Social networks, agricultural innovations, and farm productivity in Ethiopia

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Abstract

This paper examines the existence of social learning in agriculture in Ethiopia. We use a 'random matching within sample' technique to collect data on social networks and elicit details of the relationships and information exchange between network members, complementing the analysis with information on self-reported networks. We find that, while kinship or membership in certain groups, informal forms of insurance, or having frequent meetings with network members are all associated with a higher probability of forming an information link, none of these are correlated with observed innovative behavior such as the adoption of row-planting. This may suggest that behavior is more likely to be affected by the nature of information that passes through the network, rather than the number of information links. In support of this, we find that information links that exclusively involve discussions on farming or business matters are indeed associated with a higher likelihood of adopting row-planting. We use econometric strategies to isolate social learning from that of correlated and contextual effects. After controlling for factors that might otherwise generate spurious correlation, we find a strong evidence of network externalities in the adoption of row-planting techniques and also in farm productivity. Our results imply that extension services and other programs that promote agricultural innovations and seek yield improvement may benefit from social networks but they may be more effective if they identify the 'right' networks, that is, the ones that exclusively involve information exchange regarding agriculture. This further implies that investment in group formation, rather than simply using existing networks, may be a beneficial strategy.

Keywords: Social networks, innovations, row planting, agriculture, Ethiopia

JEL codes: Q1, D02, O33, D83, D62

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1. Introduction

Eighty-two percent of the population in Ethiopia live in rural areas (World Bank, 2012), with the majority depending on agriculture or related activities for their livelihood, either directly or indirectly. Despite some improvements in agricultural production in recent years, overall agricultural growth falls short of the rapid population growth and importing food (in the form of aid and to some extent commercial imports) has become an important component of food supply in the country with an equivalent of 6.4% of the national food production between 1996 and 2010 on average (Graham et al, 2012). Ethiopian agriculture is characterized by low productivity which is associated with low input usage (such as improved seed varieties and fertilizer), significant post-harvest loss, population pressure, poor farming practices, and land degradation, among others (Negatu, 2004; Rashid, et al., 2010; Yao, 1996).

Besides measures that would take population pressure off agriculture, potential remedies lie in the promotion of agricultural innovations to sustainably improve agricultural productivity whilst increasing the efficiency of smallholder agriculture. Risk aversion (Yesuf and Bluffstone, 2009; Yu and Nin-pratt, 2014), perceptions about new technologies (Negatu and Parikh, 1999), access to extension and advisory services; (Ragasa et al., 2013; Yu and Nin-Pratt, 2014), and access to credit (Bekele and Drake, 2003) have been identified as the major determinants of technology adoption in Ethiopia. Other socio-economic factors also identified in these articles include human capital, livestock holdings, land size and tenure security, for example.

Although there is an extensive literature on the diffusion of innovations and its determinants, one of which is social interactions, (Rogers, 1983; Feder et al, 1985, Feder and Umali, 1993; and Foster and Rosenzweig, 2010), studies on Ethiopian agriculture largely ignore the role social networks play in technology adoption. Only a few studies (Wossen et al., 2013; Kassie et al., 2012; Dessie et al., 2012) investigate the effects of social networks for improved farming and natural resource management practices.

Evidence from other countries, however, suggests that social networks play a central role in people's lives in so many ways including in shaping beliefs, preferences, and decisions (Jakson, 2011). There is, for example, evidence on the role of social networks on the diffusion of information, new products, and technologies (Jackson and Yariv, 2011); informal insurance and risk sharing (Fafchamps, 2011); and labor and credit networks for economic activities (Munshi, 2011).

This paper adds empirical evidence to the existing literature on the role of social networks for the adoption of agricultural innovations and for farm productivity in rural Ethiopia. Specifically, we examine the determinants of information and learning links among farmers, and whether those information links and their structure affect the adoption of innovations, mainly row planting in this context. We also identify social externalities in the adoption of row-planting methods, and in yield improvement as explained next.

We choose row-planting as an indicator of innovative behavior for it is a recent practice in Ethiopian agriculture, which makes it convenient to test the existence and role of social learning in technology adoption. Recent studies conducted in Ethiopia show that yields are very responsive to this improved practice. By comparison to the conventional broadcasting technique, for example, Alemu et al. (2014) find an average of 14.6 percent higher wheat yields with row-planting, while Vandercasteelen et al. (2014) find an increase in *teff* yields between 12 and 13 percent in farmers' experimental plots and 22 percent in demonstration plots managed by extension agents. Other on-the-field experimental trials in the country, however, report a more significant yield increase (for example, about 70% increase in teff yields (ATA, 2013)) that encouraged the country's extension system to up-scale promotion of this agronomic practice in 2013. As is the case for other agricultural innovations, diffusion of this innovation requires farmers to experiment by themselves and also to learn from others before fully adopting the technique. Because of the potential importance of adopting row-planting, we examine whether social learning with respect to the adoption of row-planting takes place and whether evidence for an effect on yields exists.

The remainder of this paper is organized as follows: the next section presents the background to this study, reviews the literature our study relates to, and sets the conceptual framework of the paper. Section 3 presents the data we use, including descriptive statistics. The empirical strategy and results are discussed in Section 4, Section 5 concludes.

2. Background and conceptual framework

There is little doubt about how central a role innovations can play for development. Yet, existing literature suggests that innovations, particularly in poor countries, are constrained by lack of information and market inefficiencies such as the absence of well-functioning credit and insurance markets. Networks may provide practical solutions in such circumstances and can guide policy decisions such as targeting. To be specific, social networks facilitate interaction, which is a central part of the innovation systems framework that understands the capacity for continuous innovation as a function of linkages, working practices, and policies that promote knowledge flows and learning among all actors (Hall et al., 2006). The underlying idea is that wider knowledge and information are embodied in different actors and interaction among them enhances their innovation behavior and performance. Social networks are the channels for such interactions and for social learning to occur.

Conceptually, we mainly draw on the theory of innovation diffusion outlined in the early 1960s by Everett M. Rogers in this paper. According to Rogers (1983), innovation adoption is preceded by a process of knowing about the existence of an innovation, developing an interest and making a decision about adoption. Rogers reflects on the relevance of social networks within the two main elements of diffusion: communication channels and social structure. For example, while mass-media such as ICTs and related channels are considered as the most rapid and efficient means in creating knowledge of innovations, interpersonal channels are more effective in persuading an individual to adopt innovations (Rogers, 1983). This, according to Rogers, occurs because people depend mainly upon a subjective evaluation of an innovation that is conveyed to them from other individuals like themselves who have previously adopted the innovation. This may be the case because individuals believe that the other person has superior information and hence they may try to learn; or, simply because individuals want to imitate others for reasons related to conformism, jealousy, and paternalism (Manski, 2000); or because neighbors are subject to related unobserved shocks (Conley and Udry, 2010). Despite enormous challenges of identification, this essentially underscores a central role that social networks can play in the adoption of innovations.

A set of connections (edges) among a collection of individuals (nodes) represent a network through which information, money, goods or services flow (Maertens and Barrett, 2012). Social networks may facilitate knowledge externalities as interactions among network members influence individual behavior. This is partly because individuals update their beliefs for their behavior - aspirations and expectations - are shaped not only by their own past experience but also by experiences of others in their network (Ray, 2006). Hence, interaction among network members is necessary for observations and learning to occur.

However, the degree of knowledge spillovers depends on the structure of the network (Rogers, 1983). It determines who interacts with whom, but as the determinants of the structure can be strategic or not (e.g. like-mindedness), any observed behavioral change may or may not be a result of interconnectedness. As an example, some nodes in the network may act as "opinion leaders" and informally influence the attitudes of other individuals (Rogers, 1983) which may be a case of network effects, while in other instances factors that determine the formation of links in the first place may also affect individuals' behavior or decisions (referred to as 'homophily' (Jackson, 2011).

On the other hand, network effects also very much depend on the extent to which relationships are transitive, that is, "the extent to which if node i is linked to node j, and j is linked to k, then i is linked to k", (Jackson, 2011: p.527). According to Jackson (2011), the frequency with which such transitivity is present is referred to as clustering, and clustering impacts the extent to which connections reach out to new nodes and can thereby affect information transmission. This issue of transitivity could be particularly interesting to research in the context of male versus female networks among members of the same households, the spouses' network being assumed to display different frequencies than the husbands'.

The other important factor for social learning is network size measured by the number of individuals linked through the network. While the literature on labor or credit networks, for example, predicts that individuals with access to stronger networks should have superior outcomes, Munshi (2011) argues that selective entry into the network and endogenous network size (strength) might give rise to a spurious network effect.

The central idea of social learning in the empirical literature has evolved from that of having insignificant variation within a given village (e.g. Foster and Rosenzweig, 1995) to the concept of innovation systems which assumes heterogeneity among network members, for example with respect to their knowledge about technologies, and puts interactions at the center of innovation processes (Hall et al., 2006). Further, networks can be defined in different ways. Some empirical studies including Foster and Rosenzweig (1995), Munshi (2004), and Isham (2002) define networks based on membership to certain groups, such as village, which essentially imply that experience from all farmers in the group is relevant. This approach might also disregard the possibility of links or information flows outside the group that may be critical to the information circulated within the group, which is also referred to as "the strength of weak ties" (Granovetter, 1973).

Despite significant differences on definition and measurement of social networks, there is growing evidence for learning externalities or network effects on the adoption of agricultural innovations, highlighting learning spillovers in terms of the rate of adoption of the innovation (Foster and Rosenzweig, 1995), the role of technology specificities in learning from neighbors (Munshi, 2004), or the impact of ethnicity and social affiliations on adoption rates (Isham, 2002).

More recent studies measure networks in more detailed and structured manner that could account for various channels of information flow (e.g. self-reported networks, family, religious groups, kinship in Bandiera and Rasul, 2006, Matuschke and Qaim, 2009, or van den Broeck and Dercon, 2011). With the exception of a few studies such as Conley and Udry (2010) and Maertens and Barrett (2012), much of the existing empirical literature relies on data which defines networks based on such group membership or on self-reported links. Yet, these network measures are criticized for the possibility of ignoring important links outside the group or sample and of suffering from unobserved heterogeneity which might influence both the formation of links and that of the variable of interest (Maertens and Barrett, 2013; Munshi, 2011; Santos and Barrett, 2008). According to Maertens and Barrett (2012), 'random matching within sample' may help address some of these shortcomings and allow identification of endogenous (peer) effects separately from correlated and contextual effects.[1] The limitation with this technique, however, is that the number of information contacts in the sample is smaller than the farmer's actual number of information contacts (Conley and Udry, 2010) and may be missing a key contact from the defined network (Maertens and Barrett, 2012). Using random matching within sample, Conley and Udry (2010) find evidence of social learning among farmers in Ghana as the latter align their use of an innovative technique with successful farmers in the previous period.

Networks, however, do not necessarily encourage innovations: Network externalities may introduce free riding in experimentation and hence strategic delays of technology adoption since neighbors' and own experience could be substitutes (Bandiera and Rasul, 2006, Foster and Rosenzweig, 1995, Kremer and Miguel, 2007). To sum up, the existing literature, both theoretical and empirical, highlights the importance of social networks for innovations. Yet, interaction effects vary with network characteristics including the type of network, network structure, network size, the frequency of interactions among members, the transitivity of relationships, technology specificity, and individual heterogeneity. However, the identification of network effects is challenging as it requires finding the 'right' networks, and, even in this case may suffer from problems of identification due to omitted variables, due to homophily (Jackson, 2011), or because mean behavior in the group is itself

[1] According to Manski (1993), endogenous, contextual and correlated effects, respectively, arise wherein the propensity of an individual to behave in some way varies with: the behavior of the group; the exogenous characteristics of the group; and, wherein individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments.

determined by the behavior of group members. Manski (1993) defines the latter simultaneity bias as the 'reflection problem'.

