Networks and Low Adoption of Modern Technology: The Case of Pearl Millet in Rajasthan, India

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Abstract

We study the role of social networks in the context of low adoption of a modern technology for pearl millet, an important dry land crop in India. Rajasthan, the subject of this study has the lowest adoption of modern hybrid seeds of pearl millet among all producing states in India. We do find evidence for the existence of endogenous social effects. However, going a step further, we use a comprehensively mapped social network with its intensity and explain the extremely low rate of adoption in terms of the nature of networks effective for adoption. Only close knit networks that – in light of social fragmentation – can limit benefits to few have a significant effect on adoption of modern technology. The non-functionality of information sources and services that in principle could be less exclusionary (such as farmer organizations, media and government extension services) and thus could reach a larger group can be a contributing factor underlying low adoption of modern technology.

Key Words: **S**ocial networks, technology adoption, reflection problem, endogenous effect, exogenous effect, correlated effect

JEL Classification: D83,O13, O33,Q16

I. Introduction

A persistent question in development economics is why are some distinctly profitable technologies not adopted widely in agriculture? Duflo et al (2008) and Dercon and Christiaensen (2007) present strong evidence for strikingly low adoption of eminently profitable technologies in Kenya and Ethiopia, respectively. Low adoption rates of agricultural technologies such as fertilizers and improved seed varieties are very important from a development perspective, having accounted for stagnation in agricultural productivity in different countries (World Bank 2008). There can be several explanations for low adoption of technologies, for example, access to credit, supply constraints, etc.; one of the important channels however is social learning (or the absence of it) through social networks.

Processes of social learning have been much studied in this context (Bandiera and Rasul 2006, Conley and Udry 2010, Foster and Rosenzweig 1995, Munshi 2004). If social learning is sufficiently important, low adoption equilibria may persist in spite of potentially high returns (Zeitlin et al 2010). In this paper we study one such case: low adoption of modern varieties of pearl millet in Rajasthan, India.

Significant research efforts worldwide have been targeted towards enhancing productivity through breeding of high yielding cultivars suited to arid and semi-arid environments. Such efforts resulted in an increase in productivity of pearl millet (a crop locally known as Bajra) for dry and marginal land in India from 323 kg/ha during 1950-54 to 991 kg/ha in 2010 (Bidinger et al 2008). Nationally, High Yielding Varieties (HYVs) now cover about 50% of total pearl millet area in India, which is highest among coarse cereal crops. Area under HYVs is highest in the state of Gujarat (more than 90%).

On the other hand, although Rajasthan has the highest area under pearl millet, historically, adoption of HYVs in this state has been extremely low (25-30%). The situation in Rajasthan with respect to adoption of HYVs is worst among the pearl millet growing states. In recent times this figure has somewhat improved. Yet, until as recently as 2010, it had only 1.75 million hectares under HYVs, which accounts for only 39% of the area under pearl millet (Manga and Kumar 2011).

In this paper, we want to study this strikingly low rate of adoption (compared to other producing states such as Gujarat and Maharashtra that have become almost completely hybridized) of modern varieties of pearl millet in Rajasthan from a social network perspective. Towards this we take the route of mapping out the complete (or as comprehensive as possible) network of individuals/households. We start by being specific about the possible nature of networks in the Indian context. We thereby constitute a reference group for each household that takes into account geographical proximity as well as social identity.

The definition of group/network is in general open ended and is subject to researcher discretion. Broadly, reference group for a person is defined by the individuals whose mean outcome and characteristics influence the individual's own. Here, we argue that reference groups defined solely based on geographical proximity do not fit the Indian context given the social fragmentation that is at the forefront of the social structure, especially in the rural areas. The reference group of a farmer in a particular village could comprise farmers in a village other than his own who belong to the same caste group. Our construction of reference groups is along the lines of Fontaigne and Yamada (2011) who in the context of urban India define reference groups based on education, age, geographical proximity and caste.

Within this broadly defined group individual farmers can have specific individual interactions with varying intensity. We start by being completely agnostic about what sub-networks can be relevant for technology adoption. We take it as important that these be comprehensive in scope as well as coverage (i.e., types of nodes and intensity of interaction that each node contains). This is so not only because networks of different types – local as well as non-local, personal as well as institutional – can have a bearing on technology adoption but also because individual effects of each of the networks or information sources are best estimated conditional on the state of other networks. Effectiveness of media for example could depend on the types of friends and family interactions.

Once we define the network/reference groups in terms of social identity and geographical proximity we utilize the intensity of interaction with different network nodes to identify the presence of endogenous effects. In particular, we use the interaction of intensity of social exchange with the group level adoptions to establish the presence of endogenous effects. Note that, with adequate controls, greater intensity of interaction having a bearing on technology choice can only happen when there exists social learning (endogenous effect) and cannot be associated with other forms of social effects (viz. exogenous and correlated effects). Our interest however is not so much on the size of endogenous effects but in showing that they exist.

To emphasize the usefulness of this strategy we first note that estimating endogenous social effects in a linear-in-means regression is subject to *reflection problem* (Manski 1993, Bramoulle et al 2009); endogenous effects may not be isolated from exogenous and correlated effects, in particular, due to unobserved group characteristics. We use group fixed effects to account for group unobserved heterogeneity. However, this also means that group averages are subsumed in the fixed effects and cannot be identified. We, therefore, need variation in individual level variable(s) that links group average outcomes to individual outcomes. The detailed information that we have on each individual's network provides us with individual-level variation in intensity of network interaction. Under the assumption that the individual's network is embedded within his/her group, we can identify the existence of endogenous effects by interacting network interaction intensity with group average.[1] Coefficient of this interaction is identified even with group fixed effects.

[1] As discussed above (as well as in Section II and III, in greater detail) the social segregation in rural India is an ideal case for this setup.

At some level, our identification of endogenous social effects is along the lines of Bandiera and Rasul (2006). Bandiera and Rasul (2006) observe a pattern of relationship between adoption by networks and individual farmer's choices which they argue can spring up only due to endogenous social effects. In this paper, the significance of intensity of interaction of some elements of network as well as of adoption levels of network crossed with intensity of interaction on technology adoption works on similar elimination principle.

Further, from a policy perspective our main draw is from not finding effects of more inclusive networks (such as associations) and sources of information (media) that could affect technology choice.

