux (1998) and Munshi (2002) find evidence that similar ethnic origins and religious affilitations have a role in explaining the adoption of innovation in the context of sanitation and agricultural production respectively.

As previously noticed, it is difficult to understand the role of social structures without looking at the specificity of the social context. That is why prior to proposing a model we need to understand the setting where it will be used. Previous work on Côte d'Ivoire has focused on the positive impact of extension services on the productivity of farmers, mainly as far as food crops are concerned (Romani 2002). The central idea is that the farmer who receives extension, and has invested in the acquisition of information about the innovation, may in the course of this process communicate with neighbours, maybe to receive help with the application of the innovation, or additional advice. The observed positive impact of extension services on food crops, and not on the more valuable perennial crops (coffee and, most imporantly, cocoa), is the effect of the crisis in the international prices of the soft commodities over the years in analysis. Old plantations were not replaced by new ones, causing a decrease in yield levels. Extension became increasingly unable to sustain the cocoa sector in particular, in a context were farmers were turning their effort to food crops to provide for their households. Crops like maize and cassava were mainly selected as they can grow on short term fallows and require little work. Lowlands were also exploited with flooded rice, which became increasingly improtant. The usage of inputs in the cocoa production almost stopped: especially phytosanitary equipment was not maintained and became unusable. An interesting case study from a village in the Gban region in central Côte d'Ivoire reveals that once the farmers realized that the price crisis was there to stay and was not temporary as some of the previous ones, they stopped any maintainance of the cocoa plots, sometimes leaving abandoned as much as 5 ha of land (Chavueau in Ruf, F. and Siswoputranto, P.S. (eds) 1995). This profound change in the economic structure of the village went along with a reorganizaiton of the ethnic hierarchy: this change exacerbated social tensions in a delicate and complex political moment, in which ethnic differences play a critical role.

We try to integrate these aspects by focusing on two characteristics of the diffusion of knowledge.

We propose a simple model to determine the probability for a farmer who is not directly involved in extension services to access knowledge about the innovation. The greater the opportunity of meeting and discussing among farmers the higher is the probability that our farmer will exchange information with "knowledgeable" neighbours and replicate the innovation. We can define this dimension through the presence of participatory organizations in the village as a tool to construct effective networks among the nearby farmers and increase the probability of exchange.

The extent to which farmers that innovate will be willing to share such information may vary according to farmers' characteristics. We may suppose, in line with the literature reviewed earlier, that the greater the similarity in terms of backgrounds, customs, production crops between the farmer who innovates and his/her neighbours the higher is the probability for the information to be passed on - what is known as the peer-group effect (Pomp and Bruger 1995). Indeed recent models of proximity tend to prefer to a merely geographical definition of distance a more complex concept defined over different spheres of household characteristics, geographical and not (Conley and Ligon 1998), more on the lines of a "social proximity". Ethnic characteristics are a suitable dimension to define the likelihood of matching among households, particularly, as we said, in the context of the crisis: various patterns of land accumulation and production choices along ethnic lines have emerged from the beginning of the 1990s, different ways of adopting to the slump of the cocoa cycle.

While similar research was conducted in some recent literature, often the results were based on cross sectional data. As noticed in Ravallion (2002) testing for externalities among units located in the same geographical areas with cross sectional data poses critical identification problems: individual outcomes and geographical variables are likely to be correlated. This is an endogenous effect due to the households' unobservable characteristics, and therefore origin of non-casual correlations. The availability of a panel dataset allows us to use a fixed effect model that increases significantly the capability to identify externalities and network effects among households "cleaned" of possible spurious effects which would invalidate the precision of the result. Manski (1993) goes one step further, trying to pinpoint what information is necessary to identify whether the average behaviour of a certian reference gourp influences the behaviour of the individuals that comprise the group. Inference is not possible unless some prior information specifying the composition of the group is available, and the relationship between the variables defining reference groups and those directly affecting outcomes are moderately related in the population. This condition, that derives from what is known as the refelction problem, is one of the main hurdles in the existing literature. This paper attempts to avoid this identification problem by not using the tradition average affect approach to networks, but rather trying to develop a variable to express the probability of each farmer to access knowledge through his/her participation in the network and his/her ethnic characteristics.