Based on the existing literature, we investigate whether individuals belonging to the same group tend to behave similarly in terms of adopting row planting, a recent innovation in Ethiopian agriculture due to: 1) endogenous or peer effects, 2) exogenous or contextual effects, and 3) correlated effects, and test for effects on farm productivity. To overcome some of the problems related to identification discussed above, this study uses a random assignment of matches within the sample, and controls for the lagged outcomes of peers. To complement our results, we, furthermore, use self-reported ties as a second measure of social networks, also to see whether they can be an independent source of information, similarly to van den Broeck and Dercon (2011).

3. Data

3.1. Sampling and measurement issues

We conduct a household survey between January and March 2014 in Ethiopia, which builds upon an existing sample of agricultural households surveyed in 2006 and again in 2010 in Oromia region under an NGO project that promoted agricultural innovations and ended in 2010.[2] The baseline survey used a mix of purposive and random sampling procedures to select 390 households from three study sites (Aredo, et al. 2008). The primary sampling unit consisted of a pair of neighboring districts or *woredas* which were chosen based on the density of cultivation of the major crop and on the presence of active farmers' cooperatives. In the second stage, *kebeles* (sub-districts) with active farmers' cooperatives were purposively selected. Finally, using the number of participating households within a cooperative as the sampling frame, households were then randomly selected. The major crop and total sample size in each research site are summarized in Table 1.

Table 1: Geographical distribution of the sample

	Bakko-Siree (major crop: maize)		*Lume-Adaa* (major crop: teff)		*Hettosa-Tiyyo* (major crop: wheat)		Total
District	Bakko	Sibu Siree	Lume	Adaa	Hettosa	Tiyyo	
Sample size at baseline (2006/07)	65	65	65	65	65	65	390
Number of households	64	63	63	64	62	63	379

Our survey covered 379 households but some households rented out their land and others did not cultivate any one of the main crops (maize, wheat or teff) either in the present or previous production seasons. We exclude these from the subsequent analysis because of the need for complete data, also on lagged values of yields, which reduces the final sample size to 350 households. Nevertheless, since part of the data is at the individual level

[2] The analysis in this paper mainly relies on the 2014 data as the variables of interest in this analysis (networks and row-planting) are missing in the preceding surveys. Yet, we make use of lagged values of some explanatory variables for identification.

(separately for the household heads and their spouses if married), the sample size for the individual level analysis is 681.

3.2. Social networks

As noted before, early studies on networks define the latter based on membership to certain groups such as the village, clan or as otherwise determined by social and cultural characteristics. As discussed in Section 2, these definitions may ensure that networks are exogenously determined but they allow limited room for variation among households. More recent studies, on the other hand, rely on individual level links reported by the respondent either inside or out of a sample. While these more recent approaches may allow variations among individuals and households, they suffer from a truncation bias, especially if respondents are allowed to name only a certain number of links. To be specific, their true networks may be much wider or key nodes and important links may have been forgotten (Maertens and Barrett, 2012).

Our approach follows Maertens and Barrett (2012) and Conlay and Udry (2010) to collect network data using a random matching within sample where each respondent is matched with six randomly drawn individuals (three male and three female ones) from the sample and the same village (or *kebele*). Conditional on knowing the match, we construct network measures by eliciting details of the relationship between the individual and the match, and combine this information with household level background characteristics. Since information flows occur not only between, but also within households (thereby highlighting the importance of transitivity in terms of information flow and clustering within networks) we match the household head and his spouse separately to six individuals each, with each of the six matches being randomly drawn from different households of the sample within the village.

Further, to complement the analysis and to minimize the chance of omitting a key network node due to the random matching within sample, we also ask each respondent for the four other individuals they know best and elicit details of their relationships. These four contacts per respondent, that is, a maximum of eight per household, may include both the ones whom the respondent mostly interacts with for information or business matters and those whom the respondent relies upon as an informal source of insurance. These self-reported links are left out from our estimation of network effects for technology adoption as we do not have the matches' background characteristics that are crucial for identification because self-reported links may come from outside the surveyed sample. Therefore, we solely use these self-reported links to estimate the determinants of information or learning links.

Before we move on to the econometric analysis, we briefly examine the characteristics of networks. Tables 2 and 3 present gender disaggregated network characteristics from both self-reported networks and from networks elicited through random matching within sample, respectively. Out of the four network partners the respondents mention, the descriptive statistics in Table 2 suggest that a little over half of the links do not have family ties with the respondent. By comparison, male respondents quote a higher percentage of close relatives among their links. Yet, the descriptives also suggest that both male and female respondents identify network partners who are around their own age, who mainly reside in the same village, and have the same native language, religion, and gender as the respondent. Furthermore, almost all respondents claim that their network partners and themselves help each other in times of need (or provide each other with an informal type of insurance). In terms of occupation, male respondents are, on average, more likely to identify links who are mainly farmers; and they report having discussions on farming or business matters with their network partners more often than female respondents do.

The data presented in this paragraph seem to support the criticism against heavily relying on definitions of networks based on membership in a specific group and support our choice of using random matching within sample for the key analysis. For example, if we were to rely only on networks defined along kinship, we would likely end up using a radically smaller network and miss important links as more than half of the links the respondents mention do not also belong to the respondent's family. Similarly, relying on definitions of networks based on, for example, religion, area of residence, ethnicity, and others would result in the omission of important links as shown in Table 2.

Table 2. Characteristics of self-reported network connections by gender of the respondent

	Female	Male
Network connections	N=1392	N=1313
	Percent	Percent
Self-assessed relationship:		
• Close relative (binary)	23	38
• Distant relative (binary)	20	11
• No family link (binary)	57	51
Male (binary)	23	93
Similar age (binary, difference<=5 years)	35	32
Same village (binary)	89	84
Discussion of business/farming matters (binary)	63	87
Same mother tongue (binary)	92	93
Same religion (binary)	87	86
Same *iddir* (binary)	70	77
Farmer (binary)	51	84
Help each other when in need (binary)	98	99

Note: 350 female and 331 male respondents.

In Table 3, we find that female respondents know a smaller proportion of their randomly drawn matches than their male counterparts. To be specific, female respondents know 3.7, male respondents 4.4 individuals on average out of their six random matches. Of those matches known to the respondent, less than 13 percent are related to the respondent (by blood or by marriage) for both sexes, while significantly more male respondents report belonging to the same *iddir* as their match.[3] Female respondents are less likely to discuss farming and business matters with their matches than male respondents, but quote an equal share of their matches to help them in case of needs.

[3] An *iddir* is a community-based funeral organisation that is common in Ethiopia.

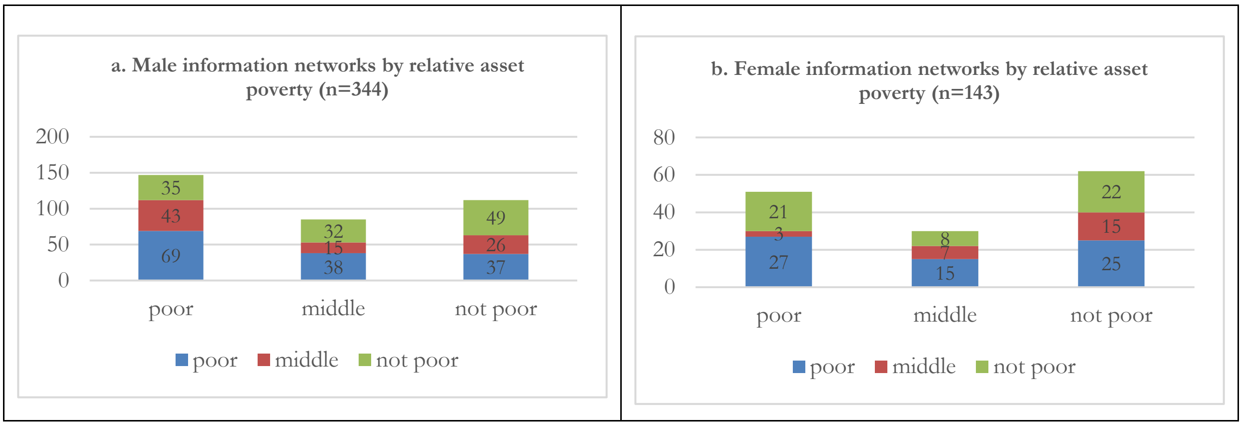
Table 3. Characteristics of network connections derived through random matching within sample by gender of the respondent

	Female	Male
Network connections	N=1288	N=1450
	Percent	Percent
Respondent knows the match (binary)	66	79
Conditional on knowing the match:		
Related by blood or marriage (binary)	10	12
Male (binary)	51	52
Discussion of business/farming matters (binary)	12	24
Same *iddir* (binary)	33	51
Help each other when in need (binary)	36	40
	Mean (Std. Dev.)	
Distance between households (in minutes walking)	21 (19)	21(20)
Average number of matches known by the respondent	3.68 (1.75)	4.38 (1.38)
Average number of matches known by the household	7.22 (2.78)	

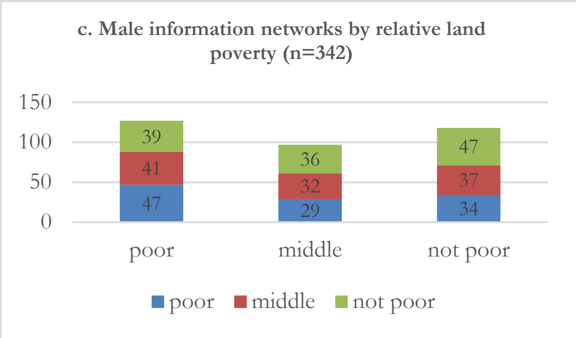
Note: 350 female and 331 male respondents.

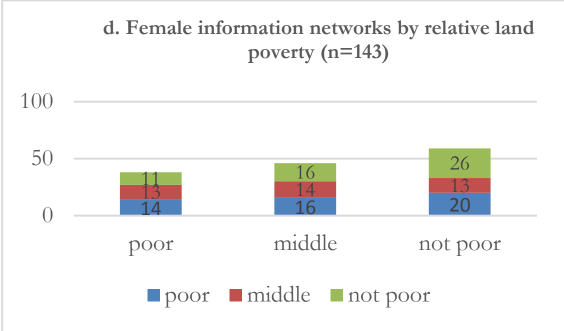
Another way of looking at network characteristics and in particular the characteristics of matches is to group respondents and their matches based on their relative poverty standing as proxied by the value of their asset and land holdings.[4] Since we expect that knowledge spillovers relating to agricultural innovations would come from networks that involve discussions regarding farming matters, we only consider network connections with whom respondents report having discussed farming and business matters. As shown in Figure 1, male respondents who are relatively poor along both asset- and land-based poverty measures are linked mainly to individuals who are also relatively poor. Similarly, those who are not poor are also connected mainly to individuals of a similar standing along both relative poverty measures. This pattern of interactions within social class is also evident for poor female respondents for both poverty measures, but all other classes (middle groups for males and females, non-poor class for females) show less clear interaction trends.

Figure 1. Network characteristics based on relative poverty measures



[4] Following Bandiera and Rasul (2006), we calculate relative poverty measures using two indicators: the size of own land holdings and the value of household assets including livestock. Hence, a household is considered: 'poor' (if the corresponding value is smaller than 75% of the sample average), 'middle' (if the value is between 75% and 125% of sample average), and 'not poor' (if the value is bigger than 125% of the sample average).