In a world where traditional varieties dominate, the breadth of networks could be an important driver of the choice of modern varieties. If networks that are effective tend to be local and segmented, the adoption of modern technology could be spatially restricted. Information or other inputs relevant for adoption could then largely come from close knit networks. Aggregating up, this would show up as overall low levels of adoption since only a selected group would reap network benefits. *Prima facie* this seems to be the situation in adoption of modern varieties of pearl millet in Rajasthan.

We find that those who adopt a modern variety have specifically been influenced by close knit networks such as family and friends, and religious gatherings – the exclusionary channels. The greater the intensity of these interactions, higher is the likelihood of adoption of modern technology. Common pool sources of information, networks or services such as media,~~–~~, associations, etc., – networks and information channels that are generally non-exclusionary – have had no significant effect on adoption of modern variety of pearl millet in Rajasthan.

From a policy perspective this finding is quite important for two reasons. First, it is the non-exclusionary networks or information/services channels that are the mainstay of policies towards large adoption programs. Secondly, since the endogenous effects are operating only through exclusionary channels the social multiplier (if any) is likely to be constrained and may not even render itself to be effectively exploited by policy tools.

This paper contributes to a growing body of literature that has tried to identify the social effects in technology adoption (see for example Foster and Rosenzweig 1995 and Pomp and Burger 1995). The identification of effects of group level adoption on individual farmer's technology choices are subject to the classical reflection problem as shown in the pioneering work of Manski (1993).

Recently, identification of social effects through individual networks has been gaining ground (see Bramouelle et al 2009 and Calvó-Armengol et al 2009). With the exception of Bandiera and Rasul (2006) and Conley and Udry (2010), few studies have adopted this approach in technology adoption in the rural contexts of developing countries, primarily because of the need to collect large amounts of data. Our dataset with its detailed network structure and constitution of each social exchange is very well suited for this approach.

Among the studies of agricultural technology adoption one that is of particular relevance here is Matuschke and Qaim (2009) who look at this issue in the context of adoption of hybrid varieties of wheat and pearl millet in Maharashtra, India. Recall that Maharashtra is one of the two states in India where there is near complete takeover by hybrid varieties of pearl millet. What this paper deals in is a starkly different setting where adoption of modern variety turns out to be low.

This paper is distinct from Matuschke and Qaim (2009) in other ways as well. The focus on Rajasthan implies that this study aims to address both lack of adoption as well as choices in favor of modern variety. Our mapping of network at the individual level with an extensive set of nodes is comparatively comprehensive. Matuschke and Qaim (2009), much like Bandiera and Rasul (2006), proxy for group effects by adding village fixed effects as a regressor. Underlying this idea is the notion that groups are circumscribed at the village level. As discussed above the span for networks in this paper is broader and not confined to village of residence.[2]

The paper is organized as follows. Section 2 presents the data and summary statistics based on the primary survey geared towards mapping of networks, its contributions and the outcome in terms of varietal choice. Section 3 outlines the methodology for analyzing social effects in technology adoption first in terms of establishing the networks that are effective in technology adoption followed by methods for establishing presence of endogenous social effects if any. Section 4 presents the results of regression analysis and section 5 concludes with some policy implications.

II. Data and Summary Statistics

The sampling methodology used to select the farm households that were interviewed was a combination of stratified random sampling and probability proportionate to size (PPS) methods. The sampling design was for a large random sample comprising 1750 households where about 350 households were chosen for survey related to social networks. Sampling design consisted of four stages. First, based on background research, out of the ten agro-climatic zones in Rajasthan, six were found conducive to *bajra (pearl millet)* production. The sampling frame comprised all the six *bajra* zones. Second, from Government of Rajasthan (Figure 1) we used recent (2007-08) block level data on area under *bajra* production in the six agro-ecological zones in which *bajra* is produced. These zones comprise 213 blocks out of 245 blocks which make up the state of Rajasthan.

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[2] Social networks measure an individual's connectedness to others in the society. We measure an individual's connectedness along five dimensions: interaction within family, interaction with friends and relative, telephones communication with networks of less frequent interactions, exposure to media and participations in organizations.

The 213 *bajra* producing blocks were ranked in an ascending order according to the total area under *bajra* production and split into four groups based on 25%, 50% and 75% cut off points of total land under *bajra* production. All the blocks in high-medium and high crop area groups were selected. Mechanism of selection ensured that we also had blocks from the low-medium and low crop areas. Data were collected from all five high *bajra* area blocks, almost all (13 out of 14) high-medium *bajra* area blocks, four low-medium *bajra* area blocks and 23 low *bajra* area blocks. Figure 1**Error! Reference source not found.** shows the share of agricultural area dedicated to *bajra* in each of the 213 *bajra* producing blocks and Figure 2 shows the 45 selected blocks that constitute the sample.

Depending on the total number of villages in each block, four to six villages were randomly selected in each block. The selection of villages was based on stratification according to the distance to the center of the block. In each block two or three villages closer to the block (market) center and one or two villages further away from the block (market) center were randomly selected among long lists of such villages. Finally, in each village, depending on the population of the village, 3 to 5 households were randomly selected to be interviewed. To select the respondents a cross sampling method was used, i.e., a cross "X" was drawn on the village map and every nth household was interviewed. Not all households were administered the questionnaire with social network questions given the high intensity of the questionnaire on social networks. About 1400 more households were interviewed just to gather information about varietal choice and some basic socio economic characteristics.

Since the choice of variety was critical for analysis in this paper, we had different supplementary surveys with which we triangulated in order to identify the varieties correctly. These included a socio-economic survey of the farmers different from households covered for the social networks survey (extra 1400 households from the same villages mentioned above), and two other surveys of the input suppliers and government Block Agricultural Officers, respectively. This was done to validate patterns of varietal choices from our social network oriented household survey and also to create measures of group level adoption.

In total, 320 households had usable data on modules related to social networks in 15 districts and 45 blocks. In each household 2-3 adult members of the family were interviewed given that we conceptualize networks at the individual level. Under the assumption that the varietal choice is a decision by the household head, we use the network map of the household head that emerged from the responses to the social network module.

To obtain a comprehensive map of the individual's network, questions were asked about the following categories of interaction/activities:

(i) Intra-household network

(ii) Network of friends, family and neighbors

(iii) Network of less frequent interactions (through telephones, etc.)