3 The model

The starting platform for the analysis is the Feder and Slade model of technology adoption in the context of agricultural production (Feder and Slade 1984). We expand it to include knowledge similarly to what proposed in Isham (forthcoming): a production function that, besides the usual inputs, is increasing in knowledge

$$Y_i = F(L_i, g(K_i), N_i) \tag{1}$$

where Y_i is the total production for farmer i, K_i is his/her knowledge about the innovation, L_i is land and N_i is the positive amount of the variable input used by farmer i that is likely to be affected by the introduced innovation. The general impact of knowledge originates from $g(.)$ which is a concave function. As K increases, $g(.)$ converges to an upper limit g^* as the farmer's cumulative knowledge increases to its maximum . Farmers who do not receive extension are limited to K_0 and, consequently, to g_0^* while farmers that receive extension can accumulate knowledge up to K_1 and reach $g_1^* > g_0^*$. We expand this model introducing the concept of probability to access knowledge. For the moment, we restrict the knowledge to be categorical: either people know how to use the input optimally ($K = 1$) or they don't ($K = 0$), so that g can only assume values g_0^* or g_1^*. The knowledge, by allowing g to take the top value g_1^* will have the potential to boost the overall output Y. The probability to have access to the information for a farmer who is involved in extension is, by definition, unity. The probability "to know" for a farmer who is not in extension must be lower than 1.

Let us consider a social context where there are $N = 1, ..i..., n$ individuals who are not members of extension and $M = 1, ..j.., m$ individuals in extension. Each "social context" will be one village,. so that individuals i and individuals j will be neighbours. At each moment t an event occurs: the event is either an interaction between two members of the two different groups or nothing. We can define θ as the distribution generating function of these events, independent of the history of the system. An interaction between i and j happens with probability θ_{ij}. If $\theta_{ij} > 0$ then i and j become partners and the information is exchanged.[1] We are interested in defining such probability function. In words: what makes i more or less likely to interact and exchange information with a member of M? We believe this probability to depend on two parameters: the number of "knowledgeable" farmers linked directly to the farmer i (B) and the fact that these farmers might be more or less willing to share the information (v):

$$\theta_{ij} = \theta(B_i, v_j) \tag{2}$$

So θ_{ij}, at this point, can be simply introduced into our farmer's production function, which will be:

$$Y_i = F(L_i, \theta_{ij}, N_i) \tag{3}$$

Notice that θ_{ij} now represents the probability of accessing our $K = 1$ and therefore to reach g_1^*: in other words the probability might change, but the *quality* of the information is the same for all. To make it concrete we can think of this as a set instructions to use a new modified seed: either the farmer knows how to use it or he/she does not know.

Let us now relax the assumption that knowledge is a *una tantum*, and allow knowledge to be accumulated. Concretely we can think about a more diversified extension system that provides information about several crops and techniques, which increases with exposure to the agent and varies from farmer to farmer. This will not change our definition of probability to know, but will add a new variable in our already augmented production

[1] The model used here is a slightly modified version of a model analysed in Raub and Weesie (1990).

function, which is the knowledge function we defined before:

$$Y_i = F(L_i, \theta_{ij}, g(K_i), N_i) \tag{4}$$

Where now K is a stock variable, free to take any positive value. The magnitude of K will depend on the overall stock of knowledge available in the network of our farmer i. It is assumed that overall productivity is increasing in θ_{ij} (the probability to know) and in knowledge $g(K_i)$. Notice how now, as opposed to equation 1, the impact of knowledge on total output will be conditional to θ_{ij}, the probability to access such knowledge. We can define $\theta * K$ as the value of expected knowledge available to farmers.

4 The data

The data comes from a panel data survey managed by ANADER on a sample of 2500 households evenly spread across the territory. The survey was collected between 1997 and 2000, and contains information about production during the ending farming season (so data collected in 1999 pertain to the 1998-1999 farming season). This survey is collected among a sub-sample of a bigger survey (comprising more than 10000 households), with additional information about the households, collected only once between 1996 and 1997. This data was also available for the analysis. The panel data survey focused on farmers production capabilities, with precise information about single plots and crops for each household. Both the panel sub-sample and the bigger cross sectional sample include information about the ethnic origin of the household and on the membership in both extension services (only available for the sub-sample) and in participatory organizations (available for both the panel and the cross sectional sample). Table 1 summarizes the trends in average production per household, average total land surface per household, average crop density, and yields for of some of the crops object of the analysis during the period 1998-2000.