Lastly, it is worth noting from both self-reported and randomly allocated matches that, while both sexes are likely to similarly identify own links along gender, cultural or geographic lines, the nature of their relationships slightly diverge when asked whether they had discussed farming or business matters with the link. To be specific, the share of matches male respondents claim to have discussed farming or business matters with is twice the size female respondents report (Table 3). Yet, this should not be surprising: as men are generally perceived as decision-makers and involved in these activities in rural Ethiopia, which may have biased women to underestimate and underreport the significance of their own interactions. Another point that is apparent from the descriptive statistics of the two types of networks is that there seems to be a lack of significant variation in the data when networks are measured based on self-reported links, which suggests endogenous network formation. As this is likely to complicate the identification of network effects, we rely on random matching within sample as described above.

3.3. Other descriptive statistics and variable definition

Table 4 presents a general overview of the socio-economic and demographic characteristics of the sample households. The data suggest that 10 percent of the households in the sample are female-headed, the average age of the household heads is 50 years. Furthermore, about one third of household heads have not attended any schooling, while the average level of schooling attended by household heads is 4.6 years. Households in this sample appear to hold larger land holdings on average compared to the smallholder country average of about one hectare.[5] We report indicators of wealth such as the values of consumer durables and production assets in Ethiopian Birr (ETB) based on the own estimations of respondents.[6] We define household productivity as the value of all crops the household produced in a given production year divided by the hectare of farm land the household had access to. Using the official consumer price indices from 2006 to 2014, we deflate current market prices to 2006 constant prices as we will be making use of lagged values in subsequent analysis. The average livestock holding is 8.3 tropical livestock units and households are located around 20 minutes walking time to the

[5] Note, however, that, in terms of land holdings, households in the three study sites in general hold more land than the country average, also outside of our sample.

[6] The official exchange rate during the time of the survey was 1 USD=19 ETB according to the National Bank of Ethiopia (see http://www.nbe.gov.et/market/searchdollarcurrencies.html, accessed last February 9th, 2016).

nearest asphalt road or to the office of the agricultural extension agent. Other service centers such as markets, coop offices, input dealer shops, district towns and the nearest micro finance institution are all located in the range of 35 to 90 minutes walking time one way on average.

Table 4. Descriptive statistics related to socio-economic characteristics (N=350)

Variable	Mean	Std. Dev.	Med	Min	Max
Sex of household head (1 if Female)	0.10	0.30		0	1
Age of household head (years)	50.4	13.3	50	25	88
Number of years of schooling completed by household head	4.62	4.10	4	0	16
Household size (number of household members)	6.76	2.36	7	1	16
Number of adult household members	3.66	1.57	4	0	8
Total land size owned by household (hectares)	2.21	1.40	2	0	8.25
Total current value of production assets (ETB)	5670	14723	1635	0	203765
Total current value of consumer durable assets (ETB)	7981	31803	2800	0	561950
Total livestock holdings (TLU)	8.23	5.23	7.6	0	35.05
Household treated in past NGO project (binary)	0.71	0.46	1	0	1
Household adopted row planting (binary)	0.63	0.48	1	0	1
Farm productivity 2014 (output/ha), value at 2006 prices	5071	6290	4234	2.11	85024
Farm productivity 2010 (output/ha), value at 2006 prices	3783	1983	3417	41	14551
Farm productivity 2006 (output/ha), value	3928	2457	3448	317	21917
Number of days listening to radio over the past year	220	143	206	0	365
Number of days watching television over the past year	133	151	48	0	365
Access to services/institutions (walking time in minutes)					
Distance to asphalt road	19.4	11.78	17	2	60
Distance to market	64.5	31.60	60	11	158
Distance to district town	93.3	37.66	93	20	185
Distance to coop office	35.2	17.08	34	4	98
Distance to input dealer	72.0	31.40	68	21	160
Distance to farmer training center (FTC)	23.2	11.41	20	7	78
Distance to micro-finance institution (MFI)	89.9	36.00	90	21	180

4. Empirical strategy and results

4.1. Empirical strategy

We analyze the role of networks in four parts. Firstly, we examine the determinants of learning links among farmers based on both the self-reported network connections and those that were allocated based on the random matching within sample. Next, we test whether network size and structure are correlated with the probability of adopting row planting. In the two remaining parts we then examine the effects of social learning on the likelihood of adopting an innovation (row planting in our case) and on average farm productivity.

We begin by defining that a 'learning link' or 'information link' exists if the respondent discussed farming or business matters with the network partner in the past 12 months. Following van den Broeck and Dercon (2011), De Weerdt (2002), and Fafchamps and Gubert (2007), we explore the determinants of information links in a dyadic regression framework where attributes z_i and z_j, for example, of network partners or nodes i and j enter regressions in differences, (z_i - z_j), and in sums, ($z_i + z_j$). For example, if z denotes age, then age enters the regression twice: fist as the difference between the ages of node i and node j, and simultaneously as the sum of the ages of the two nodes. According to Fafchamps and Gubert (2007), this approach allows capturing the effects of differences in attributes and also of the combined level effect of the attributes on the variable of interest, respectively.

Let the binary variable L_{ij} represent the existence of an information link between network nodes and take a value of one node i discussed farming or business matters with node j and zero otherwise. A regression equation for the determination of a learning link can then be specified as:

$$L_{ij} = \alpha_0 + \alpha_1 w_{ij} + \alpha_2(z_i - z_j) + \alpha_3(z_i + z_j) + u_{ij} \quad , \qquad (1)$$

where w_{ij} captures attributes which do not vary between paired households such as geographic distance, z denotes other individual and household-level attributes that may determine the probability of a link between i and j, and u_{ij} is the error term. Since individuals that form networks and the networks of each node may have similar characteristics, the residuals are likely to be correlated. We allow for the error variances to be correlated through two-way clustering of the standard errors at the individual and at the match's level (Cameron et al., 2011 and Petersen, 2009).

To see whether an existing link and other characteristics that determine link formation are also correlated with observed behavior such as row planting, the following regression equation is estimated:

$$R_i = \alpha_0 + \alpha_1 L_{ij} + \alpha_2 w_{ij} + \alpha_3(z_i - z_j) + \alpha_4(z_i + z_j) + u_{ij} \quad , \qquad (2)$$

where R_i is an indicator variable that takes a value of one if farmer i adopts row planting and zero otherwise. L, w, and z are defined as before. Estimating equations 1 and 2 already helps us understand the nature of link formation and how links may be correlated with actual behavior but neither is able to identify a causal relationship between observed behavior such as the adoption of an innovation and network effects as link formation and own innovative behavior may both be driven by confounding factors.

Further, networks are mechanisms in which group behavior may influence individual behavior, and measuring network effects is tantamount to estimating neighborhood or peer effects, which is prone to simultaneity bias. As we recall from Section two, Manski (1993) refers to this as the "reflection problem" and hypothesizes that individuals belonging to the same group tend to behave similarly due to endogenous peer effects, exogenous or contextual effects, and correlated effects.[7] Since policy will have a social multiplier effect in the presence of endogenous effects (Manski, 1993), we identify endogenous effects separately from correlated and contextual effects. Hence, following Manski (1993), we employ the standard linear-in-means empirical model to estimate network effects, which can be specified as:

[7] According to Manski (1993) endogenous, contextual and correlated effects arise when the propensity of an individual to behave in a specific way varies with the behavior of the group, the exogenous characteristics of the group, and when individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments, respectively.

$$y_{ikt} = \beta \overline{y}_{-ikt} + \overline{x}_{-ikt}\gamma + x_{ikt}\lambda + \delta_j + \varepsilon_{ikt} \quad , \tag{3}$$

where y_{ikt} denotes an outcome (the adoption of row planting or average farm productivity in our case) for individual i who belongs to network k at time t; $\overline{y}_{-ikt}$ denotes the average outcome of the peers excluding i at time t; $\overline{x}_{-ikt}$ denotes the average value of the observable characteristics of peers excluding i; x_{ikt} denotes a vector of i's observable characteristics; δ_k denotes location fixed effects and controls for unobservable characteristics common to all network points in the village or district that may influence adoption or productivity; and ε_{ikt} is a time-variant unobserved component. $\beta \neq 0$, $\gamma \neq 0$, and $\delta \neq 0$ suggest the existence of endogenous-, contextual- and correlated effects, respectively, λ denotes direct effects.

However, as it stands, equation (3) is unable to solve the reflection problem since the behavior of the individual also affects the mean behavior of his group or network. Hence, to improve identification we introduce dynamism to the model as suggested by Manski (2000) by replacing $\overline{y}_{-ikt}$ with its lagged value $\overline{y}_{-ikt-1}$ of individual i's reference group (more on this in Section 4.2.3). We allow for differentiated effects by estimating equation (4) with a focus on the network connections of the household head, and on the connections of both the household head and the spouse combined.

$$y_{ikt} = \beta \overline{y}_{-ik,t-1} + \overline{x}_{-ikt}\gamma + x_{ikt}\lambda + \delta_k + \varepsilon_{ikt} \tag{4}$$

4.2. Results and discussion

As pointed out in the preceding section, we present the analysis of econometric results in four parts. We first examine the determinants of a learning link in part 1 and we follow that up by analyzing whether network size and structure are actually correlated with the probability of adopting row-planting technique (part 2).[8] We identify social learning effects on adoption of row-planting technique and average farm productivity in parts 3 and 4, respectively. All continuous variables excluding those which enter regressions in differences (or changes) are log-transformed.

4.2.1. Determinants of information links

As mentioned above, we define a link as an 'information' or a 'learning' link if the respondent had discussed farming or business matters with the match in the past twelve months prior to the survey. Tables 5 and 6 present the marginal effects of Probit estimations of equation 1, that is, the determinants of whether a randomly allocated or self-reported link is an information link, respectively. We use a dyadic framework and estimate the relationship for household heads, male respondents, female respondents, or the latter two combined. To be specific, column 1 of Table 5 relates to all respondents combined regardless of gender and relationship of the respondent to the household head, while the results in columns 2 and 3 refer to male and female respondents, respectively. Column 4 and 5 are based on heads of households without and with the sums of certain control

[8] We find very little, if any, change of results when bootstrapping the standard errors in all estimations of Sections 4.2.1 and 4.2.2. Results not reported but available upon request.

variables. Table 5 suggests that belonging to the same *iddir*, having blood ties, and having high frequency of meetings with the match all significantly increase the likelihood of a learning link regardless of the gender and whether the respondent is the household head or spouse. Other forms of network partnership such as being one that could be used in times of need also improves the likelihood of a learning link. These results also hold for self-reported networks (Table 6) except that belonging to same *iddir* appears to improve the likelihood of a learning link only for female respondents while having an insurance partner seems to be important only for male respondents.