(iv) Involvements in (local non-religious) local organizations

(v) Involvements in organized religious activities (temples, churches, mosques, etc.)

(vi) Exposure to different forms of media

Our extensive coverage of connections across a large set of nodes contrasts with most studies dealing with social networks in technology adoption. Usually the focus in these studies has been on networks of friends, family and neighbors either as a primal node or at times as the sole node. Our premise is that because of reasons such as improvements in communication and transportation, etc., different types of networks are potentially important. For example, network of less frequent interaction, though sporadic, could be an important source of information especially when individuals with whom such interaction occurs could be located in places which are better informed.

Additionally, we try to identify the clearly actionable nodes for policy such as media, farmer organization, etc. It is thus important to assess their effectiveness with the proviso that their roles can only be judged conditional on other nodes. Apart from extending the scope of relevant networks, following Putnam (1995) our dataset also contains the intensity of social interaction.

Table 1 presents some descriptive statistics from the social network data. It lists the intensity of interaction at each of the extensive set of social network nodes. As discussed above we measure intensity in terms of time spent with the network. If the number of hours spent with a household member for example is higher, then we treat that network node to be more intense.

In the sample less than half of the farmers have chosen modern variety of pearl millet (Table 1). There is very low participation in organizations in general and in farmer associations in particular. As expected close knit networks such as that of household members, friends and relatives comprise the most intensive interactions. On average an individual in our sample spends about 43 hours a week interacting with the household members and about one third of that time interacting with friends and relatives. All media combined has a share of 14 hours per week.

Among the household characteristics, note that the average landholding size is quite small with only 0.32 hectares as the average size dedicated to Bajra even though overall average land sizes are much bigger.

In considering social learning, it becomes important how we define the reference group. We assume that the agrarian households in our sample are divided into 3 caste categories: upper caste, scheduled caste/tribe or SC/ST and other backward casts or OBC ($k = 1,2,3$). Table 2 presents the distribution of sampled households across these caste categories. We also categorized the state of Rajasthan into 6 geographical areas ($j = 1,...,6$). These classifications are based on districts of geographical proximity (see Table 2 and Figure 3). We interact the variables (k, j) to construct groups, i.e., for each caste category within each area.

Recent work by Foster and Rosenzweig (2010) points that in technology adoption literature it might be worthwhile to explore whether or not information flow within the village is not constrained by networks based on kinship or social status. They argue that it seems particularly relevant in the light of recent works showing the importance of caste networks in determining access to credit in India (Munshi and Rosenzweig, 2009).

Table 3 presents the same descriptive statistics by socio-economic groups and by the six geographical areas. There is significant heterogeneity across castes and geographical areas. Areas 3 and 6, i.e. districts of Bikaner, Churu, Jaisalmer and Barmer, have substantively lower adoption of hybrid varieties of pearl millet. Part of the reason is agro-ecological. To the extent that hybrid varieties require more water, these drier districts would naturally have smaller adoption. Yet, spatial differences in adoption patterns exist over and above pure agro-ecological factors. Areas like Jodhpur have comparatively high adoption along with Jhunjunu and Sikar districts which are not particularly well endowed with water. Further, spatially the differences in adoption rates are quite significant. These data indicate that factors other than those that are agro-ecological (such as social networks) could be playing a role in determining technology choice.

III. Methodology

In this section we outline the methodology for identifying the effects of networks on choice of modern technology. Our motivation comes from Calvó-Armengol, Patacchini, and Zenou (2009). Below we present a brief description of their model.

Let $y_i^0 > 0$ denote the effort such as adoption of technology by individual i. Let z_i^0 denote the outcome due to peer influence. The individual outcome is the sum of two efforts

(1) $y_i^*(x,g) = y_i^{0*}(x) + z_i^*(x)$,

where the individual outcome is assumed to be a combination of peer influence ($y_i^{0*}(x)$) and factors that are separate from it, x denotes idiosyncratic characteristics of the individual that comprises m attributes. The variables on the right hand side of equation (1) are defined as,

(2) $y_i^{0*}(x) = \theta_i(x) = \sum_{m=1}^{M} \beta_m x_i^m + \frac{1}{g_i} \sum_{m=1}^{M} \sum_{j=1}^{n} \gamma_m g_{ij} x_j^m$,

(3) $z_i^*(x) = \mu g_i + \phi \sum_{j=1}^{n} g_{ij} z_j$.

Where μg_i denotes the network itself (it's size or intensity - in our formulation we will capture it in terms of intensity) and $\phi \sum_{j=1}^{n} g_{ij} z_j$ depends on the outcomes of the peers (in our case the varietal choice), $g_i = \sum_{j=1}^{n} g_{ij}$ is the number of direct links of individual i. Now, suppose that there are K networks. In the above formulation θ_i introduces the heterogeneity that captures the observable differences across individuals. The empirical counterpart of the formulations (for n individuals with K networks) above is as given below. For $i = 1,2,...,n,\ \ k = 1,2,...,K,$ and $\nu_{i,k}$ defining an error component,

(4) $y_{i,k} = \underbrace{\sum_{m=1}^{M} \beta_m x_{i,k}^m}_{\text{individual characteristics}} + \underbrace{\frac{1}{g_{i,k}} \sum_{m=1}^{M} \sum_{j=1}^{n_k} \gamma_m g_{ij,k} x_{j,k}^m}_{\text{group characteristics (exogenous effect)}} + \underbrace{\eta_k}_{\substack{\text{correlated effect} \\ \text{Network FE}}} + \underbrace{\mu g_{i,k}}_{\substack{\text{measures of} \\ \text{network} \\ \text{size/intensity}}} + \underbrace{\phi \sum_{j=1}^{n} g_{ij} \varepsilon_{j,k}}_{\text{endogenous effect}} + \nu_{i,k}$.

Figure 4 presents the schematic explaining the social effects in individual choices related to technology adoption. The social effects comprise the following:

Endogenous effect: group behavior influencing individual behavior.

Exogenous effect: individual behavior varying with the exogenous characteristics of the group (example-family background).

Correlated effects: individuals in the same reference group tend to behave similarly because they are alike or face a common environment (can be unobserved).