The yields levels for cocoa seem to have deteriorated considerably from 1998 to 2000. Quite interestingly the average size of the cocoa cultivated areas tend to decrease substantially, especially from 1999 to 2000. This result is consistent with the more accurate analysis possible through panel data: in fact following the households from period to period we come to a similar conclusion. With the exception of some few farmers who increased cocoa cultivated areas extensively, on average there was a contraction in the size of cocoa cultivated areas. No information was provided in the survey as to whether the farmers actually removed cocoa trees or simply did not use their full potential of cultivation, perhaps not using the older trees. The anthropological survey carried out by J.P. Chavueau in the Gban region, in central Côte d'Ivoire, offers an interesting insight on the new cultural arrangements over the greater competition for limited resources linked to the slump in the cocoa cycle. Often farmers decided not to maintain old plantations, to give space for new forest growth and terrain renewal as, in their judgement, the cost of forgoing cocoa production in a period of depressed prices is estimated lower than the present value of the profit of expected future production. Facing unaffordable prices for inputs such as pesticides and fertilizers, farmers extended the size of their plantations, without maintaining them accurately, given the very low marginal cost of expaning the cultivated surface (Chavueau in Ruf, F. and Siswoputranto, P.S. (eds) 1995). Generally, whatever the solution adopted by the farmers, the result is a contraction of the average cocoa operation confirmed by the decrease in average output per household. Similar conclusions, regarding the size of the plots, can be drawn from the analysis of the coffee data. The reduction in output is also drastic: this could be due to a reduction in the effort and land dedicated to coffee cultivation and harvesting during a period of low prices and consequent low profitability. The case study mentioned above helps us understand some of the factors connected to the labour input as well. Bigger farms adapted quickly to the new constraints, reducing drastically the daily labour hired for the miantainance of the plots. Smaller farmers, given the lack of secondary inputs, had to incresingly rely on labour to maintain production levels as far as it was possible (and convinient) to substitute these two factors.[2] This was done almost exclusively by using family labour, as they could not afford hired labour. Eventually, as the profitability of the cocoa plantations kept decreasing, farmers started moving their effort (and their family labour force) away from perennials to focus on food crops.

Table 2 summarizes the information about ethnic origin by region. The distinction is between indigenous farmers, non indigenous farmers (which are farmers belonging to different kin but of Ivorian citizenship) and foreign farmers. It is clear that the regions where cocoa and coffee are grown experienced significant immigration in the past, particularly during the boom years in the cocoa markets in the 80s and early 90s. Despite the innovations in the production techniques, the high level of cocoa production in the country from 1988 onwards can be attributed to the new migrations associated with deforestation and creation of new plantations. This is particularly true for the south-west cocoa growing region, which developed only after the opening of the road from Abidjan to Sassandra[3]. All these areas held the largest reserves of primary forest in the country. The government limeted the customary rights of native people and practically gave away the forests as free concessions to the newcomers. The opening up of these forest lands induced a huge influx of immigrant labour, coming mostly from the centre-north of the country and from neighbouring Mali and Burkina Faso. The government, following the slogan "the land belongs to those who develop it" assured the transfer of land to farmers who would show the ability to quickly develop their smallholdings. This mechanism of exchanging land for labour fuelled a sort of "gold rush" to the forest, accompanied by

[2] Ruf (1995).

[3] For a comprehensive description of the migration flows in Côte d'Ivoire, see Ruf (1993), chapter 3, p. 199-221.

a mushrooming of frontier settlements. Land settlement and deforestation continued in a inevitable self-feeding mechanism in which the strongly needed extra labour could be attracted only by providing the newcomers with land to settle on. Older settlements, owned by indigenous farmers, found it increasingly difficult to compete the new frontier areas where newer trees and abundant cheap workforce were available.

Yam and cocoa inter-planting methods were widely adopted by the newcomers. Cocoa is planted in April/May, then plantain and cassava are added to the fields. The marginal cost of growing cocoa in this setting is close to nothing, thanks to the almost perfect complementarities among these plants. The food crops remunerate, during the first year, the investment in the plot. After the yam is harvested, the cocoa provides for weed control, reducing maintenance work required. Density of the cocoa trees is then reduced until production period. The sustainability of this widespread system is not very good, and after some years of exploitation it reaches its "ecological ceiling". Bad timing made this stage correspond, for many of the settlements, with the decrease in international prices. This was another factor that caused farmers increase their food crops cultivations, especially in the form of shade-food crops, which grow underneath the cocoa trees. More traditional food crops started substituting dying cocoa trees (Chavueau in Ruf, F., F and Siswoputranto, P.S. (eds) 1995).

5 The role of ethnic diversity

The probability to have access to knowledge which was defined in section 3 is the key element in our model. We have to be able to identify the two main determinants of the probability which we described earlier on: the number of "knowledgeable" farmers that the "non-knowledgeabe" farmer i knows (B) and the fact that these farmers might be more or less willing to share the information with our farmer (v). The dataset we use contains information that is connected with the these determinants. In particular we use information about membership in cooperatives to define the network of each farmer. We assume, by this, that farmers who belong to cooperatives have a significantly higher chance of meeting among themselves in a context in which they are likely to discuss production issues[4]. Cooperatives are sociable places, where the farmer goes regularly to sell his goods, to purchase inputs or simply to check the most recent prices before heading for the nearby market. Cooperatives, normally, do not offer production advice, but mainly marketing services or - in some cases - sell inputs. Membership in cooperatives seems to be decreasingly associated with better ability to purchase inputs, as was the case previously. In fact these institutions, during the crisis period, lacked the cashflow needed to affort big purchases of inputs. Still they seem to play an improtant role as information centres, particularly as far as organizing work groups to help farmers who lack sufficient family labour during harvest or intensive maintanance periods.

