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FELLOW ADDRESS

Information acquisition and the adoption of improved crop varieties

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Abstract

Inadequate information on the benefits of and knowledge about innovative agricultural technologies continue to be a major constraint to technology adoption among smallholder farmers in developing countries. The low adoption of new technologies is one of the causes of low productivity and high poverty incidence among smallholder farmers, particularly in Africa. In this paper, I briefly review the literature on social networks and technology diffusion, and argue that the diffusion potential of social networks is underexplored. I then present results from two empirical studies on the impact of social networks on the adoption of improved crop varieties in Ghana and Ethiopia. The results reveal that farmers' peer adoption decisions and experiences, as well as information from trained development agents positively and statistically influence their adoption decisions. I also find that network structural characteristics such as lower segmentation within networks, high credibility of the information, and high effectiveness and efficiency of the amount of information flow tend to improve information acquisition and speed up diffusion of improved crop varieties.

KEYWORDS

improved crop varieties, information acquisition, social networks, technology adoption

JEL CLASSIFICATION

D83, O33, Q16

1 | INTRODUCTION

The importance of promoting new agricultural technologies to increase productivity and output in underdeveloped countries has been widely documented (e.g., Just & Zilberman, 1988). Improved varieties are responsible for about 50%–90% of the increase in world crop yield (Bruins, 2009). Productivity-enhancing agricultural technologies can help reduce poverty by reducing food prices and stimulating economic growth in the rural nonfarm sectors, making input technological change fundamental to rural transformation. The use of improved, high-yielding crop varieties by rural households can mean a difference between improved livelihoods and staying trapped in poverty and hunger. Likewise, it facilitates the transition from low productivity subsistence agriculture to a more productive agro-industrial economy (Gollin et al., 2005). Although there is a proliferation of improved crop varieties on the markets across African markets, farmers continue to use traditional, low-yielding varieties. Although the area planted to improved varieties between 1970 and 2014 increased by 990% in Asia, only about 15.6% increase was observed in Africa during the same period (Gatto et al., 2021).

The low adoption of new technologies is one of the causes of low productivity and high poverty incidence among smallholder farmers, particularly in Africa. Extension services are underfunded, and weak and ineffective at serving the needs of widely dispersed smallholder farmers, making inadequate their access to information about new technologies. The insufficient availability and limited access to public learning has led to considerable interest in social learning. Given the significance of social learning, the impact of farmers' information networks and extension services on technology adoption has received considerable attention in the theoretical and empirical literature (e.g., Bandiera & Rasul, 2006; Conley & Udry, 2010; Foster & Rosenzweig, 1995; Krishnan & Patnam, 2013; Maertens & Barrett, 2012; Mohammed & Abdulai, 2022), with mixed findings, as studies by Bandiera and Rasul (2006), Conley and Udry (2010), and Beaman et al. (2021) reported positive effects of social learning on adoption, whereas a few others (e.g., Duflo et al., 2011) found no effects. An issue that has become clear with observational data is that unless the social networks are exogenously formed, they suffer from the problem of identifying the network effects (Chandrasekhar & Lewis, 2016; Manski, 1993). This has partly resulted in increased efforts to use experimental data in studying the diffusion of agricultural technologies in developing countries.

In this article, I examine the role of information flow through farmers' social networks, network structures, and extension agents in the adoption of improved crop varieties. First, I discuss the puzzle of slow diffusion of improved crop varieties in Africa. Second, I outline a simple conceptual framework to analyze technology adoption. Then, I present results from two empirical studies from Ghana and Ethiopia, using both observational and experimental data. Finally, I discuss some policy implications and future research ideas in the area.

2 | THE PUZZLE OF LOW ADOPTION RATES OF IMPROVED CROP VARIETIES IN AFRICA

Over the last 4 decades, an impressive theoretical and empirical literature has been developed on the factors that influence the diffusion of new agricultural technologies in developing countries (e.g., Bachewe et al., 2018; Conley & Udry, 2010; Yitayew et al., 2021). These factors are generally categorized into demand and supply-side and mediating constraints (Cai et al., 2015; De Janvry et al., 2016). The demand-side factors include, among others, endowments and behavioral traits, whereas the supply-side factors involve the local availability of the new technologies and farmers' access to information on the technologies. With regard to supply-side factors, Yitayew et al. (2022) report that smallholder farmers exposed to improved new varieties marketed in small quantities and affordable prices to increase local availability have a higher tendency to try the new varieties. Numerous studies (e.g., Abdul Mumin et al., 2022; Adhvaryu, 2014; Bandiera & Rasul, 2006; Beaman et al., 2021; Conley & Udry, 2010; De Janvry et al., 2016) have also demonstrated the importance of farmers' access to information on improved varieties for adoption of these varieties.