Typically, social effects are estimated using the following linear-in-means regression,

(5) $$y_{i,k} = \beta_0 + \sum_{m=1}^{M} \beta_1^m x_{i,k}^m + E(x_{i,k} \mid k)'\beta_2 + \beta_3.E(y_{i,k} \mid k) + \beta_4 \eta_k + \xi_{i,k},$$

where, β_2, β_3 and β_4 measure exogenous, endogenous and correlated effects, respectively, and $\xi_{i,k}$ is the error term. As Manski (1993) shows, these effects are not identified in this regression, primarily due to the *reflection problem*, which arises because even in the absence of correlated effects, simultaneity in behavior of interacting agents introduces a perfect collinearity between the expected mean outcome of the group and its mean characteristics.

This reflection problem hinders the identification of the endogenous effect from the exogenous effects. Is group behavior actually affecting individual behavior, or group behavior is simply the aggregation of individual behaviors (if the individual outcomes increase so will the group average)? In other words, even after accounting for observed group characteristics, there can always be unobserved ones that can be correlated both with individual outcome and group outcome. So, we cannot distinguish if a group member's action is the cause or the effect of peers' influence, which is the well-known reflection problem.

The important distinction between equation (4) and equation (5) is that, in the former, the assumption is that people interact in networks (k denotes network). Different individuals can belong to the same network but their relative positions in the network are usually different. As a result, this approach can utilize individual level variation even within the network. In equation (5), the assumption is that people interact within group (k denotes group). As a result, individual variation within group cannot be exploited (see Bramoulle´, Djebbari and Fortin (2009) for details).

In our analysis, while we do not have the information to span the dyadic relations within a network, we do have a variety of intensity measures. We, therefore, adopt an approach that is a combination of both the above approaches. In the spirit of equation (4), we utilize the intensity measures to identify the endogenous effect at the *group* level. The advantage is that we are able to exploit the individual level variation. We start by assuming that networks are embedded in groups.[3] Individuals interact in networks with different intensities. Under this setup, consider the regression,

$$(6) \qquad y_{i,k} = \beta_0 + \sum_{m=1}^{M} \beta_1^m x_{i,k}^m + z'_{i,k}\pi_1 + \delta_k + \xi_{i,k} \,,$$

where $z_{i,k}$ measures the intensity with which individual i interacts in network k (the empirical counterpart of $\mu g_{i,k}$ in equation (4)), and δ_k is the indicator variable for group. Clearly, endogenous, exogenous and correlated effects cannot be estimated in equation (6) since the network dummy subsumes all of these effects. Now, consider the following rendition of equation (6),

$$(7) \qquad y_{i,k} = \beta_0 + \sum_{m=1}^{M} \beta_1^m x_{i,k}^m + z'_{i,k}\pi_1 + E(y_{i,k} \mid k) * z'_{i,k}\pi_2 + \delta_k + \xi_{i,k} \,.$$

In this regression, $\pi_2 \neq 0$ only when there exists an endogenous effect.

By using group level fixed effects we purge out the elements that would undermine establishing presence of true endogenous effects. With group fixed effects, group level adoption does not have an identifiable coefficient but its interaction with intensity of social exchange does. A significant coefficient of the interaction would establish the presence of endogenous social effects. Unless there are endogenous effects there should be no variation in the effects of group choices with the intensity of interaction in individual networks. The logical element of this

[3] Given the social structure in agrarian rural societies in Rajasthan this, we believe, is a reasonable assumption (see discussions above).

argument is akin to the one in Bandiera and Rasul (2006). The non-linear relationship that Bandiera and Rasul (2006) obtain is used as evidence for existence of endogenous social effects. This pattern is expected only when there are endogenous effects working. Similarly, the interaction of group adoption with intensity of social exchange having a bearing on technology choice, we can take this as evidence of the presence of endogenous social effects.

IV. Results

IV1. Main Results

In this section we present the results of the regressions of technology choices on the individual's position in the network (in terms of intensity of interactions), first in isolation and then in combination with group averages and group fixed effects. We want to highlight the importance of caste in the construction of reference groups. Hence, we also compare results between different makings of the reference groups, once where it is defined based on both geographical proximity and caste, followed by the case where groups are defined solely by geography (tables 5 and 6, respectively). While these are the main results, we start with some preliminary regression in Table 4.

The marginal effect from preliminary probit regressions presented in table 4 look at the associations between group level adoption and choice of a farmer between modern and traditional varieties. Column 1 presents the most basic model without inclusion of intensity of individual network variables. With some basic controls of socio-economic characteristics there is significant correlation between group (based on caste and geographical proximity) adoption of modern variety and individual farmer's choice.

Subsequently in column 2 intensity of interaction with individual networks are introduced across various nodes. There is significant association between the time spent with family and friends and the probability of adoption of a modern variety. Other than the close knit connections, greater intensity of any other social interaction or information sources does not have a bearing on choice of modern varieties of seed. In column 3 with the inclusion of components of group fixed effects (area and caste dummies separately), the fixed effects tend to explain most of the variation rendering group adoption insignificant.

Table 5 presents the results of the specification in column 2 that would establish the presence of endogenous social effects: group level unobserved heterogeneity is controlled for through group fixed effects. After controlling for group level unobserved heterogeneity, the interaction of intensity with group level average adoption implies presence of endogenous social effects.

For two measures of intensities, time spent with friends and relatives and in religious activities, interaction with group (caste and location) adoption there are significant effects at 5 percent level. For a given level of group adoption, a unit increase in hours per week spent with friends and relatives increases the probability of adoption of a modern variety by about 4 percentage points. The marginal effects are higher at 29 percentage points in case of religious activities. Alternatively, these could be interpreted as effects of group adoption on individual farmer choices for given intensities of interaction with friends and relatives and of participation in religious activities.

From the data, it is not possible to figure out how distinct are identities of individuals in these networks vis-à-vis others. Religious organizations in India to a large extent tend to be exclusionary not only along religious lines but on caste lines as well. In some temples for upper castes, lowest castes are typically denied entry. In general, especially in rural societies, individuals attend masses in the temples of their own castes.

With the establishment of the endogenous social effects, there could be several channels for this type of effect. For a given level of adoption of modern variety by the reference group, more interaction could result for example in better processing of signals. It could also provide supplementary information and resources needed for translating the signal into actual decision of adoption. These mechanisms essentially comprise the pathways for working of the social effects in an endogenous way. Note that we are not quantifying the size of endogenous effect but merely establishing its existence.