Once we have characterized the network-participation of farmers by their membership in a cooperative, we can easily calculate the probability to meet a neighbour in extension (B): it will be equal to the number of cooperative members who are also extension members over the total number of cooperative members in the community. To define the second determinant we start from the fact that ethnic diversity seems to play an important role in determining membership in extension. Table 3 reports the results of a probit estimation on the factors that make a household more or less likely to be a member of an extension group. We include a number of households characteristics on the right hand side, of which we report only the most important ones. Interestingly the results indicate that belonging to the minority ethnic group reduces significantly the probability of being

[4] The dataset contains information about membership in several types of cooperatives, which we generalized in one category. This will not cause probalmes, as far as networks are concerned, as in each community there is rarely more than one cooperative. The heterogeneity of cooperative types - in other words, is intervillage and not intrevillage.

a member of extension services, even after controlling for other household characteristics. We can take this result one step further and look at whether the ethnic origin has an overall effect on the characteristics of the farming activity, i.e. whether - once they receive extension - they benefit from it as much as households belonging to the dominant ethnic group. Table 4 reports the results from a production function fixed effect panel regression for the entire sample during the period 1998-2000. The results are similar to the ones reported in Romani (2002), but the effect of extension is now interacted with the ethnic origin of the farmers and the type of crops (food crops and perennials). The coefficients on the interaction variables tell us, therefore, what is the impact of extension services on food crops and commercial crops for the two ethnic categories separately. Interestingly the positive effect on food crops, which was the main result found in that study, seems to be common for both ethnic minority farmers and for ethnic majority farmers, but with only a significant difference in the magnitude of the impact. This indicates that in the (relatively unlikely) case in which the ethnic minority farmers do receive extension, they are able to benefit from it a little less than the households belonging to dominant ethnic groups. Are non-indigenous farmers more or less effective in farming? We cannot answer this question looking at our fixed effect regression, given that the ethnic origin is part of the unobservable characteristics "swept out" by our fixed effects estimates. We therefore look at the production function derived from the cross sectional survey collected on the same farmers in 1997. We run a production function including a number of characteristics of the households to compensate for the lack of control for unobservable differences, given we are not using now a fixed effect technique. The results (reported in table 5) indicate that the ethnic minorities are not disadvantaged in food crops production and, on the contrary, seem to be advantaged as far as perennial crops are concerned, even after controlling for the age of the plants[5].

[5] This is an important factor, given that most foreign and ethnical minority farmers are usually people

We identified in this section two main facts:

1. Foreign and non-indigenous farmers are less likely to be involved in extension services and therefore to become members of extension groups

2. Once they are members of extension they benefit from it less than dominant ethnic group members in terms of returns to their food crops.

It is clear that the ethnic origin of the farmers plays a role in determining whether and in what ways the information that arrives into the village through extension effects productivity. We therefore will model our parameter v, the willingness to share, along ethnic lines. This will allow us to construct probabilities which vary according to the ethnic origin of the farmer and the ethnic specific share of knowledgeable farmers he/she can meet through cooperatives. The assumption here is that farmers tend to network more within their own ethnic group, even if they all belong to a common network, such as a cooperative.

With v and B we now have the two elements to define the overall probability "to know a neighbour who knows" in each village. This little table summarizes the probability for each group:

Probability of "knowing a neighbour who knows"		Membership in extension	
		yes	*no*
Membership in the cooperative	*yes*	$Pr[K=1]=1$	$Pr[K=1]\geq 0$
network	*no*	$Pr[K=1]=1$	$Pr[K=1]=0$

The case in which $Pr[K=1]\geq 0$ (not a member of extension but a member of the

who moved to cocoa growing areas during the cocoa boom in the 80s and, therefore, tend to have younger and more productive trees. Indeed the age of the trees, and perhaps the adoption of different perennial/annual crop combinations are at the basis of the different effects of cocoa-cycles on indigenous and non-indigenous farmers (Ruf, 1995).

cooperative network), the probability is equal to:

$$\theta_i = \frac{\text{\# of village members who belong to the cooperative and to extension}}{\text{tot \# of cooperative members in the village}} \tag{5}$$

which is the probability of "knowing a neighbour who knows" as this is defined for each village. Including the ethnical component the probability becomes :

$$\widetilde{\theta}_i = \frac{\text{\# of village members who belong to the cooperative, to extension and of i's ethnic group}}{\text{total \# of cooperative members of i's ethnic group in the village}} \tag{6}$$

which is the probability "to know a neighbour who knows of my ethnic group".