Table 5. Determinants of learning links (using random matching within network data), marginal effects of a Probit estimation‡

(Dependent variable: 1 if i discusses farming or business matters with j, 0 otherwise)

	ALL		MALE		FEMALE		HH_HEAD1		HH_HEAD2	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
Same ethnicity+	0.01	0.02	-0.01	0.04	0.01	0.03	0.01	0.04	0.00	0.04
Same religion+	0.01	0.02	0.05	0.03	0.00	0.02	0.03	0.03	0.03	0.03
Same iddir+	0.08 ***	0.02	0.06 *	0.03	0.06 **	0.03	0.08 **	0.03	0.07 **	0.03
Help when in need+	0.15 ***	0.03	0.17 ***	0.04	0.11 ***	0.03	0.18 ***	0.04	0.17 ***	0.04
Related(blood/marriage)+	0.14 ***	0.04	0.15***	0.06	0.13 ***	0.04	0.15 ***	0.06	0.14 ***	0.06
Meeting frequency	0.00 ***	0.00	0.00 ***	0.00	0.00	0.00	0.00 ***	0.00	0.00 ***	0.00
Geo.dist.(i,j)(ln)	-0.02 **	0.01	-0.04 **	0.02	-0.02	0.01	-0.03	0.02	-0.03	0.02
Having plots nearby+	0.03	0.03	0.05	0.06	-0.01	0.03	0.09*	0.06	0.06	0.05
Radio list.(freq)	0.00	0.00	0.00 ***	0.00	0.00 *	0.00	0.00 ***	0.00	0.00 ***	0.00
Tv watch.(freq)	0.00 ***	0.00	0.00 **	0.00	0.00 **	0.00	0.00 **	0.00	0.00 **	0.00
Travel to town.(freq)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Diff. gender dummies	-0.03	0.02	-0.24 ***	0.03	-0.03	0.02	-0.2 ***	0.03	-0.1 ***	0.04
Diff. of age (i,j)	0.00 ***	0.00	0.00 *	0.00	0.00 ***	0.00	0.00	0.00	0.00	0.00
Diff. educ (i,j)	0.00	0.00	0.00	0.00	0.01 **	0.00	0.00	0.00	0.00	0.00
Diff. HH size (i,j)	0.00	0.01	0.01	0.01	-0.01	0.01	0.00	0.01	0.00	0.01
Diff. no. of men	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Diff. land size	-0.01*	0.01	-0.02*	0.01	0.00	0.01	-0.01	0.01	-0.01	0.01
Diff. treatment status	0.02	0.02	0.02	0.03	0.01	0.02	0.01	0.02	0.02	0.03
Sum gender dummies	0.10 ***	0.02	0.00	-		-			0.12 ***	0.04
Sum of age (i,j)	0.00	0.00	0.00	0.00	0.00	0.00			0.00	0.00
Sum of educ (i,j)	0.00	0.00	0.00	0.00	0.00	0.00			0.00	0.00
Sum of HH size (i,j)	0.00	0.00	0.00	0.01	0.00	0.00			0.00	0.01
Sum no. of men	0.00	0.01	0.00	0.01	0.00	0.01			0.00	0.01
Sum of land size	0.01	0.01	0.01	0.01	0.00	0.01			0.01	0.01
Sum treatment status	0.02	0.02	0.04	0.02	0.01	0.02			0.04*	0.02
Hitossa-Tiyo+	0.01	0.03	0.02	0.05	-0.02	0.03	0.01	0.05	0.05	0.05
Adaa-Lume+	0.02	0.03	-0.02	0.05	0.01	0.03	-0.03	0.04	-0.02	0.05
Observations	2339		1285		1054		1402		1402	
Log lik.	-878.6		-530.6		-302.7		-601.3		-584.7	
Pseudo R2	0.24		0.27		0.22		0.24		0.26	

+Note: dy/dx for factor levels is the discrete change from the base level. Other covariates fixed at their means.
‡Probit coefficients are reported in the appendix as Table A1.

The age difference variable is positive and statistically significant in Table 5 (columns (2) and (3)) for both male and female respondents implying that younger people are more likely to mention older ones as their learning link. This is in contrast with the results from self-reported links (Table 6), which suggest that the likelihood of a learning link is higher within age groups. Gender of the network partner does not seem to be an important factor for the establishment of a learning link for female respondents, while the existence of a learning link with opposite sex seems less likely for male respondents and male household heads (Table 5). Yet, there seems to be a level effect on learning links across same gender and it is especially the case among male household heads. This again is also in line with results from self-reported networks (Table 6) which suggest that having a network partner of the same gender improves the likelihood of a learning link for both female and male respondents.

Table 6. Determinants of learning links (using self-reported networks), marginal effects of a Probit estimation‡

(Dependent variable: 1 if i discusses farming or business matters with j, 0 otherwise)

	ALL		MALE		FEMALE		HH_HEAD	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
Same ethnicity	0.02	0.05	-0.01	0.04	0.02	0.09	0.02	0.05
Same religion	-0.04	0.04	0.02	0.03	-0.10*	0.06	0.00	0.03
Same iddir	0.11***	0.04	-0.01	0.03	0.14***	0.05	0.02	0.03
Close family	0.13***	0.03	0.06**	0.02	0.16***	0.05	0.07***	0.03
Distant family	0.10***	0.03	0.05**	0.03	0.16***	0.05	0.07***	0.02
Same village	0.01	0.06	0.12	0.07	-0.08	0.10	0.09	0.07
Same kebele	-0.01	0.08	0.05	0.03	-0.07	0.14	0.05	0.04
Same gender	0.22***	0.04	0.11**	0.05	0.15**	0.06	0.11***	0.04
Same age	0.07***	0.02	0.03	0.02	0.09**	0.04	0.04**	0.02
Farmer	0.20***	0.03	0.22***	0.06	0.09*	0.05	0.23***	0.05
Meet less than 1/week	0.20***	0.06	0.15*	0.07	0.17**	0.08	0.15**	0.07
Help when in need	0.11	0.12	0.26	0.18	0.01	0.14	0.36**	0.17
Max of age from i & j‡	0.00*	0.00	0.00*	0.00	0.00	0.00	0.00*	0.00
Education 0-4(dummy)	0.05	0.04	0.05	0.03	-0.02	0.07	0.07**	0.03
Education 5-8(dummy)	0.03	0.04	-0.02	0.04	-0.06	0.08	0.00	0.04
Education 8+(dummy)	0.06	0.05	-0.04	0.05	0.05	0.09	-0.01	0.05
Radio list.(freq)‡	4.8E-05	9.2E-05	8.5E-05	8.3E-05	-2.0E-04	1.5E-04	2.4E-05	8.4E-05
Tv watch.(freq)‡	2.0E-04	1.3E-04	1.1E-04	9.8E-05	3.3E-04*	1.9E-04	4.1E-05	1.0E-04
Travel to town.(freq)‡	4.7E-04**	2.3E-04	1.3E-04	1.3E-04	1.0E-03	6.3E-04	2.0E-04	1.5E-04
Land size (ha) (ln)‡	0.02**	0.01	0.02**	0.01	0.02	0.02	0.02**	0.01
Hitossa-Tiyo (dummy)	-0.07	0.05	0.01	0.04	-0.10	0.08	0.02	0.04
Adaa-Lume (dummy)	-0.11**	0.05	0.03	0.03	-0.23***	0.07	0.03	0.03
Observations	2565		1270		1295		1400	
Log lik.	-1233.5		-362.57		-772.19		-436.3	
Pseudo R2	0.1465		0.258		0.0956		0.2401	

‡These covariates are fixed at their means. dy/dx for factor levels is the discrete change from the base level.
‡Probit coefficients are reported in the appendix as Table A2.

Contrary to expectations, other socio-economic indicators such as education, household size, and the size of land holdings seem to be less important for the likelihood of learning links. In addition, while evidence suggests that living near the match tends to only weakly improve the likelihood of learning links among male respondents, the location of residence in relation to the network partner does not appear to be important in general and for self-reported networks in particular. Rather, having a network partner who is also a farmer increases the likelihood of a learning link in self-reported networks. These results therefore suggest that our findings are not only driven by correlated and contextual effects, and hence endogenous formation of networks seems to be of less a concern in this specific case.

Further, since it is essential to control for all potential sources of information in estimations of 'learning links' (Matuschke and Qaim, 2009; Maertens and Barrett, 2012), we do so by accounting for the frequency of travel the respondent makes to the nearest town and the frequency that the respondent listens to the radio and watches television. We proxy for other information sources such as extension services, markets, and also other fixed effects by controlling for district dummies. Our results suggest that frequently following mass-media such as radio and television facilitates the chance of a learning link but only from estimations using networks from the 'random matching'-exercise. The frequency of travel to nearest town does not appear to be important in the probability of a learning link at individual level analysis in both methods of sampling networks. Yet, the frequency of travel matters at the household level for self-reported networks. Finally, the results do not qualitatively change when we include indicators for smaller geographic units (such as *kebele*) instead of district dummies.

4.2.2. The effect of social network size and structure on the probability of adopting row planting

In this section we directly examine whether learning links are correlated with innovation behavior. We start by noting that our data do not suggest that spouses individually hold farms and hence we assume that the adoption of an innovation is a household-level decision, represented by behavior of the household head. Thus, unlike the investigation of determinant of learning links at the individual level, we conduct household-level analyses in this and the subsequent sections. Marginal effects of probit estimation from a dyadic regression framework as outlined in equation 2 relating the adoption of row planting to the characteristics of the household head, the match and the nature of their relationship, and other controls are presented in Table 7, conditional on knowing the randomly allocated match. We specify the nature of the link between nodes, which may involve advice; informal insurance; kinship; belongingness to same *iddir*, ethnicity or religion; frequency of meetings between the two; the distance between the households; and whether they hold adjacent plots.

Table 7. The effect of social network structure on the probability of adopting row planting, marginal effects of a Probit estimation‡

(Dependent variable: 1 if i adopts row planting, 0 otherwise)

	Household head 1		Household head 1	
	dy/dx	Std. Err.	dy/dx	Std. Err.
Discussion on farming/business⁺	0.066**	0.028	0.059**	0.028
Help when in need⁺	-0.053	0.028	-0.044	0.028
Related(blood/marriage)⁺	-0.018*	0.042	-0.018	0.041
Meeting frequency	0.000	0.000	0.000	0.000
Geo.dist.(i,j)(ln)	-0.041**	0.017	-0.036**	0.017
Having plots nearby⁺	0.011	0.047	0.018	0.046
Radio list.(freq)	0.000	0.000	0.000	0.000
Tv watch.(freq)	0.000***	0.000	0.000***	0.000
Travel to town.(freq)	-0.001***	0.000	-0.001***	0.000
Diff. gender dummies	0.014	0.026	0.012	0.026
Diff. of age (i,j)	-0.002*	0.001	-0.001	0.001
Diff. educ (i,j)	0.001	0.003	0.001	0.003
Diff. no. of men	0.006	0.006	0.006	0.006
Diff. land size	0.051***	0.008	0.053***	0.008
Diff. treatment status	0.041**	0.018	0.034*	0.018
Sum gender dummies	-0.051*	0.027	-0.048*	0.026
Sum of age (i,j)	0.000	0.001	-0.001	0.001
Sum of educ (i,j)	0.004	0.003	0.004	0.003
Sum no. of men	0.008	0.006	0.008	0.006
Sum of land size	0.039***	0.008	0.041***	0.008
Sum treatment status	0.063***	0.019	0.064***	0.019
Same ethnicity⁺	0.027	0.030	0.013	0.029
Same religion⁺	0.039	0.033	0.024	0.032
Same iddir⁺	0.016	0.028	0.027	0.028
Dist. asphalt road (minutes)(ln)			0.001	0.001
Dist. market (minutes)(ln)			0.000	0.000
Dist. district (minutes)(ln)			0.000	0.001
Dist. coop office (minutes)(ln)			0.000	0.000
Dist. input dealer (minutes)(ln)			0.000	0.000
Dist. FTC (minutes)(ln)			0.000	0.001
Dist. MFI (minutes)(ln)			-0.001*	0.001
Hitossa-Tiyo⁺	-0.699***	0.037	-0.669***	0.042
Adaa-Lume⁺	-0.849***	0.026	-0.804***	0.036
Observations	1402		1404	
Log lik.	-567.8		-557.9	
Pseudo R2	0.37		0.38	

⁺Note: dy/dx for factor levels is the discrete change from the base level. Other covariates fixed at their means.
‡Probit coefficients are reported in the appendix as Table A3.

Table 7, column 1, shows that the 'advice link'- *having discussed farming or business matters with the network partner*- is statistically significantly associated with the likelihood of adopting row planting. Perhaps this might be indicative of suggestive evidence of learning externalities, which we formally test in the next part. While the statistical significance of the variable for the distance between households may cast doubt on the existence of correlated behaviors, other potential network indicators such as kinship, belonging to same *iddir*, ethnicity or religion, having plots next to each other, are not statistically significantly associated with the probability of adopting this innovation. Further, in addition to indicators for mass media such as radio and television, the results remain robust in column 2 after controlling for more potential sources of information and extension services proxied by average distance between farmer's residence and offices of the extension agent, cooperative offices, input dealer shops, nearest markets, nearest micro-finance institutions, district towns, and nearest asphalt road. Surprisingly, none of these additional sources of information and other services appear to be strongly associated with the probability of adopting row planting.