In both tables 4 and 5, among the other variables that are included, we have the average valuations of consumption traits (except when group fixed effects are included). Since, the varietal choice could be based on this valuation (on a Likert scale) it can account for some of the group heterogeneity (in specifications where we do not have group fixed effects). As the valuation of attributes can never be exhaustive, admittedly, this method can only create a partial proxy to account for unobserved heterogeneity. This variable, however, does not have a significant coefficient.

There is evidence for farmers with larger land sizes being less likely to adopt a modern variety. Bajra being a marginal crop, this is most likely owing to lower importance of Bajra in the cropping portfolio of larger farmers. Incentives for adoption of a high yielding but riskier variety could be lower for this group of farmers.

The evidence of no significant effect of common pool networks on farmer’s choice of modern variety of pearl millet is striking. The government of India spends significant resources on mass media programs to support its outreach activities in agriculture. The government, for example, runs television programs under the Mass Media Support to Agriculture Extension Scheme. These programs are available on public channels and include features, documentaries, success stories of farmers, research inputs, quizzes, crop seminars and a live phone in program. The programs are also available in local languages in different states.

Similarly on extension working through mandates i.e. associations (see below), an entire institute – the National Institute of Agricultural Extension Management – was setup under the Ministry of Agriculture by the government of India. Its objective is to assist the State Governments, the Government of India and other public sector organizations in effective management of their agricultural extension and other agricultural management systems (GOI-http://indiagov.in). The state of Rajasthan has also tried to improve its extension services. Recently, it has adopted group based approaches to extension with village extension workers operating mainly through *Kisan mandate* (group of 20 farmers). The state has also been encouraging NGOs to participate in extension activities and has been contracting out some extension activities to them, particularly in the far flung areas where public extension is comparatively weak (Sulaiman and Hall 2006).

IV.2. The Importance of Caste

We have emphasized the importance of caste in social networks in the Indian context. Beyond the conjecture we want to assess the importance of caste little more systematically. In this section we conduct two tests based on alternative definitions of group, one in which groups are more broadly defined (location based) and other in which they are more narrowly defined (location, caste and landholding size based) than the specification used for results in table 5.

In Table 6, we thus redefine the reference groups based solely on geographical proximity (the standard in most papers) and apply the same methodology as before (when groups were based on both social identity and geographical proximity). The variables of interest are again the interaction of intensity measures with group level adoption. Treating location as the perimeter of networks/reference group, greater intensity of different social exchange no longer has effect in its interaction with group level adoption of modern variety. As before results show a strong and positive association between group adoption and choice of a modern variety by an individual farmer.

By excluding caste from the reference group, results establish the importance of caste in social network analysis in the Indian context. If adoption of farmers in the locality is higher, greater intensity of social interaction by a farmer in this context (table 6) does not translate into greater likelihood of adoption of modern variety. This is in sharp contrast with the results in table 5 where group definition incorporated caste as well. Similarly, in case of time spent at temples/mosques there are no significant effects now. In our dataset interactions for most of the farmers with friends was generally confined to same caste that they belonged to. The redefining of reference group i.e. bereft of caste creates a situation where endogenous effects would tend to weaken.

In case of meeting with friends and relatives as well as interactions in religious centers such as temples, there is sorting along caste lines. Hence, it is quite informative that interaction of intensity with group that does not take into account caste composition has no effect on technology choices. Assuming that there is sorting in activities and interactions along caste lines, the insignificant effects in table 6 and significant effects in table 5 has important implications. The interaction of intensity measures with group adoption point to the fact that the coefficient in table 5 provides evidence for endogenous social effects.

Next we define the reference group more minutely. In particular we decompose the biggest caste group (in terms of numbers), i.e., OBC, into two land size classes, high and low. High land size corresponds to land that are larger than median holdings in the sample. In a large caste group such as OBC, a decomposition like this could be apt for getting the right reference group. Social learning would require similarity on a larger set of characteristics for the caste group comprising the OBC.

In Table 7, we present the results after redefining the group to be determined by location, caste and land sizes. The interaction between group and intensity measures for the close knit networks and those related to socialization in religious places remain significant. Compared to results in table 6 where these effects were insignificant, the interaction terms in case of narrowly defined groups provides further evidence for existence of endogenous social effects.

V. Conclusions and policy implications

In this paper we study the low adoption of modern variety of pearl millet in the Indian state of Rajasthan from a social network perspective. We show that close knit networks and religious organizations have been effective for farmers in determining their technology choice. Specifically, these connections could comprise family and friends or religious gatherings, and are in general restrictive. For these connections we also establish existence of endogenous social effects. In a socially fragmented set up like the rural agrarian society of India, there are, however, limits for these social effects to translate into social multipliers.

With fragmentation large scale adoption programs would require networks, sources of information and services that are less exclusionary. We hypothesized these nodes to be the media and non-religious organizations, in particular, along with the public sector managed agricultural extension services. Our empirical results show that for these channels, there is no significant association with farmer's decision towards adopting a modern variety. This finding is extremely crucial for policy since these channels comprise direct policy levers in a fragmented society like

India. Indeed several government programs in India have relied on these channels to run large scale adoption programs. Their ineffectiveness could be a prime factor for such limited dissemination of technology in Rajasthan.

In different settings, social fragmentation could be an important factor in determining outcomes. The evolving consensus in the literature based on several studies is that ethnic fragmentation has potentially negative consequences on macro-economic performance (see for example Alesina and Tabellini, 1989 and Collier, 2000). In microeconomics literature the role of fractionalization is somewhat under-studied. With fragmentation, there can be significant micro-level impacts (for instance low technology adoption of a crop) if channels that are inclusive are not well developed.

The finding that channels like extension services, media or organizations are not effective in determining choice of technology does not mean that they should not be tapped. Our empirical findings suggest that in their current form in the state of Rajasthan, the roles played by these are limited. The policy implications would be to develop these systems in a way that there is a greater uptake. Recall that less than 4 percent of the respondents got information on seeds from media sources, an extremely low number. There is certainly scope for increasing the outreach of these channels that are much more important for spread of agricultural technology in a fragmented society.

References

Alesina, Alberto, and Guido Tabellini, 1989. “External Debt, Capital Flight and Political Risk,” Journal of International Economics, XXVII. 199–220.