Next we relax the assumption of K taking only values 0 and 1, and we consider K being an accumulable stock of knowledge ($K \geq 0$). We want K to increase with the overall amount of knowledge present in i's village. We define, therefore, K as the number of members of the extension group present in i's community. We then derive the values for the "expected knowledge" very simply in the following manner:

$$\theta_i * K = \frac{\text{\# of village members who belong to the cooperative and to extension}}{\text{tot \# of cooperative members in the village}} * K \tag{7}$$

for the non-ethnical specific network effect. The ethnical specific expected knowledge is derived similarly:

$$\widetilde{\theta}_i * K = \frac{\text{\# of village members who belong to the cooperative, to extension and of i's ethnic group}}{\text{total \# of cooperative members of i's ethnic group in the village}} * K. \tag{8}$$

Notice that these variables, by construction, will take values between 0 and K.

6 The Empirical Formulation

The main hypothesis that we derive from the theory combined to the ethnic element we identified is that information moves more fluidly between neighbours with a higher social proximity (in terms of our model with a higher v, i.e. the amount of information farmers share in the network). In other words we expect the $g^*|\theta$ (that is the upper limit of the impact of information on production, given a certain probability to access knowledge) to be higher among "homogeneous" ethnic groups. We will arrive to this test gradually.

We start from a standard multi crop production function, augmented with an extension membership dummy (ext_{it}):

$$y_{it} = A(z) l_{it}^{a_l} n_{it}^{a_n} e^{a_{ext} ext_{it}} \tag{9}$$

where l_{it} represents fixed inputs and n_{it} variable inputs. Cultivated land constitutes the fixed input, and it is crop specific. Only limeted information is available on variable inputs, in particular for labour for which the only information we can use is the number of working age members in the household over the number of plots belonging to the household. While it would be preferable to have more precise information, such as hours worked, it must be said that, especially in the context of the crisis, hired labour is a form of input that only larger farms can afford. Indeed, as noticed in Ruf and Siswoputranto (1995), bigger families were advantaged during the crisis period when due to the lack of other inputs more intense labour was the only response: "Such a strategy is only possible when farmers have a sizable family work force (...) this explains why the strategy is mostly adopted by planters who migrated from Burkina Faso and Mali. These ethnic groups can rely on their family or village networks to provide them with a stable but not too demanding labour force."[6]. We propose to first test for our simpler model (equation 3), in which knowledge

[6] See Ruf and Siswoputranto, 1995 (p.138). While more precise information on labour, such as hours

K takes only values 0 or 1 (the case in which we hypothesized - to clarify the model - that the innovation consisted in a new modeified seed):

$$y_{it} = A(z) l_{it}^{a_l} n_{it}^{a_n} e^{a_{ext} ext_{it}} e^{a_\theta \theta_{it}} \tag{10}$$

where θ_{it} is the probability "to know a neighbour who knows" as defined in (5). We assume that the probability enters our relationship exponentially similarly to extension. Linearizing and adding the error term and the fixed effects we obtain:

$$\log y_{it} = \log A(z) + a_l \log l_{it} + a_n \log n_{it} + a_{ext} ext_{it} + a_\theta \theta_{it} + \varepsilon_{it} + \omega_i \tag{11}$$

This equation will therefore test whether the probability to know somebody who has access to extension, whatever his or her ethnic group, is associated with higher output levels, controlling for other determinants of production. This can be interpreted as a test of the amount of knowledge sharing going among the network members, where the network is the cooperative.

Secondly we proceed to the more complex model, where we introduce the ethnic element. Now we will be testing whether the probability to know somebody who knows and is a member of the same ethnic group is associated with higher output levels.

$$y_{it} = A(z) l_{it}^{a_l} n_{it}^{a_n} e^{a_{ext} ext_{it}} e^{a_K (\widetilde{\theta}_{it})} \tag{12}$$

Log-linearizing and adding the error term and the fixed effects we obtain the following

worked, would be preferable, it could introduce some simultaneity between the regressor and the error term. If in fact unobservable shocks were to be correlated with the labour variable the coefficient of the regressor would be biased. Using an exogenous measure such as number of household members over number of plots to proxy for labour solves this problem.

linear specification:

$$\log y_{it} = \log A(z) + a_l \log l_{it} + a_n \log n_{it} + a_{ext} ext_{it} + a_\theta \widetilde{\theta}_{it} + \varepsilon_{it} + \omega_i \tag{13}$$

where $\widetilde{\theta}_{it}$ is the ethnic specific probability defined in 6. This equation tests whether there is an intra ethnic exchange of information.