The widely accepted mediating constraints generally include infrastructure, property rights, input and output markets, insurance markets, and access to credit facilities. Access to credit, which promotes adoption of risky technologies through the relaxation of liquidity constraints as well as boosting farmers' risk bearing ability, is hardly available to resource poor farmers for many reasons (Abdul Mumin & Abdulai, 2021; Abdulai & Huffman, 2005; Sunding & Zilberman, 2001). However, some studies suggest that credit is unlikely to be the main constraint on adoption and that low uptake of new technologies is still observed when credit is available (Crépon et al., 2015; Karlan et al., 2014; Yitayew et al., 2022). Reardon et al. (1992) demonstrate that non-farm income may be more important for agricultural technologies than access to credit, because it relaxes financial constraints that farmers may be facing. A number of studies have also shown that poor infrastructure makes technology unprofitable for farmers, discouraging them from the uptake of new technologies (Abdul-Rahaman & Abdulai, 2020; Marenya & Barrett, 2009; Suri, 2011).

The recent literature tends to indicate that even if policies relax the mediating constraints like markets, infrastructure, and institutions, but constraints on supply-side factors, such as local availability and access to information about the new technologies, exist, low adoption is still likely to persist (Bandiera & Rasul, 2006; Conley & Udry, 2010; De Janvry et al., 2016; Mohammed & Abdulai, 2022). As argued by Beaman and Dillon (2018), lack of reliable and persuasive sources of information about new technologies, their relevance to local agronomic conditions, and details on how to apply them are potential deterrents to adoption. The empirical literature on social learning and technology diffusion has largely focused on the effects of various types of networks on technology adoption, whereas centrality has received much attention in studies analyzing the impact of network structures of a given type of network. Moreover, little attention has been given to the role of quality of the information transmission from research centers through extension agents to farmers. However, as pointed out by Beaman et al. (2021), there may be some friction in the transmission of information about benefits and know-how of new technologies in less cohesive and highly segregated farmers' networks, resulting in low adoption, and providing the need for additional empirical evidence.

I argue that heterogeneity in land quality and growing conditions in Africa is significant in explaining different adoption rates in the region. In this line of argument, three zones can be differentiated to explain differential adoption rates in the region. The first zone is the area where land quality and growing conditions are unfavorable, such as in the Northern Sahel region, where farmers are just involved with coping strategies. The second zone refers to the area where land quality and conditions are quite favorable for agricultural production, and farmers tend to be informed about improved agricultural technologies. This is mainly the tropical rainforest region. The third zone covers the area where the land quality and growing conditions are just suitable for farmers to cultivate food and cash crops (e.g., Guinea Savannah). In this zone, improved varieties are available, but farmers tend to lack information on the benefits and knowledge about them, resulting in low adoption rates. This area is the focus of the present study, although the analysis may apply to the other zones.

Simple interventions by extension agents in the Guinea Savannah zone to provide useful information on farming methods, without considering other binding constraints involved in information flow, may not lead to increased adoption of improved crop varieties. In analyzing the role of information flow on the adoption of new improved varieties, I consider the technology transfer in the context of upstream innovation development by the national agricultural research centers (NARS) and private sector, which is then transferred through extension services and farmers' social networks, acting as midstream communicators, to farmers as downstream beneficiaries. In this context, the provision of incentives necessary for efficient and smooth transmission of information on improved varieties from upstream innovators (NARS and private sector) to downstream agents is quite crucial.

Although the empirical and theoretical literature demonstrate the significance of information diffusion through extension services and farmers' social networks, I contend that the diffusion potential of social networks is underexplored. In particular, the extent to which network structural features such as modularity (segmentation within communities) and transitivity (credibility of the information), as well as quality of information flow from extension agents to farmers affect information acquisition and technology diffusion is underexplored. Empirical analysis of network structures and quality of information from extension agents can reveal the extent to which specific biases and/or patterns exist in communities with regard to social interactions (Jackson et al., 2017), and this can be important for policy interventions to promote adoption of new technology options. In particular, if policies fail to consider the existence of such structures or biases, this could result in policy impacts focusing on specific segments of the villages rather than the entire village or implementing ineffective extension policies.

3 | CONCEPTUAL FRAMEWORK

The empirical analysis on information acquisition and technology adoption is based on the conceptual framework of the target input model outlined in Bardhan and Udry (1999). The focus here is on social learning, where farmers learn about new technologies from their social network members, with emphasis on the characteristics of the social network structure. Basically, it is assumed that farmers can improve their initial knowledge about the cultivation of the improved crop variety by learning from other farmers that have adopted in the past and by their own experience after adoption. Farmers may give more or less credibility to the information about input and yield, depending on the strength of the social ties between them. I also assume that the social ties increases if the neighborhood is connected by mutual friendships, personal attributes, or shared responsibilities. Thus, the cohesiveness of the neighborhood is assumed to be positively related to credibility of the information that flows between farmers.