Watching television more frequently appears to affect the probability of adopting row planting positively and statistically significantly. This may show the power of visual aids in convincing farmers more strongly than other sources of information specified in this study and may be in line with Bernard et al. (2015) who establish the effectiveness of video-based interventions in inducing behavioral changes in rural Ethiopia. Surprisingly, however, making more frequent travels to the nearest town seems to negatively affect the likelihood of adopting this innovation. This may be because the cost of receiving new information and knowledge from such travels outweighs the potential benefits because row planting is currently still perceived as a labor-intensive practice in Ethiopia and making frequent travels to towns may just induce a trade-off between the required labor supply and the chance of receiving new information. Although it is beyond the scope of this paper, this could potentially be investigated by testing the separability of household labor supply and demand.

Moving on to other results, the sum and difference in land holdings between the farmer and the match are both positive and statistically significant, thereby implying that innovation adoption is more likely among networks with both large and small farmers. This is in line with expectations as the size of land holdings is a very good predictor of wealth in rural Ethiopia, and as farmers with more wealth are likely to experiment with new innovations, which may create the possibility of knowledge spillovers to smaller farmers in their network. Our results also suggest that farmers having more links with farmers of similar age are more likely to adopt the new technology. The result, however, is only weakly statistically significant and not robust to different specification. In contrast, the variable that represents the sum of male dummy is negative and significant implying that links with more male household heads are less likely to adopt row planting. This is less intuitive, however, because having many male network connections may mean more learning links as we find in the previous section. Yet, we cannot rule out the fact that the results may present evidence of strategic delays in the adoption of this innovation when there are many male links in one's networks.

On the other hand, variables that represent the sum and difference of farmers who were treated by an NGO project in the past are both positive and statistically significant.[9] This implies that non-treated farmers who are linked with past project beneficiaries are more likely to adopt row planting, which is in line with expectations as the NGO project promoted related agricultural innovations and farmers may learn from others. In summary, having controlled for many factors that could proxy for correlated behavior within networks, the results in this section suggest that learning from network connections exists among the study households, which we formally test in the next section.

4.2.3. The effect of networks on technology adoption

We noted in Section 2 that the identification of social network effects is complicated due to the presence of omitted variables and simultaneity. Our rich dataset allows us to effectively control for factors that may otherwise generate spurious correlation. To correct for the reflection problem, Manski (2000) suggests to introduce dynamism to the model and to relate individual behavior to lagged rather than contemporaneous values of group mean behavior. An alternative approach Manski suggests is to use instrumental variables that directly affect the outcomes of some, but not all group members. The latter is equivalent to Angrist and Pischke's (2009, p.196) suggestion to use "some measure of peer quality which predates the outcome variable and is therefore unaffected by common shocks." We fit equation 4 using a slightly modified combination of the two options as explained next.

Row planting is a recent innovation in Ethiopia and our data were collected in 2006 and again in 2010 long before this innovation was promoted in 2012/13. Therefore, we expect that lagged indicators such as farm productivity measured as output per hectare from the baseline period to be unaffected by present common shocks or the new innovation (or row planting). In addition, only some of the study households were treated by an NGO project during the baseline period (2006-2010) and, again, we do not expect that the new innovation would affect their past treatment status. On the contrary, we expect that both past productivity levels and past treatment status would affect a farmer's present innovation behavior. Our data refer to the production years 2006/07, 2009/10 and 2013/14 and since this innovation was promoted half-way between the second and third data points (and that innovation adoption being a rather slow process) we believe that we have a reasonable lag length, not to mention availability of the data as such. Our two identifying variables are therefore the change in productivity between 2006/07 and 2009/10 and past treatment status of the farmer and his peers. We choose the change in productivity rather than levels because doing so helps to control for time-invariant characteristics as well as it would reflect past trend in the innovation behavior of farmers, which is likely to be correlated to present ones. Further, we use various specifications and the change in productivity between 2013/14 and 2009/10 as identifying variables for a robustness check.

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[9]The NGO project promoted various agricultural technologies and practices (such as improved varieties and improved natural resource management practices excluding row planting). The project was terminated before the data in 2010 were collected.

Tables 8a and 8b present results that identify endogenous (network) effects separately from correlated and contextual effects. In both tables, columns 1 and 2 report results using networks from only the household head, while columns 3 and 4 are based on networks from both the spouse and the household head combined. Results clearly indicate that there is strong evidence of network externalities in the adoption of row planting in the study areas. For example, the results in column 1 of Table 8a suggest that the average change in peers' productivity between 2009/10 and 2006/07 is strongly associated with the probability of a farmer adopting row planting. This result is even stronger when we use the wider network, i.e. combined networks from both spouses (columns 3 and 4), which may be interpreted as evidence of transitivity of relationship or clustering among networks as described above. Furthermore, the number of treated individuals in one's network statistically significantly increases the probability of adopting row planting (columns 1 and 3). This evidence of endogenous effect is present even after controlling for own past treatment status.

Table 8a. The effect of social learning on the adoption of row planting, marginal effects of a Probit estimation‡
(Dependent variable: 1 if i adopts row planting, 0 otherwise)

	Networks of the household head				Networks of both spouses			
	dy/dx	Std. Err	dy/dx	Std. Err	dy/dx	Std. Err	dy/dx	Std. Err
Average value of peers' characteristics								
Change in ave. yield (2006-2010)	4E-05*	2E-05	2.1E-05	2E-05	8E-05***	3E-05	5.3E-05**	2.6E-05
Share of treated	0.19*	0.12	0.13	0.11	-0.12*	0.20	-0.26	0.18
Ave. age(years)(ln)	0.12	0.17	0.10	0.16	0.21	0.24	-0.02	0.23
Ave. HH size(ln)	0.05	0.20	0.04	0.19	0.07	0.04	0.05	0.04
Ave. value of prod. assets(ln)	0.04	0.03	0.02	0.03	0.01	0.04	-0.04	0.04
Ave. value of cons. durables(ln)	0.02	0.03	0.01	0.03	0.08	0.14	0.15	0.12
Ave. livestock holdings(TLU)(ln)	0.03	0.12	0.01	0.10	-0.14	0.11	-0.03	0.10
Ave. landholdings(ha)(ln)	-0.02	0.10	0.01	0.10	0.24	0.13	0.09	0.12
Household characteristics								
Female HH head+	0.02	0.08	0.01	0.08	0.03	0.08	0.03	0.07
Age of HH head (years)	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01
Square. of age of HH head	8.7E-05	0.0001	6.9E-05	1E-04	5E-05	1E-04	3.5E-05	1.1E-04
Education 0-4(dummy)+	-0.02	0.08	-0.04	0.08	0.00	0.08	0.00	0.07
Education 5-8(dummy)+	0.11	0.07	0.09	0.06	0.11*	0.06	0.09	0.05
Education 8+(dummy)+	0.07	0.08	0.07	0.07	0.07	0.07	0.08	0.06
Radio list.(freq)	1.5E-04	2E-04	1.5E-04	2E-04	5E-05	2E-04	4.1E-05	1.6E-04
Tv watch.(freq)	0.00**	0.00	0.00**	0.00	0.00***	0.00	0.00**	0.00
Nonfarm/business activities+	-0.02	0.07	-0.04	0.06	-0.02	0.06	-0.06	0.06
HH size (ln)	0.00	0.08	0.00	0.08	0.01	0.08	0.00	0.07
Size of own land (ha)(ln)	0.18***	0.05	0.18***	0.05	0.18***	0.05	0.17***	0.04
Treated+	0.18***	0.07	0.15**	0.06	0.17***	0.06	0.14***	0.06
Dist. asphalt road (minutes)(ln)			0.07	0.06			0.08	0.07
Dist. market (minutes)(ln)			-0.09	0.07			-0.16	0.08
Dist. district (minutes)(ln)			-0.04	0.28			0.90	0.39
Dist. coop office (minutes)(ln)			-0.02	0.05			-0.08	0.06
Dist. input dealer (minutes)(ln)			0.00	0.08			0.01	0.10
Dist. FTC (minutes)(ln)			-0.03	0.06			0.09	0.07
Dist. MFI (minutes)(ln)			-0.23	0.28			-1.24	0.40
Hitossa-Tiyo+	-0.7***	0.10	-0.7***	0.10	-0.6***	0.11	-0.5***	0.14
Adaa-Lume+	-0.96***	0.10	-0.7***	0.10	-0.9***	0.11	-0.6***	0.16
Observations	346		346		348		348	
Log lik.	-140.1		-135.3		-137.3		-129.5	
Pseudo R2	0.39		0.41		0.40		0.45	

+Note: dy/dx for factor levels is the discrete change from the base level. Other covariates fixed at their means.
‡Probit coefficients are reported in the appendix as Table A4a.

None of peers' exogenous characteristics including age, household size, the value of production assets, the value of consumer durables, livestock holdings, and land size holdings are statistically significantly associated with a farmer's probability of adopting row planting, which suggests the absence of contextual effects, i.e. farmer's innovation behavior is not correlated with the exogenous characteristics of his reference group.

We control for correlated effects using district dummies. By comparison to the Bako-Sire study site, it appears that farmers in Lume-Adda and Hitossa-Tiyo are less likely to adopt row planting. This does not come as a surprise as, among many other factors, the main crop in the reference study site is maize, whose agronomic management is less labor demanding, when using the existing practice, by comparison to *teff* and wheat, which are the main crops in the other two study sites.

Most of the individual and household-level characteristics such as gender, age and religion of the household head, and household size do not appear to be strongly associated with the probability of adopting row planting. Farmers with primary education seem to be more likely to adopt row planting compared to those with no education. Having a larger land size is also strongly associated with the likelihood of adopting row planting. We also control for potential sources of information and extension services including radio, television and other proxy variables such as the average distance between the farmer's residence and offices of the extension agent, cooperative offices, input dealer shops, the nearest market, the nearest micro-finance institution, district town, and the nearest asphalt road. We find that farmers who frequently watch television are more likely to adopt row planting, which is in line with expectations and our findings in the preceding section on the correlates of adopting row planting.

Similarly, our results suggest that farmers who are located further away from services such as markets and micro-finance institution are less likely to adopt row planting. Another result which seems less intuitive is that those who reside closer to district towns are less likely to adopt row planting. This could be because these farmers may tend to frequently travel to towns and doing so may leave them little time to adopt this labor-intensive technique. Nevertheless, the coefficient on the dummy that represents whether any of the household members engages in other income-generating activities is negative but not statistically significant. This indicator variable may be a poor proxy for picking up the effect of making frequent travels and engagement in non-farm activities and testing for separability of household labor supply and demand might help, but it is beyond the scope of this paper.

Robustness check

As mentioned above, we also use the average change in peers' average productivity between 2009/10 and 2013/14 as identifying variables for a robustness check of our findings on the existence of social learning. All other controls are the same as before. We find that the coefficient for the change in peers' average productivity between 2009/10 and 2013/14 is negative and statistically significant (Table 8b). This again is evidence of network externalities but of the opposite sign. We propose two possible reasons for the negative sign. First, the peers' contemporaneous data (2013/14 data) is being used to calculate the change in productivity and doing so may not properly satisfy the requirements of using a lagged value as an identifying variable. Secondly, we note in the descriptive statistics that the average change in peers' average productivity between 2009/10 and 2013/14 is positive while the change between 2006/07 and 2009/10 of the same indicator is negative. Our interpretation is that, when farmers observe a decline in average productivity of the reference group, individual farmers may tend to improve their own productivity by doing something different or by employing a new technology while they otherwise could stick to their old practice if everybody else is doing well. In any case, our results suggest that there is indeed evidence of network externalities, which is also reflected by the second identifying variable: The average number of treated farmers in the reference group is statistically significantly associated with the probability of adopting row planting (columns 1 and 3). Further, the results regarding the other controls are similar to the main results.