We proceed similarly to construct the empirical formulations for the"expected knowledge" model, using the definitions given in (7) and (8) where K is the number of extension members in each community. First without the ethnic element in the definition of the networks:

$$\log y_{it} = \log A(z) + a_l \log l_{it} + a_n \log n_{it} + a_{ext} ext_{it} + a_\theta (\theta_{it} * K) + \varepsilon_{it} + \omega_i \tag{14}$$

and with the ethnic-specific probability:

$$\log y_{it} = \log A(z) + a_l \log l_{it} + a_n \log n_{it} + a_{ext} ext_{it} + a_\theta (\widetilde{\theta}_{it} * K) + \varepsilon_{it} + \omega_i \tag{15}$$

7 The results

Table 6 summarizes the results of the fixed effects regression for the first specification, where K can take only discrete values. Column one and two report the results for the non-ethnic based definition of the probability, as in equation (11). The difference between the two columns is the following: while in the first one the probability variable incorporates the result due to direct extension (in other words extension members have a probability to know of one), the second column splits the variable in two, the direct effect of extension a nd the effect of the probability to know for people who are not in extension. The results in column one indicates that there is a strong effect of the probability to know for the food crops, with a coefficient of 0.616. Once we split the probability variable, though, we observe that while the direct extension coefficient stays positive and significant (with coefficient implying an elasticity around 60%, in line with the results obtained in Romani 2002) the network coefficinet does not stay significant.[7] This result therefore excludes an effect linked to the exchange of information between extension members and non-extension members. In columns 3 and 4 we repeat the exercise but now defining probabilities along ethnic lines as in equation (13). Column 3 reports the result incorporating the direct extension effect in the probability variable. Again the probability seems to be associated with higher output levels for food crops, with a coefficient varying between 1.13 for the dominant ethnic group to 0.69 for the minority ethnic group. Once we split the result between extension and probability to know (for people not in extension) the direct extension for food crops stays positive and significant (with the usual coefficient implying an elasticity of 60%), but there is no evidence of any effect linked to the exchange of information between extension members and non members within each ethnic group. Basically we cannot identify any network affect when we define knoweldge as a dichotomous variable.

In Table 7 we proceed to relaxing the assumption on K being discrete and we adopt the model where knowledge is a stock variable (as described in equation 14). We carry out similar tests, but now the probability variables will represent the expected knowledge, and take values between 0 and K. The results reported in column 1 indicate that once we split the variable into direct extension effect and expected knowledge effect for farmers not in extension, the coefficient associated with expected knowledge for food crops stays significant (now at the 5% level) and positive, with a magnitude of 0.109. Notice that this result does not supplant the effect of direct extension, which stays basically unchanged

[7] the formula used to obtain the elasticity to extension is the following: $100 * g = 100 * \{\exp(c) - 1\}$ were g is the relative effect (so that $100 * g$ is the percentage effect, and c is the estimated coefficinet for the dummy variable). See Halvorsen and Palmquist (1990) for details about the calculation of dichotomous variables elasticity in a semi logarithmic setting.

with a coefficient implying an elasticity of a little more than 60%. This result provides evidence that there is an exchange of information going on between extension members and non-members. But is this exchange of information neutral to the ethnic component? To answer this question we proceed to test the final model proposed, where the expected knowledge variable is defined along ethnic lines, as descried by equation 15. Column 3 reports the result where we distinguish between the direct extension effect and the expected knowledge effect, now defined for each ethnic group separately. Again we find the familiar result for direct extension on food crops (with the usual elasticity a little above 60%); the result for expected knowledge is also positive and significant, with a coefficient of 0.116 for the ethnic minority but non-significant for the ethnic majority. This result suggests that farmers belonging to ethnic minorities who are excluded from extension services benefit from exchanging information with their ethnic peers who are members of extension. So, even if these farmers are not as likely as farmers belonging to the dominant ethnic group to be extension members, they have a way of accessing and benefitting from the information that reaches their communities. [8] The last column provides an additional test to our theory. Here we define total knoweldge available in the village along ethnic lines, i.e. summing up the presence of extension separately for indigenous and non-indigenous farmers. In this specification we want, therefore, to associate to farmers in a specific ethnic group only the knowledge stock available in their own ethnic group. This is particularly important for the ethnic minority, given their discrimination they face as far as accessing knowledge. The results in column 4 do not change significantly from the pervious one, confirming the presence of a network effect within non-indigenous farmer groups.

[8] This result is robust to other specifications which were tested, notably to redefining the production function in terms of output values, using price information. The results were also tested for robustness using, when considering knowledge as a stock variable, a total knowledge variable instead of a direct extension dummy to control for extension effect. These additional results are available from the author.

8 Conclusions

This paper investigates the role of knowledge networks in determining yields. In particular we investigate the role of social proximity, interpreted not only as physical vicinity but also along the line of ethnic similarities among neighbours. To do so we defined the probability to know a neighbour who has access to the knowledge, which was diffused to some farmers only in the community by an extension agent. Such probability is identified by three characteristics: geographical vicinity, membership in a network organization and the extent to which people are ready to share with their neighbours. To proxy these variables we used a panel dataset collected in Côte d'Ivoire in the period between 1997 and 2000 and containing detailed information on agricultural production and on membership in a organizations and institutions, such participatory organizations (which is our network organization); the ethnic origins of farmers is used to define the "social proximity", and therefore their willingness to share knowledge with neighbours. We test two distinct models for a on/off type knowledge and for knowledge as a stock variable, which increases proportionally to the amount of extension going on in the community. We use a panel data fixed effects methodology to identify this effect.