The model, which is based on Bayesian updating, assumes that farmers know the underlying production function of the improved variety up to a random "target" of the optimal input use and transitory random shocks. By observing the yields and inputs of farmers that have adopted in the past, and yields and inputs from their own experience once they have adopted, farmers are able to learn about the optimal use of the input. An important point worth noting is that the farmers' learning process depends both on the number of their direct social links (i.e., networks), and the cohesiveness of their neighborhood, as well as the level of segregation of the network and the farmer's centrality (i.e., importance) within the social network.

The target-input model postulates that the farmer's expected output of production of the improved variety at a specific point in time is given by the maximal physiological output minus the squared difference between the applied input and the farmer's belief about the optimal input use and the variance of the transitory random shocks that influence output. The variance of the farmer's beliefs in turn depends on the precision of the initial and posterior beliefs, the information the farmer received from their own trials, as well as the information obtained from his peers. Thus, the farmer can update his beliefs based on observable information given by the share or number of peer adopters in his neighborhood, the inputs applied by his neighbors, and by the observed yields of the improved variety of the neighbors. This learning process is what characterizes the flow of information.

Although the farmer's direct learning possibilities depend on the farmers who are directly connected to him, these possibilities tend to be higher if his neighbors are well-connected so that they can effectively pass on information from their neighbors. The learning possibilities are influenced by the network structures such as centrality, transitivity, and modularity. If the network metric is based on the number of links the farmer's neighbors have, this is referred to as "degree centrality," but if the links of the entire network are used in the computation, it is referred to as "eigenvector centrality." Although transitivity describes the local cohesiveness and measures how close the neighborhood of a farmer is to being a complete network, modularity represents segregation of a network into modules. Farmers in highly segregated networks tend to face either weak or no information flow between the segregated modules, resulting in farmers being only likely to learn from others if their module consists of adopters. Thus, the segregation of a network can influence the rate of diffusion of the improved technology, such that highly segregated village networks result in slow diffusion at the village level (Jackson, 2010).

Depending on the updated information about the yields of the improved variety and the farmer's discount rate, he can determine the stream of expected benefits of current and future production of the improved and traditional varieties. It is assumed that the farmer will adopt the improved variety once the sum of the expected benefits of current and future production of the improved variety is greater than the sum of the expected benefits of the current and future production of the traditional variety.

4 | EMPIRICAL STRATEGY

4.1 | Empirical specification for network effects on improved soybean variety

As indicated above, farmers can determine the stream of expected benefits of current and future production of the improved and traditional varieties, based on the updated information. Thus, the farmer adopts the improved crop variety at time t if the sum of the expected benefits from current and future production of the improved variety outweigh the value of waiting for an increase in knowledge and managements skills or improvements in the technology. Let us assume $Y_{\mathrm{it}} = 1$, if a farmer adopts the new crop variety at time t, and $Y_{\mathrm{it}} = 0$ otherwise. Because information on adoption of the technology in this study were observed on annual basis, and the focus here is on the timing of adoption decisions, I use the discrete-time proportional hazard model[1] in the specification. This model analyzes the rate at which farmers will adopt the technology in time t, conditional on not having adopted it earlier, and is known as the hazard rate at time t (see, e.g., Abdulai & Huffman, 2005; Kerr, 2003).

The empirical strategy employed in examining the impact of farmers' social network structures on the adoption of the improved crop variety assumes a lag transmission of social network effects as in Manski (1993). Thus, the probability of adoption at time t, given that the farmer has not already adopted, can be expressed as the following:

$$\Pr[T = t | T \geq t, Z, Y_0 \ldots Y_t, E_0 \ldots E_t, X] \tag{1}$$

$$Y_{\mathrm{it}} = \alpha Z_t Y_{t-1} + \sigma Z_t E_t + \delta_1 L_t + \delta_2 S_t + \delta_3 Z_t S_t + X' \varphi_1 + X' Z_t \varphi_2 + \omega_t + \widehat{\xi}_t + \tau_Z + \mu_t,$$

where T is a random variable that denotes the time of adoption of the improved variety, Z_t is a normalized social network matrix, and $Z_t Y_{t-1}$ is the share of past adopting peers. The term α is an estimated parameter on how the share of past peer adoption decisions affects the conditional probability of adoption. E_t is the farmer's experience in cultivating the improved variety, $Z_t E_t$ is the yearly peer experience in the cultivation of the variety interacted with the yearly social network matrix to obtain average peer experience over time, and σ is the estimated parameter on the impact of peer experience on the conditional probability of adoption at time t. S_t is a vector of the farmer's level network statistics (i.e., local transitivity and centrality measures), $Z_t S_t$ is the yearly farmer's average peer network statistics, L_t is the yearly modularity of the network, and δ_1, δ_2 and δ_3 are vectors of parameters to be estimated, φ_1 and φ_2 represent contextual effects; ω_t is a flexible baseline hazard that indicates the pattern of duration of dependence in the diffusion process overtime and accounts for time fixed effects. The parameter τ_Z accounts for network level effects that might drive