Table 8b. The effect of social learning on the adoption of row planting, marginal effects of a Probit estimation‡

(Dependent variable: 1 if i adopts row planting, 0 otherwise)

	From networks of the household head				From networks of both spouses			
	dy/dx	Std. Err	dy/dx	Std. Err	dy/dx	Std. Err	dy/dx	Std. Err
Average value of peers' characteristics								
Change in ave. yield (2010-14)	-2E-05***	6E-06	-2.5E-05***	7E-06	-1.7E-05	1E-05	-2.6E-05*	1.4E-05
Share of treated	0.26**	0.12	0.18	0.11	0.26*	0.14	0.10	0.13
Network size	0.09	0.11	0.07	0.10	0.01	0.05	0.01	0.04
Network-size sq.	-0.01	0.01	-0.01	0.01	5E-04	0.003	0.00	0.00
Ave. age(years)(ln)	0.09	0.18	0.07	0.17	-0.03	0.21	-0.22	0.19
Ave. HH size(ln)	0.13	0.20	0.09	0.19	0.39	0.25	0.09	0.25
Ave. value of prod. assets(ln)	0.03	0.03	0.02	0.03	0.05	0.04	0.04	0.04
Ave. value of cons.durables(ln)	0.03	0.03	0.02	0.03	0.02	0.04	-0.03	0.04
Ave. livestockholdings(TLU)(ln)	0.04	0.12	0.02	0.11	0.06	0.14	0.13	0.13
Ave. landholdings(ha)(ln)	-0.01	0.10	0.02	0.10	-0.13	0.11	-0.02	0.11
Household characteristics								
Female HH head⁺	0.03	0.08	0.02	0.08	0.07	0.08	0.05	0.07
Age of HH head (years)	-0.01	0.02	-0.01	0.01	-0.01	0.01	-0.01	0.01
Square. of age of HH head	0.00	0.00	8E-05	1E-04	6E-05	0.00	0.00	0.00
Education 0-4(dummy)⁺	-0.04	0.08	-0.05	0.09	0.00	0.08	0.00	0.07
Education 5-8(dummy)⁺	0.11	0.07	0.10	0.06	0.13*	0.07	0.11*	0.06
Education 8+(dummy)⁺	0.08	0.08	0.08	0.07	0.07	0.08	0.08	0.06
Radio list.(freq)	0.00	0.00	0.00	2E-04	9E-05	0.0002	0.00	0.00
Tv watch.(freq)	0.00**	0.00	0.00**	2E-04	5E-04**	0.0002	0.00**	0.00
Nonfarm/business activities⁺	-0.01	0.07	-0.03	0.07	-0.02	0.07	-0.07	0.06
HH size (ln)	-0.02	0.08	-0.02	0.08	-0.02	0.08	0.00	0.07
Size of own land (ha)(ln)	0.18***	0.05	0.19***	0.05	0.18***	0.05	0.17***	0.04
Treated⁺	0.18***	0.06	0.16**	0.06	0.17***	0.06	0.14***	0.06
Dist. asphalt road(minutes)(ln)			0.06	0.06			0.10	0.07
Dist. market (minutes)(ln)			-0.09	0.07			-0.16***	0.09
Dist. district (minutes)(ln)			-0.05	0.28			0.86	0.40
Dist. coop office (minutes)(ln)			-0.02	0.05			-0.10	0.06
Dist. input dealer(minutes)(ln)			-0.01	0.08			0.01	0.10
Dist. FTC (minutes)(ln)			-0.02	0.06			0.09	0.07
Dist. MFI (minutes)(ln)			-0.20	0.29			-1.24***	0.41
Hitossa-Tiyo⁺	-0.8***	0.10	-0.73***	0.10	-0.74***	0.09	-0.57***	0.13
Adaa-Lume⁺	-1.0***	0.10	-0.81***	0.09	-0.89***	0.05	-0.67***	0.15
Observations	346		346		348		348	
Log lik.	-138.1		-133.4		-139.3		-130.6	
Pseudo R2	0.39		0.41		0.39		0.43	

†Note: dy/dx for factor levels is the discrete change from the base level. Other covariates fixed at their means.
‡Probit coefficients are reported in the appendix as Table A4b.

Finally, we include network size[10] measured by the number of links identified from all matches and its square for an additional test of robustness (Table 8b). We observe that the main findings do not qualitatively change, thereby confirming that our main results are not driven by endogenous network size. This is further supported by the fact that neither network size nor its square are statistically significant.

[10] We also control for the fraction of randomly allocated matches the household knows in order to measure their connectedness in general. But results remain unchanged.

4.2.4. The effect of social learning on farm productivity

Social learning may occur not only in adopting a single innovation such as row planting but also in many other innovations and aspects, the collective effect of which may improve yields. In this context, we regress farm productivity (output/ha) on average values of group or network characteristics and other controls including individual and household-level characteristics as well as community-level fixed effects. We report regression results in Tables 9a and 9b. Results in columns 1 through 4 relate to networks of only the head of the household, while the remaining columns are based on the networks of both spouses taken together. To capture network externalities, we use average productivity of the reference group measured by present yields, past yields, and by the change in average productivity in a similar approach to the preceding section.

Referring to Table 9a column 1, our results suggest that own farm productivity is strongly associated with the average productivity of the reference group for the same production year. This result remains statistically significant when we extend the reference group to that of both spouses (column 5), thereby again presenting evidence of transitivity of relationships and clustering among networks. Even though these may suggest evidence of learning externalities, we cannot rule out the presence of a reflection problem since we are using peers' outcome from the same production year. Therefore, we re-estimate the model using lagged values of average productivity of the reference group. As the results in columns 2 and 6 show, the coefficient is positive and highly statistically significant, thus suggesting strong evidence of social learning or endogenous effects. Further, the coefficient on average livestock holdings of the reference group (columns 1-4) is positive and statistically significant, thereby suggesting that farm productivity increases with the increase in livestock holdings of one's networks. This evidence of contextual effects is not surprising as it is customary among rural households in Ethiopia to exchange or lend out livestock as draft power or for other farming activities. Finally, we also attempt to identify network effects using the change in average productivity of the reference group but the results are not statistically significant (see columns 3, 4, 7 and 8).

Moving on to the other results, we find household size to be strongly associated with farm productivity in all specifications (columns 1-8). This may suggest that larger households have more labor which is an important input in small-scale agriculture in Ethiopia. Yet, we do not find other characteristics of the household to affect farm productivity.

Robustness check

Inclusion of network size and its square term in all the specifications as additional test of robustness do not change the results confirming that results are not driven by size of the network (Compare Table 9a against Table 9b where indicators of network size and its square term are included). Again, both indicators of network size and its square term are not statistically significant only supporting our claim that there is evidence of knowledge spill overs.

Table 9a. The effect of social externalities on farm productivity

(Dependent variable: log (value of output per hectare of land))

	(1) HH_HEAD1	(2) HH_HEAD2	(3) HH_HEAD3	(4) HH_HEAD4	(5) ALLP1	(6) ALLP2	(7) ALLP3	(8) ALLP4
Ave. yield_2014	0.28**				0.28**			
	(0.11)				(0.11)			
Ave. yield_2010		0.28*				0.33*		
		(0.14)				(0.19)		
Change in Yield 2010-2014			0.00**				0.00	
			(0.00)				(0.00)	
Change in Yield 2006-2010				0.00				0.00
				(0.00)				(0.00)
Ave. age (years)(ln)	0.15	0.05	0.16	0.08	0.39	0.19	0.42	0.29
	(0.21)	(0.24)	(0.21)	(0.22)	(0.36)	(0.40)	(0.37)	(0.37)
Ave. HH size(ln)	-0.34	-0.40	-0.30	-0.38	-0.19	-0.31	-0.12	-0.21
	(0.27)	(0.29)	(0.29)	(0.31)	(0.19)	(0.25)	(0.22)	(0.26)
Ave. value of prod. assets(ln)	-0.04	-0.01	-0.03	-0.01	-0.03	0.02	-0.03	0.01
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)
Ave. value of cons. durables(ln)	0.00	0.01	0.01	0.02	-0.03	-0.02	-0.01	-0.01
	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.09)	(0.09)	(0.09)
Ave. livestock holdings(TLU)(ln)	0.29***	0.28**	0.33***	0.32***	0.17	0.12	0.22	0.18
	(0.10)	(0.11)	(0.10)	(0.11)	(0.16)	(0.21)	(0.19)	(0.21)
Ave. landholdings(ha)(ln)	-0.07	-0.07	-0.11	-0.12	-0.16	-0.12	-0.22*	-0.22*
	(0.14)	(0.14)	(0.14)	(0.13)	(0.12)	(0.12)	(0.11)	(0.12)
Female HH head	-0.24	-0.25	-0.25	-0.24	-0.23	-0.22	-0.23	-0.21
	(0.23)	(0.23)	(0.24)	(0.24)	(0.22)	(0.23)	(0.23)	(0.24)
Age of HH head (years)	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Square. of age of HH head	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education 0-4(dummy)	0.12**	0.13**	0.13**	0.15***	0.15**	0.17**	0.16**	0.19***
	(0.06)	(0.05)	(0.06)	(0.05)	(0.07)	(0.07)	(0.06)	(0.06)
Education 5-8(dummy)	0.09	0.08	0.09	0.09	0.11	0.10	0.12	0.12
	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)
Education 8+(dummy)	0.10	0.13	0.09	0.10	0.13	0.15	0.12	0.13
	(0.10)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.12)	(0.11)
Nonfarm/business activities(dumm)	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03	-0.03	-0.02
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
HH size (ln)	0.52**	0.52**	0.53**	0.53**	0.50*	0.50**	0.50**	0.50**
	(0.25)	(0.25)	(0.25)	(0.26)	(0.25)	(0.25)	(0.25)	(0.25)

Size of own land (ha)(ln)	-0.07	-0.06	-0.07	-0.06	-0.03	-0.03	-0.04	-0.04
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
Treated	0.00	0.01	0.01	0.01	-0.00	-0.01	-0.00	-0.01
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Hitossa-Tiyo	0.49***	0.53***	0.62***	0.70***	0.48***	0.53***	0.61***	0.73***
	(0.14)	(0.17)	(0.17)	(0.10)	(0.12)	(0.15)	(0.15)	(0.07)
Adaa-Lume	0.13	0.04	0.19	0.16	0.14	0.02	0.19	0.16
	(0.15)	(0.19)	(0.17)	(0.16)	(0.13)	(0.19)	(0.15)	(0.15)
Constant	5.00***	5.23***	6.93***	7.18***	4.37**	4.51**	6.13***	6.49***
	(1.42)	(1.51)	(1.33)	(1.35)	(2.02)	(1.91)	(1.94)	(2.02)
Observations	346	346	346	346	348	348	348	348
r2	0.24	0.24	0.23	0.23	0.23	0.23	0.22	0.22

Standard errors (clustered at household and village level) in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 9b. The effect of social externalities on farm productivity

(Dependent variable: log (value of output per hectare of land))