The following concusions can be derived from the results: first ethnic minority farmers are less likely to become members of extension services. Secondly, unlike their neighbours belonging to the dominant ethnic group, they benefit significantly - in terms of higher yields in food crops - from exchanging information among themsleves. This result is true only when we define knowledge as a cumulable stock variable, a hypothesis which seems reasonable in the Ivorian context. More work is necessary to identify the workings of this sort of re-equalization mechanism adopted by the ethnic minorities. In particular future work should look at whether this ethnic network effect is still present in areas where there is no bias against the minorities in the access to knowledge through extension.

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Table 1. Descriptive statistics.

Cocoa

		Ave. Output	Ave. Tot. land surf.	Ave. Density (stems/ha)	Ave. yields
1998	Mean	2861.9	2.9	1034.5	943.9
	Median	**2010.5**	**2.3**	**1022.1**	**888.8**
	Std. Dev.	2305.5	2.4	315.4	341.7
1999	Mean	2136.4	3.1	982.8	542.2
	Median	**1476.8**	**2.2**	**977**	**453.3**
	Std. Dev.	2081.9	2.6	352.1	277.6
2000	Mean	1405.2	1.9	968.9	622.4
	Median	**966.4**	**1.3**	**977**	**586.7**
	Std. Dev.	1493.2	1.7	361.8	295.4

Coffee

		Ave. Output	Ave. Tot. land surf.	Ave. Density (stems/ha)	Ave. yields
1998	Mean	1840.5	2.6	909.1	371.1
	Median	**1530**	**2.1**	**844.4**	**357.8**
	Std. Dev.	1166.2	1.5	278.9	124.35
1999	Mean	1973.1	2.8	911.1	327.2
	Median	**1592.9**	**2.3**	**888.9**	**333.35**
	Std. Dev.	1557.5	2.1	324	145.45
2000	Mean	1499.1	2.4	836.2	328.5
	Median	**1002.4**	**1.8**	**800**	**346.65**
	Std. Dev.	1475.8	2	257.5	145.8

Rice

		Ave. Output	Ave. Tot. land surf.	Ave. yields
1998	Mean	1421.7	.88	1590.6
	Median	**1237.5**	**.77**	**1625**
	Std. Dev.	862.6	.54	366.7
1999	Mean	1846.3	.96	1756.9
	Median	**1350**	**.83**	**1812.5**
	Std. Dev.	1490.1	.54	776.4
2000	Mean	1655.1	.86	1435.9
	Median	**1232.8**	**.76**	**1406.25**
	Std. Dev.	1340.8	.49	441.5

Yam

		Ave. Output	Ave. Tot. land surf.	Ave. yields
1998	Mean	6687.9	.43	12534.2
	Median	**5019.6**	**.33**	**11500**
	Std. Dev.	4780.9	.30	3204.2
1999	Mean	6890.4	.46	1462.9
	Median	**6057.9**	**.40**	**13700**
	Std. Dev.	4914.3	.28	7351.7
2000	Mean	6121.9	.50	9984.75
	Median	**5324**	**.41**	**10045**
	Std. Dev.	4232.6	.30	2782.5

Table 2 - ethnic origin by region

Region	indigenous	non-indigenous	foreign
		%	
North	95.25	4.04	0.71
North East	80.63	5.33	14.04
North West	86.06	10.70	3.24
West	84.72	6.70	8.58
Centre	79.88	8.84	11.28
Centre-North	88.24	7.83	3.93
Centre-East	35.23	24.55	40.23
Centre-West	44.59	23.90	31.52
South-West	17.69	43.08	39.23
South	56.62	16.93	26.45

Table 3 - Probit regression: determinants of the probability to be a member of extension services.

	dF/dX
	membership in extension
years of education	.003
	0.302
land surface	-.001
	0.169
farmer from ethnic minority	**-.051****
	0.018
partic. org 1:	-0.48
common production group	0.526
partic. org 2:	0.80***
marketing group	(0.000)
partic. org 3:	0.153***
cooperative	(0.001)
partic. org 4:.	.279
trade union	(0.374)
partic. org 5:	.046
other groups	(0.499)
number of household members	.002
	(0.260)
Female household head	.004
	(0.915)
Tot. observations	3364

dF/dx is for discrete change of dummy variable from 0 to 1; informal arrangements is the omitted category in the participatory organizations variables; spatial and temporal dummies are omitted. $P > |z|$ (reported in parenthesis) are the test of the underlying coefficient being 0; *significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4 - Fixed effect production function: with ethnic interactions.