Bandiera, O., Rasul, I., 2006. “Social networks and technology adoption in northern Mozambique.” Economic Journal. 116, 869–902.

Bidinger F. R., M. M. Sharma and O. P. Yadav. 2008. “Performance of landraces and hybrids of pearl millet [Pennisetum glaucum (L.) R. Br.] under good management in the arid zone. Indian Journal of Genetics. 68(2): 145-148

Bramoulle´, Y., H. Djebbari, and B. Fortin. 2009. “Identification of Peer Effects through Social Networks,” Journal of Econometrics 150 (2009) 41-55.

Calvó-Armengol, Antoni, Eleonora Patacchini, and Yves Zenou. 2009. “Peer Effects and Social Networks in Education.” Review of Economic Studies, 76, 1239–1267.

Collier P. 2000. “Ethnicity, Politics and Economic Performance.” Economics and Politics 12, 225-45.

Conley Timothy G. and Christopher R. Udry, 2010. "Learning about a New Technology: Pineapple in Ghana," American Economic Review, American Economic Association, vol. 100(1), pages 35-69, March.

Dercon, Stefan and Christiaensen, Luc, 2011."Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia," Journal of Development Economics, Elsevier, vol. 96(2), pages 159-173, November.

Duflo E, M Kremer and J. Robinson. 2008. “How High are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya” American Economic Review, Vol. 98 (2): 482-88, May.

Fontaine Xavier and Katsunori Yamada, 2011. "Envy and Hope: Relevant Others' Consumption and Subjective Well-being in Urban India," PSE Working Papers hal-00616993, HAL

Foster Andrew D. and Mark R. Rosenzweig, 2010. "Microeconomics of Technology Adoption," Annual Review of Economics, Annual Reviews, vol. 2(1), pages 395-424, 09.

Foster, A. D. and Rosenzweig, M. R. (1995), ‘Learning by doing and learning from others: Human capital and technical change in agriculture’, The Journal of Political Economy 103(6), 1176–1209.

Manga V.K. and A.Kumar. 2011. Performance of pearl millet hybrids under arid conditions. Electronic Journal of Plant Breeding. Volume : 2, Issue : 3. 320-325

Manski, C.F., 1993. “Identification of endogenous social effects: The reflection problem.” Review of Economic Studies 60, 531–542.

Matuschke, I. and Qaim M. 2009. The impact of social networks on hybrid seed adoption in India, Agricultural Economics, Vol. 40(5), pp. 493-505.

Munshi, Kaivan, and Mark Rosenzweig. 2009. “Why is Mobility in India so Low? Social Insurance, Inequality, and Growth.” Brown and Yale working paper.

Munshi, Kaivan. 2004. “Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution.” Journal of Development Economics, 73(1): 185–213.

Pomp, M. and Burger, K. 1995. “Innovation and imitation: Adoption of cocoa by Indonesian smallholders. World Development. 23(3), 423–431.

Putnam, R. D. 1995. ‘Tuning in, Tuning out: The Strange Disappearance of Social Capital in America’, Political Science & Politics 28(4), 664–83.

Putnam, R. D. 1995a. ‘Bowling Alone: America’s Declining Social Capital’, Journal of Democracy, 6(1), 65–78.

Sulaiman, R.V and Andy Hall. 2008. The fallacy of universal solutions in extension: Is ATMA the new T&V, LINK News Bulletin, September 2008, Learning Innovation Knowledge (LINK) (www.innovationstudies.org)

World Bank (2008), World Development Report 2008: Agriculture for Development, The International Bank for Reconstruction and Development, Washington, D.C.

Zeitlin Andrew, Francis Teal, Stefano Caria, Richman Dzene, Petr Jansky and Emmanuel Opoku. 2010. "Heterogeneous returns and the persistence of agricultural technology adoption." CSAE Working paper 2010-37. Oxford University.