[1]The discrete-time model can be viewed as an approximation of a given continuous-time model (Jenkins, 2005).

peers' behavior to be correlated; $\widehat{\xi}_t$ is a vector of predicted residuals from the link formation model that account for unobserved factors that affect network formation at the farmer level, and μ_t is the error term. Thus, the approaches employed in accounting for the unobservables include network fixed-effects to account for potential network-specific unobserved factors (Liu & Lee, 2010),[2] and the control function for self-selection corrections with social interactions (Hsieh & Lee, 2016).

I also examine the relationship between the network structures on one hand and peer adoption decision and peer experiences on the other by interacting these variables in the estimation process. Unobserved network level effects that might drive peers' behavior to be correlated, as well as predicted residuals of the link formation model that account for unobserved factors that affect network formation at the farmer level are all considered in the estimation.

4.2 | Empirical specification for social network effects on improved *Kingbird* wheat variety

In estimating the impact of social networks and improved extension services on the adoption of the new *Kingbird* variety use a spatial linear probability model (LPM)[3] specification:

$$\begin{aligned} Y_i = {} & \alpha+\beta_1\sum Y_j+\beta_2\mathrm{DAs}_i+\beta_3\mathrm{Demo}_i+\beta_4\mathrm{DAsDemo}_i+\beta_5\sum Y_j\mathrm{DAs}_i+\beta_6\sum Y_j\mathrm{Demo}_i \\ & +\beta_7\sum Y_j\mathrm{DAsDemo}_i+\eta X_i+\gamma\sum X_j+\mu_d+u_{ij}+e_i \end{aligned} \tag{2}$$

where Y_i is the adoption decision of individual farmer i, which takes a value of 1 if a farmer adopts *Kingbird*, and 0 otherwise; DAs_i denotes training of development agents (DAs), which takes a value of 1 if household i is found in a village with a trained DA, and 0 otherwise; Demo_i denotes demonstration trials, which takes a value of 1 if household i is found in a village with demonstration trials, and 0 otherwise; $\mathrm{DAsDemo}_i$ denotes the treatment of a farmer with both DAs training and demonstration trials taking a value of 1 if farmer i is assigned in a village where there is a trained DA and demonstration trials are held, and 0 otherwise; X_i represents characteristics of farmer i; ΣY_j is the number of adopters in the group, and ΣX_j is the summation of the characteristics of the peers[4]; β_5, β_6 and β_7 are the parameters of interest, indicating the interaction effects between the number of adopters in the network and improved extension services on the adoption of the new variety; μ_d is the location fixed effects to control for correlated effects associated with sharing similar institutional environment; u_{ij} is the generalized residuals, which serves as the control function of the unobserved characteristics of individual farmer i associated with group formation (with six other farmers) to control for selection bias.

5 | DATA AND CONTEXT

5.1 | The observational data from Ghana

The data used for the first analysis come from a survey of 500 farmers in northern Ghana. A multistage random sampling procedure was used to select the farmers. Five districts were purposively

[2]See Horrace et al. (2016) and Hsieh and Lee (2016) for discussion of these approaches.

[3]I employ the linear probability model (LPM) instead of a binary choice model such as logit and probit models because the linear model allows to control for location fixed effects, without biasing the other estimates, although the estimates from either logit or probit are not robust (Caudill, 1988). Moreover, the LPM is more appropriate in estimating easily interpretable and informative interaction effects. None of the predicted values are outside the 0–1 bounds. The obvious drawback is that the variance of the error term in the LPM is not constant. This is corrected with the Eicher-White robust estimator.

[4]We use the linear-in-sum formulation, assuming the adoption decision of individual farmer i is affected by the sum of the individual farmer j behavior and characteristics. Following this, peers' behavior and characteristics are weighted by adjacency matrix that is not row-normalized, by using spatial Durbin model estimation.

selected based on their intensity of soybean production, and then 25 villages were randomly selected across these districts, with the allocation of villages done in proportion to the total households in each district. In each village, 20 household heads were randomly selected for interview and, because they are the primary decision makers, a structured questionnaire was administered to them. Information on village characteristics was obtained through interviews with village and group leaders. The farmers were asked the date at which the improved variety was first adopted. This is a key variable in the analysis. There was increased adoption overtime since the introduction of the improved variety in 2003, which is the entrance date for the adopters. However, adoption slowed down toward 2016, which is the exit date for nonadopters, because data on farm production was collected in this year.