	(1) HH_HEAD11	(2) HH_HEAD21	(3) HH_HEAD31	(4) HH_HEAD41	(5) ALLP11	(6) ALLP21	(7) ALLP31	(8) ALLP41
Ave. yield_2014	0.26**				0.28**			
	(0.11)				(0.12)			
Ave. yield_2010		0.26*				0.34*		
		(0.15)				(0.19)		
Change in Yield 2010-2014			0.00**				0.00	
			(0.00)				(0.00)	
Change in Yield 2006-2010				0.00				0.00
				(0.00)				(0.00)
Network size	-0.07	-0.10	-0.06	-0.09	0.09	0.08	0.10	0.09
	(0.20)	(0.19)	(0.19)	(0.19)	(0.09)	(0.09)	(0.08)	(0.08)
Network-size sq.	0.01	0.01	0.01	0.01	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
Ave. age (years)(ln)	0.14	0.05	0.15	0.08	0.40	0.20	0.42	0.30
	(0.21)	(0.24)	(0.21)	(0.22)	(0.38)	(0.42)	(0.39)	(0.39)
Ave. HH size(ln)	-0.33	-0.39	-0.28	-0.36	-0.16	-0.27	-0.09	-0.17
	(0.26)	(0.29)	(0.28)	(0.31)	(0.21)	(0.27)	(0.24)	(0.27)
Ave. value of prod. assets(ln)	-0.04	-0.01	-0.04	-0.02	-0.04	0.02	-0.03	0.00
	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.10)

Ave. value of cons. durables(ln)	0.01	0.02	0.02	0.02	-0.03	-0.02	-0.01	-0.00
	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.09)	(0.09)	(0.09)
Ave. livestock holdings(TLU)(ln)	0.28**	0.28**	0.31***	0.31***	0.16	0.12	0.21	0.18
	(0.11)	(0.12)	(0.12)	(0.12)	(0.18)	(0.21)	(0.21)	(0.21)
Ave. landholdings (ha)(ln)	-0.06	-0.06	-0.09	-0.11	-0.17	-0.13	-0.22*	-0.23*
	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.12)	(0.12)	(0.13)
Female HH head	-0.25	-0.25	-0.25	-0.24	-0.19	-0.21	-0.18	-0.19
	(0.25)	(0.25)	(0.26)	(0.26)	(0.27)	(0.28)	(0.28)	(0.28)
Age of HH head (years)	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Square. of age of HH head	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education 0-4(dummy)	0.11**	0.12**	0.13**	0.14***	0.16***	0.17***	0.18***	0.20***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Education 5-8(dummy)	0.08	0.07	0.08	0.08	0.13	0.13	0.14	0.14*
	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)
Education 8+(dummy)	0.09	0.11	0.08	0.09	0.15	0.16	0.14	0.15
	(0.09)	(0.10)	(0.10)	(0.09)	(0.11)	(0.12)	(0.12)	(0.11)
Nonfarm/business activities(du)	-0.04	-0.04	-0.04	-0.04	-0.03	-0.04	-0.03	-0.03
	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)
HH size (ln)	0.51*	0.51**	0.51**	0.51**	0.48*	0.50*	0.48*	0.49*
	(0.26)	(0.25)	(0.26)	(0.26)	(0.27)	(0.26)	(0.26)	(0.26)
Size of own land (ha)(ln)	-0.07	-0.06	-0.07	-0.06	-0.04	-0.04	-0.05	-0.04
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Treated	0.01	0.02	0.02	0.02	0.01	-0.00	0.01	-0.00
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)	(0.10)	(0.09)
Hitossa-Tiyo	0.48***	0.53***	0.60***	0.67***	0.49***	0.54***	0.61***	0.73***
	(0.13)	(0.16)	(0.17)	(0.11)	(0.13)	(0.16)	(0.16)	(0.08)
Adaa-Lume	0.13	0.04	0.19	0.15	0.16	0.04	0.21	0.18
	(0.14)	(0.20)	(0.16)	(0.16)	(0.14)	(0.20)	(0.16)	(0.15)
Constant	5.22***	5.50***	7.01***	7.31***	4.06**	4.14**	5.79***	6.15***
	(1.44)	(1.54)	(1.25)	(1.29)	(2.03)	(1.92)	(1.92)	(1.95)
Observations	346	346	346	346	348	348	348	348
r2	0.24	0.24	0.23	0.23	0.24	0.24	0.22	0.23

Standard errors (clustered at household and village level) in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

5. Summary and conclusions

Existing studies on Ethiopian agriculture largely ignore the role of social networks for the adoption of agricultural innovations and improved farm productivity. This study aims to contribute to filling this gap. We use purposefully collected data that combine conventionally-used network indicators such as membership in groups and self-reported networks of family and friends in addition to exogenously and randomly assigned matches. By eliciting details of the relationships between network members, their individual farming practices and yield performances, we examine the role each network type plays in terms of information or knowledge transfers for innovation and productivity. We use econometric strategies to isolate social learning from correlated and contextual effects and first examine which factors determine the formation of information links and whether those learning links are actually correlated with innovative behavior. We then examine the existence of social learning with respect to the adoption of row planting, a recent innovation in Ethiopian agriculture. Finally, we investigate social externalities in farm productivity.

Our results suggest that, as expected, belonging to certain groups such as *iddirs*, having some form of relationship with network members in terms of kinship or informal forms of insurance, or having a high frequency of meetings with a network member all seem to increase the probability of forming an information link. It appears, however, that the quality of information is more important when it comes to innovation behavior than the frequency of interaction. To be specific, we fail to find evidence for a relationship between these indicators and the probability of adopting row planting. Instead, we find that information links that exclusively involve discussions on farming or business matters are significantly correlated with the likelihood of adopting row planting.

Further, after controlling for factors that may otherwise generate spurious correlation, we find strong evidence of network externalities in the adoption of row planting and in farm productivity. Our findings are in line with similar studies such as van den Broeck and Dercon (2011). Therefore, based on our findings, we conclude that extension services and other programs that promote agricultural innovations may benefit from social networks but they may achieve maximum impact if they identify networks that exclusively involve information exchange regarding agriculture. This suggests that farmer groups or cooperatives could be important tools for better delivery of agricultural extension and advisory services. This also implies that investment in the formation of groups, rather than simply using existing networks, could also be a strategy with high returns.

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Appendix

Table A1. Determinants of learning links (using random matching within network data)

(Dependent variable: 1 if i discusses farming or business matters with j, 0 otherwise)

	(1) ALL	(2) MALE	(3) FEMALE	(4) HH_HEAD1	(5) HH_HEAD2
Same ethnicity	0.04	-0.03	0.05	0.05	-0.01
	(0.11)	(0.14)	(0.20)	(0.13)	(0.13)
Same religion	0.06	0.18	0.00	0.13	0.13
	(0.11)	(0.11)	(0.19)	(0.11)	(0.11)
Same iddir	0.34***	0.21*	0.41**	0.27**	0.26**
	(0.10)	(0.12)	(0.16)	(0.12)	(0.12)
Help when in need	0.62***	0.60***	0.69***	0.62***	0.60***
	(0.10)	(0.13)	(0.16)	(0.12)	(0.13)
Related(blood/marriage)	0.52***	0.49***	0.67***	0.48***	0.46***
	(0.13)	(0.18)	(0.17)	(0.17)	(0.17)
Meeting frequency	0.00***	0.00***	0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Geo.dist.(i,j)(ln)	-0.11**	-0.15**	-0.12	-0.11	-0.10
	(0.06)	(0.07)	(0.08)	(0.07)	(0.07)
Having plots nearby	0.12	0.18	-0.06	0.31*	0.20
	(0.13)	(0.19)	(0.19)	(0.17)	(0.17)
Radio list.(freq)	0.00	0.00***	-0.00*	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Tv watch.(freq)	0.00***	0.00**	0.00**	0.00**	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Travel to town.(freq)	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Diff. gender dummies	-0.12	-0.90***	-0.22	-0.61***	-0.41***
	(0.07)	(0.11)	(0.15)	(0.10)	(0.16)
Diff. of age (i,j)	0.01***	0.01*	0.02***	0.00	0.01
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Diff. educ (i,j)	0.02	0.00	0.04**	0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Diff. HH size (i,j)	-0.01	0.02	-0.05	0.00	-0.00
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)
Diff. no. of men	0.06	0.02	0.08	0.05	0.05
	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)
Diff. land size	-0.04*	-0.06*	0.02	-0.05	-0.05
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)
Diff. treatment status	0.07	0.06	0.07	0.05	0.08
	(0.07)	(0.09)	(0.11)	(0.09)	(0.09)
Sum gender dummies	0.47***	0.00	0.00		0.46***
	(0.08)	(.)	(.)		(0.16)
Sum of age (i,j)	0.00	-0.00	0.00		-0.00
	(0.00)	(0.00)	(0.01)		(0.00)
Sum of educ (i,j)	-0.00	-0.01	-0.00		-0.01
	(0.01)	(0.01)	(0.01)		(0.01)
Sum of HH size (i,j)	0.01	0.02	0.02		0.01
	(0.02)	(0.03)	(0.03)		(0.03)
Sum no. of men	0.00	-0.02	0.01		0.01
	(0.03)	(0.04)	(0.05)		(0.04)
Sum of land size	0.03	0.03	0.03		0.04
	(0.02)	(0.03)	(0.04)		(0.03)
Sum treatment status	0.09	0.13	0.06		0.14*
	(0.07)	(0.08)	(0.11)		(0.08)
Hitossa-Tiyo	0.05	0.06	-0.14	0.03	0.17
	(0.16)	(0.19)	(0.26)	(0.18)	(0.19)
Adaa-Lume	0.08	-0.09	0.06	-0.12	-0.07
	(0.15)	(0.18)	(0.25)	(0.17)	(0.18)
Constant	-2.63***	-1.45***	-2.58***	-1.55***	-2.43***
	(0.39)	(0.52)	(0.74)	(0.31)	(0.55)

Observations	2339	1285	1054	1402	1402
Log lik.	-878.66	-530.65	-302.75	-601.37	-584.79

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses (clustered at individual and match's level for columns 1-3, and at individual and household level for columns 4-5). Other controls include same religion and same mother tongue (neither of which are significant).

Table A2. Determinants of learning links (using self-reported networks)
(Dependent variable: 1 if i discusses farming or business matters with j, 0 otherwise)

	(1) ALL	(2) MALE	(3) FEMALE	(4) HH_HEAD
Same gender	0.64***	0.55***	0.37**	0.51***
	(0.11)	(0.18)	(0.15)	(0.16)
Same age	0.26***	0.21	0.24**	0.25*
	(0.08)	(0.15)	(0.10)	(0.14)
Same language	0.10	-0.06	0.06	0.09
	(0.16)	(0.27)	(0.22)	(0.28)
Same religion	-0.14	0.10	-0.27*	-0.02
	(0.13)	(0.17)	(0.16)	(0.17)
Close family	0.49***	0.39**	0.47***	0.47***
	(0.11)	(0.17)	(0.14)	(0.17)
Distant family	0.41***	0.39	0.45***	0.56**
	(0.14)	(0.27)	(0.15)	(0.27)
Same iddir	0.34***	-0.04	0.37***	0.08
	(0.11)	(0.23)	(0.14)	(0.19)
Same village	0.03	0.59*	-0.21	0.44
	(0.20)	(0.30)	(0.29)	(0.28)
Same kebele	-0.04	0.42	-0.20	0.32
	(0.26)	(0.36)	(0.35)	(0.33)
Farmer	0.64***	0.94***	0.25*	0.94***
	(0.10)	(0.19)	(0.13)	(0.15)
Meet less than 1/week	0.59***	0.67**	0.45**	0.66***
	(0.17)	(0.26)	(0.22)	(0.24)
Help when in need	0.01	0.98**	0.00	1.19***
	(0.01)	(0.48)	(0.01)	(0.45)
Max of age from i & j	0.01*	-0.02**	0.01	-0.01*
	(0.00)	(0.01)	(0.01)	(0.01)
Education 0-4(dummy)	0.19	0.36	-0.06	0.48*
	(0.15)	(0.30)	(0.20)	(0.28)
Education 5-8(dummy)	0.10	-0.12	-0.16	-0.02
	(0.14)	(0.26)	(0.20)	(0.23)
Education 8+(dummy)	0.20	-0.23	0.15	-0.06
	(0.19)	(0.29)	(0.27)	(0.27)
Radio list.(freq)	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Tv watch.(freq)	0.00	0.00	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Travel to town.(freq)	0.00**	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Land size (ha) (ln)	0.07**	0.15**	0.06	0.13**
	(0.04)	(0.06)	(0.05)	(0.06)
Hitossa-Tiyo (dummy)	-0.24	0.05	-0.29	0.09
	(0.17)	(0.24)	(0.21)	(0.23)
Adaa-Lume (dummy)	-0.36**	0.20	-0.59***	0.16
	(0.15)	(0.21)	(0.19)	(0.20)
Constant	-1.97***	-2.16***	-0.91*	-2.47***
	(0.36)	(0.81)	(0.52)	(0.74)
Observations	2571	1270	1301	1400
Log lik.	-1237.72	-362.57	-775.85	-436.31

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses (clustered at individual and household level). Other controls include same religion and same ethnicity (neither of which are significant).