Figures and Tables

Figure 1: Share of agricultural area dedicated to Bajra production, Rajasthan

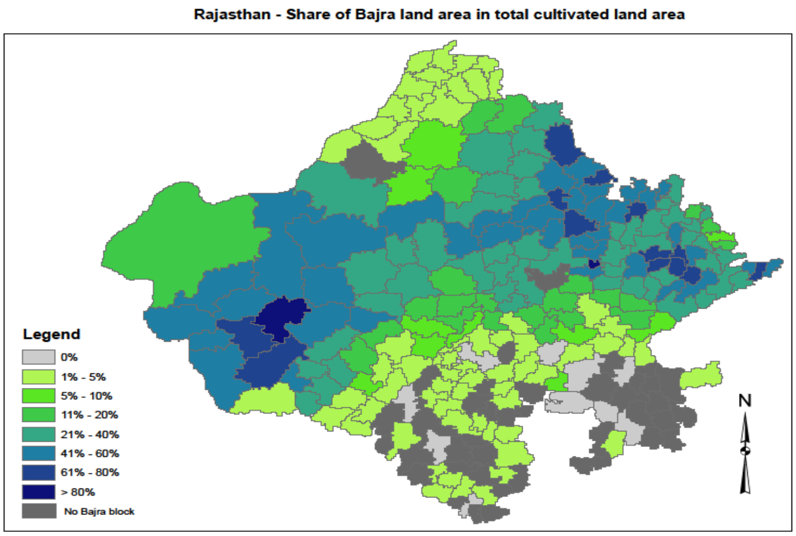

Figure 2: Bajra Blocks in Rajasthan

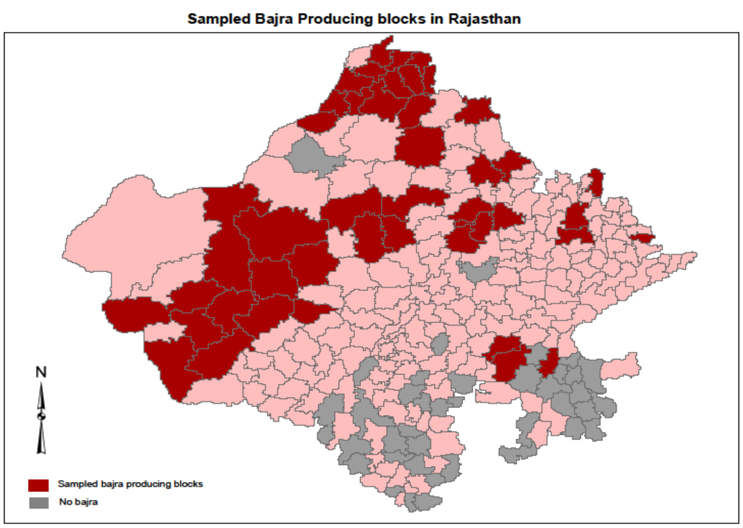

Figure 3: Districts in Rajasthan

Figure 4: Estimation Issues in Social Effects

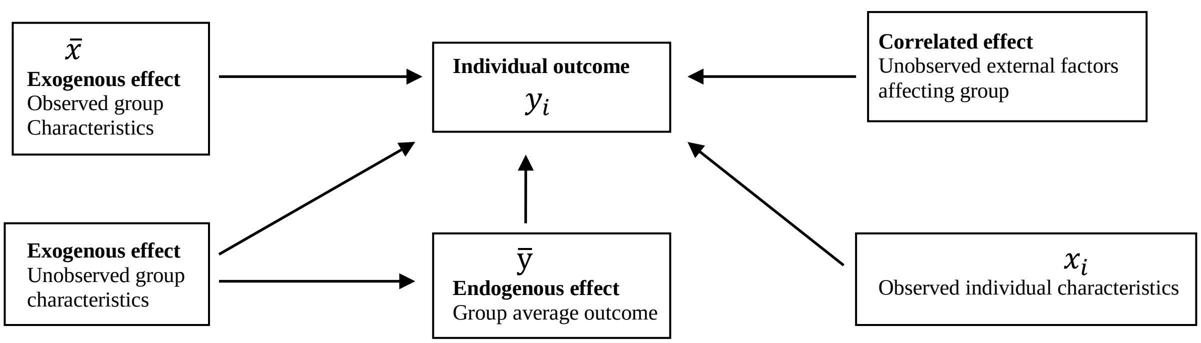

Table 1: Descriptive Statistics of the Sample

	N	Mean	SD	Min	Max
Modern Bajra Variety	320	0.49	0.50	0.00	1.00
Caste-area group average of modern variety (m)	320	0.50	0.24	0.11	0.83
Area group average of modern variety (n)	320	0.47	0.21	0.14	0.81
Hours/week with friends and relatives (p)	320	11.74	7.63	0.00	45.00
Phone calls to friends and relatives out of village (q)	320	85.48	98.54	0.00	365.00
Hours Spend a Week at Temple/Mosque/Church (r)	320	0.69	1.92	0.00	23.00
# of participations in organizations (s)	320	0.10	0.38	0.00	3.00
Hours/week with HH members	320	43.44	24.97	0.00	119.00
Hours/week with newspaper/radio/TV	320	13.57	8.19	0.00	49.00
Interaction = m*p	320	5.85	5.00	0.00	26.72
Interaction = m*q	320	40.08	52.03	0.00	268.38
Interaction = m*r	320	0.34	1.12	0.00	16.91
Interaction = m*s	320	0.06	0.24	0.00	1.74
Interaction = n*p	320	5.53	4.52	0.00	24.35
Interaction = n*q	320	39.60	52.03	0.00	222.17
Interaction = n*r	320	0.33	0.99	0.00	14.00
Interaction = n*s	320	0.05	0.22	0.00	1.83
Household Size	320	6.66	7.50	2.00	70.00
Years Lived in this Village	320	54.52	31.56	1.00	200.00
Farmland Size in Hectares	320	0.32	1.17	0.02	20.24
Off-farm Monthly Income	320	4.95	6.24	0.00	40.00
Farm Monthly Income	320	5.97	6.31	0.00	70.00
Group average of consumption trait	320	4.31	0.09	4.19	4.60

Table 2: Area classifications used

Area	Districts	Caste category	Description
1	Alwar, Bharatpur , Bundi , Kota	1	Upper caste
2	Hanumangarh, S.Ganganagar	2	Scheduled caste and scheduled tribe (SC/ST)
3	Bikaner, Churu	3	Other backward castes (OBC)
4	Jhunjhunu, Sikar		
5	Jodhpur, Nagour		
6	Barmer, Jaisalmer		

Table 3: Means by Caste and Geographical Categories

	Caste categories			Geographical (area) categories					
	Upper caste	SC/ST	OBC	Area 1	Area 2	Area 3	Area 4	Area 5	Area 6
Number of observations	41	49	230	26	65	40	63	69	57
Modern Bajra Variety	0.37	0.61	0.49	0.88	0.45	0.30	0.71	0.59	0.14
Hours/week friends and relatives	11.21	11.63	11.85	9.95	12.12	10.25	12.11	12.19	12.21
Phones to friends-relatives out of village	65.44	92.85	87.48	53.50	102.69	76.26	52.83	114.77	87.53
Hours/week at Temple/Mosque/Church	0.63	0.73	0.69	0.62	0.23	0.38	1.46	0.42	0.95
# of participations in organizations	0.05	0.08	0.12	0.08	0.02	0.07	0.32	0.04	0.07
Hours/week with HH members	42.66	40.87	44.13	41.71	34.94	50.26	64.29	38.22	32.44
Hours/week for newspaper/radio/TV	12.34	13.16	13.88	12.73	14.17	14.07	14.00	14.19	11.70
Household Size	7.32	8.06	6.24	5.23	5.75	7.55	9.00	6.48	5.33
Years Lived in this Village	57.32	53.06	54.34	55.58	42.05	66.13	61.52	45.35	63.51
Farmland Size in Hectares	0.82	0.23	0.25	0.06	0.23	0.27	0.15	0.32	0.76
Off-farm Monthly Income	6.79	4.56	4.70	3.50	4.29	4.71	3.67	5.43	7.36
Farm Monthly Income	4.01	5.26	6.48	3.83	10.09	5.76	3.92	7.72	2.57

Table 4: Marginal Effects of Probit Estimate of Choice of Modern Varieties of Bajra