Modules of household characteristics, social networks, and agricultural production were combined to construct pseudo-panel data for the analysis of timing of the improved soybean variety adoption. The survey was conducted between May and August 2017. Random matching within sample was used to generate the potential social network contacts (Conley & Udry, 2010). In each village, five household heads were randomly selected and assigned to the 19 remaining household heads as potential social network contacts. Each farm household was asked whether they knew any of the five households randomly assigned to them. On average, the respondents knew 3.14 of the households randomly assigned to them, with an average standard deviation of 1.22. As evident in Table 1, in 2016 the average farmer was 43 years old, had received 1.27 years of schooling, and had 13 years of farming experience.

To allow for time variation in the social network, each respondent was asked about how long they have known the persons linked to them. A farmer's social network was then created as a sociomatrix of each of the 25 village samples, with each village referred to as a group Z. Thus, the link entries of this sociomatrix z_{ij} is one, if the farmer i has stated he knows farmer j, and zero if otherwise. Links were defined as undirected such that i is said to have a link with j and vice versa, if any of them stated knowing the other. Answers to the question of how long the linked farmers knew each other was used to construct time varying social networks from 2002 to 2015/16, thus making it possible to index the sociomatrix with a time subscript (for detailed explanation, see Abdul Mumin & Abdulai, 2021).

As argued by Jackson (2010), the partitioning of a social network into components or segments (i.e., modularity) can strongly influence the adoption of improved technologies, such that highly

TABLE 1 Summary statistics on the characteristics of farmers and network in Ghana.

Variables	Definition of variables	Mean	*SD*
Adopt	1 if an adopter, 0 otherwise	0.67	0.47
Time	Number of years to adoption	6.67	3.58
Age	Age of farmer (years)	44.03	12.04
Gender	1 if male; 0 otherwise	0.59	0.49
Education	Number of years in school	1.27	3.27
Experience	Number of years in farming	13.06	4.02
Household	Household size (No. of members)	5.64	2.14
Landholding	Total land size of household (in hectares)	2.56	1.56
Credit	1 if farmer was credit constrained and/or not successful in applying; 0 otherwise	0.55	0.49
Current adopters in network	Number of current adopters	2.75	2.01
Past adopters in network	Number of past adopters	1.35	1.39
Degree	Number of network contacts	3.69	1.50
Transitivity	Local cohesiveness	0.46	0.32
Modularity	Segmentation within communities	0.49	0.06

segregated village networks result in slow diffusion at the village level. The data revealed an average modularity of 0.35, which declined over time, suggesting the presence of latent network structures, that appears to gradually weaken overtime. Although only 3% of peers adopted the improved variety in 2003, this proportion increased to 67% by 2016.

5.2 | The experimental and network data from Ethiopia

The data for the second empirical illustration derive from a cluster randomized control trial (RCT) in four adjacent districts in Amhara region in Ethiopia and sampled networks data collected using random matching within sample.[5] The RCT aimed at improving the traditional extension service delivery system by introducing changes to the capacity of DAs and the modality of field demonstration trials, using a 2×2 factorial design. A multistage sampling procedure was used to select 96 wheat producer villages from four districts, who were then randomly assigned into treatment and control groups.

The technology used for the intervention was *Kingbird* wheat variety, which had been introduced in the country in 2015. *Kingbird* is relatively resistant to a fungal disease called wheat rust, and none of the farmers in the study area had previously cultivated the new variety (Minot et al., 2015). The treatment groups included: (1) assigning a single DA with basic, but holistic knowledge of all the three disciplines of the mixed crop-livestock production system, who also received training on advanced communication skills to serve the farmers; and (2) changing the extension service delivery approach from model-farmer focused involving almost no field days to one that involves more farmer field days organized around demonstration trials. The experiment therefore consists of two interventions with two levels (i.e., treatment and control), leading to four treatment combinations or arms. These include (1) training DAs, (2) demonstration trials, (3) training DAs and demonstration trials, and (4) control group or no intervention.

Training for DAs assigned to the 48 treatment villages was provided at a central place before the onset of the 2017 main growing season. The training focused mainly on technical aspects and soft skills for effective facilitation and communication. The training was organized for a total of 6 days, divided into two tailored 3-day courses, with focus on technical aspects of crop production, livestock rearing, and natural resource management, followed by a 3-day training on soft skills for process facilitation and effective communication. The trained DAs were then deployed to provide their services in the 48 villages that were randomly assigned to the treatment arms involving the use of trained DAs (for detailed description, see Yitayew et al., 2021).