Table A3. The effect of social network structure on the probability of adopting row-planting
(Dependent variable: 1 if i adopts row planting, 0 otherwise)

	(1) HH_HEADN1	(2) HH_HEADN2
Discussion on farming/business	0.25**	0.22**
	(0.11)	(0.11)
Help when in need	-0.18*	-0.16
	(0.10)	(0.10)
Related (blood/marriage)	-0.06	-0.06
	(0.14)	(0.14)
Meeting frequency	-0.00	-0.00
	(0.00)	(0.00)
Geo.dist.(i,j)(ln)	-0.14**	-0.13**
	(0.06)	(0.06)
Having plots nearby	0.04	0.07
	(0.17)	(0.17)
Radio list.(freq)	0.00	0.00
	(0.00)	(0.00)
Tv watch.(freq)	0.00***	0.00***
	(0.00)	(0.00)
Travel to town(freq)	-0.00***	-0.00***
	(0.00)	(0.00)
Diff. gender dummies	0.05	0.04
	(0.09)	(0.09)
Diff. of age (i,j)	-0.01*	-0.01
	(0.00)	(0.00)
Diff. educ (i,j)	0.00	0.00
	(0.01)	(0.01)
Diff. no. of adult men	0.02	0.02
	(0.02)	(0.02)
Diff. land size	0.18***	0.19***
	(0.03)	(0.03)
Diff. treatment status	0.14**	0.12*
	(0.06)	(0.07)
Sum gender dummies	-0.18*	-0.17*
	(0.09)	(0.09)
Sum of age (i,j)	-0.00	-0.00
	(0.00)	(0.00)
Sum of educ (i,j)	0.02	0.01
	(0.01)	(0.01)
Sum no. of adult men	0.03	0.03
	(0.02)	(0.02)
Sum of land size	0.14***	0.15***
	(0.03)	(0.03)
Sum treatment status	0.22***	0.23***
	(0.07)	(0.07)
Same ethnicity	0.09	0.05
	(0.10)	(0.10)
Same religion	0.13	0.08
	(0.11)	(0.11)
Same iddir	0.06	0.10
	(0.10)	(0.10)
Hitossa-Tiyo	-2.36***	-2.26***
	(0.18)	(0.19)
Adaa-Lume	-2.95***	-2.71***
	(0.19)	(0.21)
Dist. asphalt road, minutes(ln)		0.00

		(0.00)
Dist. to market, minutes(ln)		-0.00
		(0.00)
Dist. to district town, minutes(ln)		-0.00
		(0.00)
Dist. to coop office, minutes(ln)		-0.00
		(0.00)
Dist. to input dealer, minutes(ln)		-0.00
		(0.00)
Dist. to FTC, minutes(ln)		-0.00
		(0.00)
Dist. to MFI, minutes(ln)		-0.00*
		(0.00)
Constant	1.79***	2.21***
	(0.45)	(0.44)
Observations	1402	1402
Log lik.	-567.88	-557.93

Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01.

Table A4a. The effect of social learning on the adoption of row planting
(Dependent variable: 1 if i adopts row planting, 0 otherwise)

	(1) HH_Head1	(2) HH_Head2	(3) ALL1	(4) ALL2
Average value of peers' characteristics				
Change in ave. yield (2006-2010)	**0.00***	**0.00**	**0.00*****	**0.00****
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**
Share of treated	**0.67***	**0.49**	**0.87***	**0.40**
	(0.40)	**(0.41)**	**(0.47)**	**(0.51)**
Ave. age(years)(ln)	0.41	0.37	-0.45	-1.14
	(0.59)	(0.61)	(0.72)	(0.77)
Ave. HH size(ln)	0.18	0.16	0.79	-0.07
	(0.71)	(0.72)	(0.87)	(0.97)
Ave. value of prod. assets(ln)	0.13	0.07	0.25	0.20
	(0.12)	(0.13)	(0.16)	(0.17)
Ave. value of cons. durables(ln)	0.06	0.05	0.03	-0.17
	(0.10)	(0.12)	(0.13)	(0.16)
Ave. livestock holdings(TLU)(ln)	0.12	0.05	0.26	0.60
	(0.40)	(0.40)	(0.48)	(0.51)
Ave. landholdings(ha)(ln)	-0.08	0.05	-0.53	-0.15
	(0.33)	(0.36)	(0.39)	(0.44)
Household characteristics				
Female HH head	0.08	0.05	0.14	0.23
	(0.30)	(0.30)	(0.32)	(0.32)
Age of HH head (years)	-0.05	-0.04	-0.03	-0.03
	(0.05)	(0.05)	(0.05)	(0.05)
Square. of age of HH head	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Education 0-4(dummy)	-0.07	-0.16	0.02	0.02
	(0.27)	(0.29)	(0.29)	(0.30)
Education 5-8(dummy)	0.43	0.38	0.45*	0.46*
	(0.27)	(0.27)	(0.27)	(0.27)
Education 8+(dummy)	0.27	0.28	0.28	0.39
	(0.32)	(0.33)	(0.31)	(0.32)
Radio list.(freq)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Tv watch.(freq)	0.00**	0.00**	0.00***	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)

Nonfarm/business activities	-0.08	-0.14	-0.07	-0.23
	(0.22)	(0.23)	(0.23)	(0.24)
HH size (ln)	0.01	-0.01	0.04	0.03
	(0.28)	(0.29)	(0.28)	(0.30)
Size of own land (ha)(ln)	0.63***	0.69***	0.66***	0.72***
	(0.17)	(0.18)	(0.17)	(0.18)
Treated	0.57***	0.51**	0.56***	0.52**
	(0.20)	(0.21)	(0.20)	(0.20)
Hitossa-Tiyo	-2.43***	-2.32***	-2.04***	-1.81***
	(0.40)	(0.45)	(0.46)	(0.51)
Adaa-Lume	-3.33***	-2.68***	-3.33***	-2.36***
	(0.39)	(0.53)	(0.45)	(0.65)
Dist. asphalt road (minutes)(ln)		0.27		0.34
		(0.23)		(0.31)
Dist. market (minutes)(ln)		-0.33		-0.68*
		(0.26)		(0.38)
Dist. district (minutes)(ln)		-0.16		3.90**
		(1.06)		(1.61)
Dist. coop office (minutes)(ln)		-0.09		-0.35
		(0.19)		(0.24)
Dist. input dealer (minutes)(ln)		0.00		0.06
		(0.29)		(0.42)
Dist. FTC (minutes)(ln)		-0.10		0.37
		(0.22)		(0.28)
Dist. MFI (minutes)(ln)		-0.88		-5.34***
		(1.06)		(1.69)
Constant	-1.23	5.34	-0.28	13.15**
	(2.87)	(3.92)	(3.46)	(5.43)
Observations	346	346	349	349
Log lik.	-140.10	-135.29	-137.24	-129.47

Standard errors (clustered at household and village level) in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A4b. The effect of social learning on the adoption of row-planting

(Dependent variable: 1 if i adopts row planting, 0 otherwise)

	(1) HH_Head3	(2) HH_Head4	(3) ALL3	(4) ALL4
Average value of peers' characteristics				
Change in ave. yield (2010-2014)	**-0.00*****	**-0.00*****	**-0.00**	**-0.00**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**
Share of treated	**0.91****	**0.68**	**0.90***	**0.43**
	(0.43)	**(0.42)**	**(0.49)**	**(0.53)**
Network size	0.32	0.27	0.04	0.05
	(0.38)	(0.39)	(0.17)	(0.17)
Network-size sq.	-0.02	-0.02	0.00	-0.00
	(0.05)	(0.05)	(0.01)	(0.01)
Ave. age(years)(ln)	0.33	0.25	-0.14	-0.93
	(0.62)	(0.63)	(0.72)	(0.76)
Ave. HH size(ln)	0.46	0.34	1.37	0.42
	(0.72)	(0.72)	(0.87)	(0.99)
Ave. value of prod. assets(ln)	0.10	0.09	0.17	0.19
	(0.12)	(0.13)	(0.15)	(0.17)
Ave. value of cons. durables(ln)	0.10	0.07	0.06	-0.13
	(0.11)	(0.13)	(0.13)	(0.16)
Ave. livestock holdings(TLU)(ln)	0.13	0.07	0.17	0.50
	(0.41)	(0.40)	(0.49)	(0.52)
Ave. landholdings(ha)(ln)	-0.03	0.09	-0.46	-0.07
	(0.35)	(0.37)	(0.40)	(0.45)
Household characteristics				

Female HH head	0.10	0.08	0.33	0.34
	(0.31)	(0.30)	(0.34)	(0.33)
Age of HH head (years)	-0.05	-0.05	-0.03	-0.03
	(0.05)	(0.06)	(0.05)	(0.05)
Squ. of age of HH	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Education 0-4(dummy)	-0.13	-0.19	0.03	0.02
	(0.28)	(0.29)	(0.28)	(0.29)
Education 5-8(dummy)	0.41	0.39	0.49*	0.49*
	(0.27)	(0.26)	(0.27)	(0.27)
Education 8+(dummy)	0.29	0.31	0.29	0.41
	(0.32)	(0.33)	(0.31)	(0.31)
Radio list.(freq)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Tv watch.(freq)	0.00**	0.00**	0.00**	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Nonfarm/business activities	-0.04	-0.11	-0.07	-0.25
	(0.23)	(0.24)	(0.23)	(0.24)
HH size (ln)	-0.06	-0.07	-0.06	-0.01
	(0.27)	(0.28)	(0.29)	(0.30)
Size of own land (ha)(ln)	0.63***	0.70***	0.62***	0.68***
	(0.18)	(0.19)	(0.17)	(0.19)
Treated(dummy)	0.59***	0.55***	0.54***	0.53***
	(0.20)	(0.21)	(0.20)	(0.20)
Hitossa-Tiyo	-2.79***	-2.50***	-2.46***	-1.98***
	(0.41)	(0.47)	(0.44)	(0.50)
Adaa-Lume	-3.52***	-2.88***	-3.33***	-2.38***
	(0.43)	(0.54)	(0.47)	(0.65)
Dist. asphalt road (minutes)(ln)		0.23		0.39
		(0.23)		(0.29)
Dist. market (minutes)(ln)		-0.34		-0.64*
		(0.26)		(0.38)
Dist. district town (minutes)(ln)		-0.20		3.56**
		(1.07)		(1.58)
Dist. coop office (minutes)(ln)		-0.08		-0.38
		(0.20)		(0.24)
Dist. input dealer (minutes)(ln)		-0.02		0.05
		(0.30)		(0.42)
Dist. FTC (minutes)(ln)		-0.07		0.37
		(0.22)		(0.28)
Dist. MFI (minutes)(ln)		-0.77		-5.08***
		(1.09)		(1.66)
Constant	-2.25	4.37	-2.34	11.39**
	(2.93)	(3.87)	(3.40)	(5.27)
Observations	346	346	349	349
Log lik.	-138.10	-133.50	-139.06	-130.38

Standard errors (clustered at household and village level) in parentheses. * p<0.10, ** p<0.05, *** p<0.01.