	with interaction for crops and ethnic origin
	ln(crop specific output)
ln(crop specific plot surf.)	1.38***
	0.000
ln(workforce)	.118**
	0.070
direct extension:	
on food for dominant ethnic group	**.502*** **
	0.000
on food for minority ethnic group	**.396*** **
	0.007
on perennials for dominant ethnic group	**.031**
	0.789
on perennials for minority ethnic group	**.055**
	0.688
Tot. observations	1131
Panel individuals	506
average obs. per panel	2.6
R-squared	0.7416

Notes: Ln(output) is the dependent variable. Spatial and crop dummies are not reported (available from the author). $P > |t|$ in parentheses; *significant at 10%; ** significant at 5%; *** significant at 1%

Table 5 - Cross section production function with ethnic control variable.

	food	perennials
	ln(output)	
ln(crop specific plot surf.)	.893***	.956***
	(0.000)	(0.000)
ln(work force)	.081***	.045**
	(0.002)	(0.030)
ln(fertilizers quantity)	.026	.124**
	(0.254)	(0.034)
ln(pesticides quantity)	.060*	.252***
	(0.087)	(0.000)
ethnic dummy	**.034**	**-.308*** **
(0=non-indigenous;1=indigenous)	**(0.757)**	**(0.009)**
young trees dummy	-	-1.167***
(0 if age>5; 1 otherwise)	-	(0.000)
years of educ. of hh head	.015	-.025***
	(0.191)	(0.000)
Sex of the hh head	-.130	-.309
(0=male;1=female)	(0.191)	(0.025)**
Tot. observations	9769	6726
R-squared	0.30	0.3137

Notes: Ln(output) is the dependent variable. Spatial and crop dummies are not reported (available from the author). $P > |t|$ in parentheses; *significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 - Network effects on productivity - discrete K regressions.

		(1)	(2)	(3)	(4)
		Without ethnic element		With ethnic element	
		crop specific ln(output)			
ln(crop specific plot surf.)		1.35***	1.35***	1.32***	1.35***
		0.000	0.000	0.000	0.000
ln(hhsize)		.316	.593	.184	.601
		0.652	0.380	0.794	0.375
direct extension for perennials		-	**.015**	-	**.022**
		-	**0.882**	-	**0.827**
direct extension for food crops		-	**.474*** **	-	**.469*** **
		-	**0.000**	-	**0.000**
probability to know a neighbour who knows:	**effect for perennials**	**-.043**	**-.556**	-	
		0.753	**0.169**	-	
	effect for food crops	**.616*** **	**.037**	-	
		0.000	**0.928**	-	
	For perennials and dominant ethnic group	-	-	**.077**	**-.844**
		-	-	**0.711**	**0.153**
	For perennials and minority ethnic group	-	-	**.221**	**-.467**
		-	-	**0.401**	**0.574**
	For food crops and dominant ethnic group	-	-	**1.13*** **	**-.411**
		-	-	**0.000**	**0.509**
	For food crops and minority ethnic group	-	-	**.692*** **	**.518**
		-	-	**0.009**	**0.575**
Tot. observations		1225	1311	1225	1311
Panel individuals		468	506	468	506
average obs. per panel		2.6	2.6	2.6	2.6
R-squared		.7432	.7417	.7436	.7419

Notes: Ln(output) is the dependent variable. Spatial and crop dummies are not reported (available from the author). P>|t| in parentheses; *significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 - Network effects on productivity - expected knowledge regressions.

		(1) Without ethnic element	(2) With ethnic element	(3) With ethnic element, ethnic specific k
		crop specific ln(output)		
ln(crop specific plot surf.)		1.38***	1.38***	1.38***
		0.000	0.000	0.000
ln(lab)		.127**	.128**	.129**
		0.051	0.048	0.047
direct extension for perennials		**.097**	**.092**	**0.96**
		0.336	**0.361**	**0.342**
direct extension for food crops		**.531*** **	**.527*** **	**.531*** **
		0.000	**0.000**	**0.000**
Expected knowledge				
	effect for perennials	**.085**		
		0.256		
	effect for food crops	**.109** **		
		0.042		
	for perennials and dominant ethnic group	-	**-.068**	**-.067**
		-	**0.696**	**.699**
	for perennials and minority ethnic group	-	**.114**	**.159**
		-	**0.176**	**0.140**
	for food crops and dominant ethnic group	-	**.004**	**.005**
		-	**0.983**	**0.982**
	for food crops and minority ethnic group	-	**.116** **	**.191***
		-	**0.043**	**0.053**
Tot. observations		1285	1284	1284
Panel individuals		501	500	500
average obs. per panel		2.6	2.6	2.6
R-squared		0.7486	0.7487	0.7486

Notes: Ln(output) is the dependent variable. Spatial and crop dummies are not reported (available from the author). P>|t| in parentheses; *significant at 10%; ** significant at 5%; *** significant at 1%