Social and *locational* indicators are used to define farmers' networks. The baseline information was collected from 1662 households during the 2018 production season, with a follow-up survey in the 2019 cropping season. The data used in this study were generated from a 1500 farm household survey in 2019. Structured and pretested questionnaires were used to collect household demographic and socioeconomic characteristics, and access to institutions and social networks. Random matching within sample was employed to match six farm households to each farm household in the village sample while trying to avoid strong ties bias. A random number generating procedure was used to conduct the random matching within sample. The sampled networks data were collected by matching individual households (nodes) randomly with six other households (links) in the village with an average of 17 sampled households[6].

I construct a sampled network from the data that were collected from a partial sample of nodes and then predict sampled network data into a full network setting, specifically using an adjacency matrix that consists of one row and one column for each individual. The adjacency matrix is constructed by

[5]This approach allows the pairing of each individual in the sample with a specified number of individuals randomly selected from the sample (see Santos & Barrett, 2008).

[6]The sample size required for the study was distributed to the 96 villages in proportion to their respective population sizes. This is important in network data generation process especially associated with capturing the residuals of link formation in the model estimation.

TABLE 2 Summary statistics on the characteristics of farmers and network in Ethiopia.

Variables	Definition of variables	Mean	SD
Adopt	1 if an adopter, 0 otherwise	0.08	0.26
Age	Age of farmer (years)	43.88	13.20
Gender	1 if male; 0 otherwise	0.95	0.21
Education	Number of years in school	1.64	2.61
Household	Household size (no. of members)	5.50	2.03
Landholding	Total land size of household (in hectares)	1.28	0.91
Credit	1 if farmer was credit constrained and/or not successful in applying; 0 otherwise	0.47	0.50
Degree	Number of network contacts	6.67	2.37
Current adopters in network	Number of current adopters in network	0.29	0.56
Transitivity	Local cohesiveness	0.45	0.19

setting each pair of individual i and j such that a_{ij} is equal to 1 if there is an edge (link) from i to j, and 0 otherwise, which is significant to weigh the peer behavior and characteristics, and to know their social network characteristics such as centrality and transitivity.[7] Table 2 presents summary statistics of baseline information on sample households' characteristics. The figures show that 95% of the sample households are male headed, with average age and years of schooling of 44 and 2, respectively. The households have an average size of six and average landholding of 1.28 hectares.

6 | EMPIRICAL RESULTS

6.1 | Network structure and adoption of improved soy bean variety in Ghana

The estimates of the coefficients from the hazard model are presented in Table 3. The results in Table 3 show the effects of the parameter estimates of peer adoption, peer experience, and social network structures such as transivity, centrality, and modularity on the speed of adoption.[8] Column 1 controls for the interactions of modularity on one hand and the farmer's local transitivity, degree and average peer degree, while column 2 controls for the interactions of modularity on one hand and farmer's local transitivity, eigenvector centrality and average peer eigenvector centrality. The results show that the coefficients of the variables representing peer adoption decisions and experiences are positive and statistically significant in all specifications, indicating the importance of the signals from peer adoption decisions and experiences in influencing the conditional probability of adoption. These findings indicate that farmers depend more on their direct peers or peers within their components in the network in learning from peer experiences, and possibly on both direct and indirect peers in learning about peer adoption decisions. As argued by Beaman et al. (2021), signals from increased peer adoption decisions is expected to decrease profitability uncertainty, with more experienced peers benefitting from increased learning opportunities, which eventually result in increased adoption of the improved variety.

The coefficient of the variable representing modularity is negative and statistically significant, suggesting that increased modularity reduces the conditional probability of adoption in any given year. Thus, although increasing transitivity of a network is associated with increased incidence of

[7]Degree centrality in this study measures the number of contacts in the network, whereas transitivity indicates whether individual farmers are connected with friends of a friend or neighbors of a neighbor.

[8]Transitivity or local cohesiveness measures how close the neighborhood of a farmer is to being a complete network. Modularity captures the proportion of links that lie within communities of a network minus the expected value of the same quantity in a network where links were randomly generated (Jackson, 2010).

TABLE 3 Estimates of impact of social networks on adoption of improved soybean variety.