	(1)	(2)	(3)
Caste-area group average of modern variety (m)	0.533***	0.530***	0.054
Hours/week with friends and relatives (p)		0.008**	0.010**
Phone calls to friends and relatives out of village (q)		0.000	0.000
Hours spent a week at Temple/Mosque/Church (r)		-0.008	-0.015
# of participations in organizations (s)		0.033	-0.007
Hours/week with HH members		0.001	0.000
Hours/week with newspaper/radio/TV		-0.001	-0.002
Household Size	0.003	0.003	0.001
Years Lived in this Village	0.001	0.001	0.001
Farmland Size in Hectares	-0.351***	-0.309***	-0.189*
Off-farm Monthly Income	0.001	-0.003	-0.000
Farm Monthly Income	0.012**	0.011**	0.008**
Caste-area group average of consumption trait	0.337	0.298	0.069
Upper caste			0.013
SC/ST			0.104***
Area 1			0.263***
Area 2			-0.140***
Area 3			-0.219***
Area 4			0.105
Area 6			-0.373***
Observations	320	320	320
pseudo R-square	0.111	0.133	0.207

Notes: (a) Each regression has a constant. (b) OBC and Area 5 are the omitted categories because they have the largest shares in the sample. (c) Caste-area groups 7 and 18 are dropped due to insufficient observations (one each). (d) Standard errors clustered by Caste-area groups. (e) *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Marginal Effects of Probit Estimate of Choice of Modern Varieties of Bajra

	(1)	(2)
Interaction = (Caste-area group average of modern variety)*p		0.044**
Interaction = (Caste-area group average of modern variety)*q		0.000
Interaction = (Caste-area group average of modern variety)*r		0.295**
Interaction = (Caste-area group average of modern variety)*s		-0.055
Hours/week with friends and relatives (p)	0.010**	-0.012
Phone calls to friends and relatives out of village (q)	0.000	-0.000
Hours spend a week at Temple/Mosque/Church (r)	-0.014	-0.201**
# of participations in organizations (s)	-0.006	0.043
Hours/week with HH members	0.000	0.001
Hours/week with newspaper/radio/TV	-0.002	-0.001
Household Size	0.001	0.002
Years Lived in this Village	0.001	0.001
Farmland Size in Hectares	-0.199**	-0.144*
Off-farm Monthly Income	-0.001	-0.001
Farm Monthly Income	0.009**	0.004
Caste-area group dummy 1	0.257***	0.246***
Caste-area group dummy 2	0.184***	0.191***
Caste-area group dummy 3	-0.302***	-0.269***
Caste-area group dummy 4	-0.069	0.195**
Caste-area group dummy 5	-0.238***	-0.143**
Caste-area group dummy 6	-0.276***	-0.136*
Caste-area group dummy 8	-0.331***	0.033
Caste-area group dummy 9	-0.030	0.346***
Caste-area group dummy 10	0.133***	0.223***
Caste-area group dummy 12	-0.042	0.056
Caste-area group dummy 13	-0.027	0.227***
Caste-area group dummy 14	-0.120	0.074
Caste-area group dummy 15	-0.389***	-0.345***
Caste-area group dummy 16	-0.391***	-0.051
Caste-area group dummy 17	-0.424***	-0.102
Observations	320	320
pseudo R-square	0.210	0.243

Notes: (a) Each regression has a constant. (b) Caste-area group 11 is the omitted category because it has the largest shares in the sample. (c) Caste-area groups 7 and 18 are dropped due to insufficient observations (one each). (d) In these regressions the Caste-area group averages are subsumed in the Caste-area group dummies. (e) Standard errors clustered by Caste-area groups. (f) *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Marginal Effects of Probit Estimate of Choice of Modern Varieties of Bajra

	(1)	(2)	(3)
Area group average of modern variety (n)	0.915***	0.914***	
Interaction = (Area group dummy average of modern variety)*p			0.002
Interaction = (Area group dummy average of modern variety)*q			-0.003*
Interaction = (Area group dummy average of modern variety)*r			0.371
Interaction = (Area group dummy average of modern variety)*s			-0.142
Hours/week with friends and relatives (p)		0.010**	0.008
Phone calls to friends and relatives out of village (q)		0.000	0.001***
Hours Spend a Week at Temple/Mosque/Church (r)		-0.010	-0.218
# of participations in organizations (s)		0.004	0.068
Hours/week with HH members		0.001	0.000
Hours/week with newspaper/radio/TV		-0.002	-0.002
Household Size	0.002	0.002	0.001
Years Lived in this Village	0.002*	0.002*	0.001
Farmland Size in Hectares	-0.222**	-0.174**	-0.207***
Off-farm Monthly Income	0.003	-0.001	0.000
Farm Monthly Income	0.007*	0.006*	0.008**
Group average of consumption trait	0.222**	0.210	
Upper caste	-0.003	0.002	0.025
SC/ST	0.099***	0.106***	0.100***
Area group dummy 1			0.231***
Area group dummy 2			-0.149***
Area group dummy 3			-0.267**
Area group dummy 4			0.099
Area group dummy 6			-0.420***
Observations	320	320	320
pseudo R-square	0.172	0.192	0.222

Notes: (a) Each regression has a constant. (b) OBC and Area 5 are the omitted categories because they have the largest shares in the sample. (c) Caste-area groups 7 and 18 are dropped due to insufficient observations (one each). (d) In regression (3) the Area group averages are subsumed in the Area group dummies. (e) Standard errors clustered by Caste-area groups. (f) *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Marginal Effects of Probit Estimate of Choice of Modern Varieties of Bajra

Interaction = (Caste-landsize-area group dummy average of modern variety)*p	0.047**
Interaction = (Caste-landsize-area group dummy average of modern variety)*q	-0.001
Interaction = (Caste-landsize-area group dummy average of modern variety)*r	0.263**
Interaction = (Caste-landsize-area group dummy average of modern variety)*s	-0.237
Hours/week with friends and relatives (p)	-0.013
Phone calls to friends and relatives out of village (q)	0.000
Hours spend a week at Temple/Mosque/Church (r)	-0.176**
# of participations in organizations (s)	0.132
All other explanatory variables (as in column 2 of Table 5)	yes
Caste-landsize-area group dummies	yes
Observations	320
pseudo R-square	0.246

Notes: (a) This is a robustness check. The specification is the same as column 2 of Table 5. The difference is in how the groups are defined. Here the caste categories are defined as {high caste, SC/ST, OBC with greater than median land size, OBC with smaller than median land size}. These categories then are interacted with 6 geographical areas to create 24 Caste-landsize-area groups. (b) The regression has a constant. (c) Standard errors clustered by Caste-landsize-area groups. (d) *** p<0.01, ** p<0.05, * p<0.1.