Explanatory variables	(1)	(2)
Share of peer adopters	0.90** (0.318)	0.91*** (0.312)
Peer experience	0.57*** (0.121)	0.58*** (0.114)
Modularity	−2.00** (0.911)	−2.06** (0.941)
Transitivity	1.24** (0.442)	1.23** (0.466)
Degree	0.06 (0.049)	
Average peer degree	0.08 (0.070)	
Eigenvector		0.19 (0.337)
Average peer eigenvector		0.79* (0.394)
Modularity × Transitivity	−10.64*** (3.538)	−11.37*** (3.839)
Modularity × Average peer degree	−0.99** (0.412)	
Modularity × Average peer eigenvector		−5.39** (2.262)
Controls; contextual and correlated effects	Yes	Yes
LogLikelihood	−958.6	−959.1
Clusters	25	25
N	4551	4551

Note: The asterisks ***, **, and * are significance at 1%, 5% and 10% levels, respectively. Peer experience is the number of years of peer experience in cultivating the improved variety. Correlated effects and link formation residuals are accounted for in the estimation. The standard errors clustered at the village level to account for village factors that might drive peer behaviors to be correlated, Village dummies are not used in order to avoid the incidental parameter problem.

adoption due to less structural holes and increased efficiency in information flow and diffusion, increasing modularity leads to declining probability of adoption due to the highly structured latent groups in the networks (Alatas et al., 2016). I also examine the extent to which the modularity influences the roles of transitivity and centrality in the social learning process. This is important because, the effectiveness of transitivity and centrality in the diffusion process depend on the extent of modularity of the network. High modularity networks are expected to constrain the role of transitivity and centrality in enhancing learning and diffusion in the network and vice versa.

The estimates in Table 3 show how modularity impacts the effects of the network structures like transitivity and centrality. In particular, the negative and significant coefficients of the interaction terms reveal that the association between these network structures (transitivity, average peer degree and eigenvector centrality)[9] and the conditional probability of adoption in any given year is significantly influenced by the level of network segmentation (modularity). Thus, higher levels of modularity impact negatively on the positive effects of centrality and transitivity on adoption, resulting in slower adoption. This finding demonstrates the importance of social groups (i.e., latent network segregation pattern) in social learning and in technology diffusion process, as well as the need to consider social diversity and structures in interventions that are aimed at promoting information dissemination and technology diffusion.

6.2 | Social networks, and extension services and adoption of new *Kingbird* wheat in Ethiopia

In this section, I discuss the estimates from the randomized control trial conducted in Ethiopia to analyze the effects of farmers' networks, extension services delivery system, and trained development

[9]Degree centrality measures how well a farmer is connected, in terms of direct connections. High values of degree centrality imply that the farmer is influential, whereas low values indicate that the farmer is less central. Eigenvector centrality measures the centrality of a farmer by considering how important his neighbors are. The centrality of a farmer is proportional to the sum of the centrality of its neighbors.

TABLE 4 Farmers' social networks, extension services and adoption of *Kingbird* variety.

Explanatory variables	(1)	(2)	(3)
Number of adopters in a farmer's network	−0.017 (0.025)	−0.017 (0.025)	−0.017 (0.025)
Treatment effect-DAs	0.018 (0.020)	0.020 (0.020)	0.020 (0.020)
Treatment effect-Demo	0.010 (0.020)	0.010 (0.020)	0.010 (0.020)
Treatment effect-DAsDemo	−0.005 (0.021)	−0.003 (0.021)	−0.003 (0.021)
Number of adopters in a farmer's network × Treatment effect-DAs	−0.020 (0.033)	−0.021 (0.033)	−0.022 (0.034)
Number of adopters in a farmer's network × Treatment effect-Demo	0.046 (0.036)	0.047 (0.036)	0.052 (0.037)
Number of adopters in a farmer's network × Treatment effect-DAsDemo	0.131*** (0.040)	0.133*** (0.040)	0.131*** (0.040)
Peers' characteristics	Yes	Yes	Yes
Link formation residuals	No	Yes	Yes
Location fixed effects	No	No	Yes
Constant	0.022 (0.040)	0.021 (0.041)	0.036 (0.043)
Observation	1500	1500	1500
R-squared	0.053	0.057	0.058

Note: The asterisks *** is significance at 1% level. Figures in parenthesis are robust standard errors. The peers' characteristics are the sum of the characteristics of the peers in the group. The characteristics of peers are the gender of household head, age of the household head, schooling of household head, household size, farm size, livestock owned, and credit constraints. Given that individual farmers are randomly matched with six others, generalized residuals that are generated from the dyadic model for individual links are included as control functions in Columns (2) and (3). We also control for the selection bias related to group formation.

agents on the adoption of the new *Kingbird* variety. Using the two-step control function procedure suggested by Wooldridge (2015), I account for the potential endogeneity problem due to self selection into a specific group formation. In the first step, the likelihood of link formation is estimated, whereas the effect of the network effects conditional on the link formed is estimated in the second step. Thus, the generalized residuals from the first-stage estimation of the likelihood of link formation are used in the second step to account for potential selection bias from group formation.

The estimates in Table 4 show that, in all three specifications where extension services and trained development agents are accounted for, the coefficients representing number of adopters in the farmer's network are not statistically significant. In the three columns in the table, I report the estimates of the effect of being connected to a lot of farmers by controlling for only peers' characteristics, both peers' characteristics and link formation residuals, and all control variables (i.e., peers' characteristics, link formation residuals, and location fixed effects). Column (1) reports the estimates of the combined effect of learning simultaneously from social networks and extension services on farmers' decision to adopt *Kingbird*, without controlling for endogenous group formation and location fixed effects, and Column (2) reports their effects with controls for endogenous group formation but not the location fixed effects. The estimates in Column (3) control for these variables.

The results are robust across all specifications. The endogenous group formation and location fixed effects do not appear to influence the interaction effects of peers' adopters and improved extension services, suggesting that farmers are less likely to behave similarly, as they are exposed to different treatments. In particular, in all specifications (Columns 1–3), I find a negative but statistically insignificant effect of farmers' networks on adoption of the *Kingbird* variety.

The estimates show that interacting social networks with treatment effects tends to have a positive impact on farmers' adoption decisions. In particular, the interaction effects (i.e., number of adopters in a farmer's network interacted with the treatment effect) show that social networks with different improved extension services delivery, indicating improved quality of information, tends to have positive and statistically significant impact on adoption decisions of farmers. This finding suggests complementarity between extension service delivery and farmers networks. A single extension service intervention does not appear to have any complementary effect with farmers' networks in terms of the adoption of *Kingbird*, a result that is consistent with Krishnan and Patnam (2013), who argued that the role played by extension agents and neighbors in the adoption of improved varieties and chemical fertilizers appear to substitute for each other.

7 | CONCLUSIONS

The significance of new agricultural technologies in combatting poverty and improving food security is widely discussed in the economic literature. Notwithstanding, the adoption and diffusion of new technologies in underdeveloped economies, particularly in sub-Saharan Africa, remain quite low. This study examined the role of information acquisition on the adoption of improved crop varieties in Ghana and Ethiopia, using observational data from a survey of farm households in Ghana and experimental data from Ethiopia. In the study on Ghana, I estimated the effect of learning from peers on the speed of adoption, conditional on the local transitivity of farmers' neighborhoods, connectivity to important peers, and modularity of the network, while controlling for contextual effects and using a control function approach to account for correlated effects. Analysis of the data from the randomized control trial in Ethiopia was conducted with a dyadic model to control for the unobserved characteristics that potentially result in endogenous group formation in the social interactions, using control function approach.

The findings from the study on Ghana showed that having past adopting peers and high experienced peers tend to increase the speed of adoption, but the magnitude of peer experience on the probability of speed of adoption is higher if the farmer has more peers already adopting the improved variety, suggesting that benefits and production know-how play important roles in how farmers learn from their network contacts. The results also revealed that the likelihood of adopting faster increases with high values of transitivity and centrality, whereas higher levels of modularity tend to slow down diffusion, indicating that highly cohesive networks favor the frequency and intensity of interactions.

The findings from the experimental study in Ethiopia showed higher and statistically significant propensity of adoption when improved extension service delivery system involved demonstration trials with field days organized by trained DAs that consider farmers' networks. In particular, the results reveal that improving the capacity of development agents' communication and facilitation skills can be crucial in enhancing the adoption of improved varieties. The findings generally suggest that the common assertion that the extension strategy of targeting initial and influential adopters in the network for disseminating information may not be sufficient in promoting diffusion at the network level.

Policies and interventions aimed at engineering connections among farmers to improve information flow are important in the diffusion of new technologies. Specifically, social interaction-oriented policies such as workshops and seminars, or supporting adopters' association that is open also to nonadopters, can increase the diffusion process. Thus, in addition to making extension services accessible to rural farmers, policymakers may also need to encourage or incentivize them to participate in extension activities (such as farmers' field days and demonstration site visit) to significantly increase adoption of an agricultural technology.

The recent empirical studies on technology diffusion clearly indicate that field experiments can be quite useful in explaining the adoption puzzle in developing countries. Although the use of field experiments in analyzing information flows in technology diffusion has gained increasing significance in recent years, particularly to overcome problems with identification issues, there is still the need for more research on the significance of network structures such as modularity and transitivity in explaining the adoption puzzle in developing countries. However, as recently argued by Todd and Wolpin (2023), these experiments need to include data beyond simple measurement of the treatment and the outcome, because policy makers need more information than that provided by an experiment to guide their decision making at the different stages of program design, implementation, and evaluation. A combination of structural modeling with field experiments appears to be quite promising in this direction.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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