Received: 28 January 2022 | Revised: 7 July 2022 | Accepted: 25 August 2022

DOI: 10.1111/1477-9552.12517

JAE Journal of Agricultural Economics

ORIGINAL ARTICLE

The role of social networks in the adoption of competing new technologies in Ghana

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Funding information

Deutscher Akademischer Austauschdienst and Government of Ghana; Agencia Española de Investigación (AEI), Grant/Award Number: PID2020-118268RB; Ministerio de Ciencia e Innovación (MCIN), Grant/Award Number: 10.13039/501100011033/; German Academic Exchange Service

Abstract

We use a detailed dataset to examine the impact of social networks, conditional on contextual and individual confounders, on farmers' adoption of competing improved soybean varieties in Ghana. Based on the contagion conceptual framework, we employ a spatial autoregressive multinomial probit model to examine how neighbours' varietal and cross-varietal adoption of improved varieties affect a farmer's adoption decision in the social network. Our results show that adoption decisions in a network tend to converge on one variety, such that beyond a threshold of adopting neighbours of that improved variety, the cross-varietal effects tend to lose significance in the network. If the shares of adopting neighbours of the improved varieties are equal, we find evidence that farmers are not more likely to adopt either improved variety compared to farmers with no neighbours who have adopted the improved varieties. The findings demonstrate the significance of neighbourhood effects in the adoption of competing technologies.

KEYWORDS

cross-varietal effect, Ghana, social network, soybeans, spatial model, technology adoption, threshold

JEL CLASSIFICATION

C21, D83, O13, O33

1 | INTRODUCTION

In developing countries where the reliance on agriculture is high, improving agricultural productivity and income growth through the adoption of new and improved innovations is widely accepted as important (Issahaku & Abdulai, 2020). Studies have shown that improved crop varieties are responsible for about a 50%–90% increase in world crop yield per hectare (Muange, 2014). Unfortunately, adoption of improved varieties and other forms of new technologies remains quite low, especially among smallholders in sub-Saharan Africa (Muange, 2014; Teklewold et al., 2013). Walker et al. (2014) argue that of 20 main crops grown by farmers in Africa, improved varieties account for only about 35% of the area cultivated, which underscores the significance of understanding the determinants of technology adoption for research and policy.

Modern technologies have often been introduced with the normative anticipation that such technologies will do well, as they allow peers to learn from each other, thereby displaying increasing returns as more people adopt (Arthur, 1989). Beyond this, many empirical studies have shown the importance of social networks in the adoption and diffusion of new agricultural technologies (e.g., Abdul Mumin & Abdulai, 2022; Bandiera & Rasul, 2006; BenYishay & Mobarak, 2018; Conley & Udry, 2010; Foster & Rosenzweig, 2010). Unfortunately, there is a lack of empirical evidence on how the adoption of competing technologies by agents' neighbours and the adoption rates of each of the different technologies in social networks affect the farmer's adoption decision. Previous studies on this front have mainly been theoretical, focusing on the use of economic theory to derive normative results, predicting adoption and characterising equilibrium conditions of adoption (Acemoglu et al., 2011; Kornish, 2006).

In this article, we investigate the relationship between a farmer's decision to adopt one of three available technologies and their neighbours' adoption decisions within a social network setting. A farmer's adoption of a given technology depends not only on the adoption rate of this particular technology, but also on the adoption rate of competing technologies available in the farmer's network/community (Katz & Shapiro, 1986). This study, to the best of our knowledge, provides the first empirical assessment of farmers' adoption decisions in a multiple competing technology setting, where a farmer's adoption behaviour is influenced by that of neighbours adopting all available improved technologies. This type of investigation is important for the following reasons: First, this analysis reflects the situation farmers face in contemporary economic, socio-political and technological environments, where similar and/or different technologies for the same purpose are developed (Ali & Abdulai, 2010; Teklewold et al., 2013). The current production environment facing agricultural producers is characterised by the continual development of new technologies with major resource implications (Mutsvangwa-Sammie, 2020). However, whereas some of these innovations have gained acceptance by farmers, many others have performed poorly or failed in terms of adoption and have since become obsolete (Mutsvangwa-Sammie, 2020; Razanakoto et al., 2018).[1] Thus, studying competing agricultural technologies can lead to a better understanding of the appropriateness, promotion and performance of multiple and competing agricultural technologies, which characterises improved technological development and interventions in many developing countries.

Second, and perhaps more important in the context of social network externalities, is that a farmers' decision about a given technology depends on the past and future adoption rates of each of the competing technologies in the farmer's socio-economic network (Katz & Shapiro, 1986; Kornish, 2006). However, learning about a new technology has been shown to be a non-trivial exercise for farmers, and this is true even in the context of social learning from own or neighbours' experiences (Abdul Mumin & Abdulai, 2022; BenYishay & Mobarak, 2018; Conley & Udry, 2010). This challenge becomes an uphill task, especially in the context of multiple technologies where farmers are expected to learn about each technology not as a single input, but as a potential technology from many bundles of new technologies (Dorfman, 1996). Hence, we investigate the technological uptake of a new variety, highlighting the interdependence of adoption decisions among neighbours, as well as the implications of being a lead or lag variety within a network. For instance, the higher the adoption rate of a particular variety, the higher are the associated complementary network externalities and the

[1]Existing evidence in developing countries show that farmers do abandon some innovations after they have been introduced to them. For instance, Mutsvangwa-Sammie (2020) reported farmers abandoning some conservation agricultural practices 3 years after introduction in Zambia, despite huge investments committed to the project. In our study context, the CSIR-SARI have also introduced about nine improved soybean varieties but only two of these (i.e., *Jenguma* and *Afayak*) are still in cultivation today, in addition to the traditional variety (CSIR-SARI, 2013).

likelihood of becoming a lead variety in terms of adoption. This may explain why some technologies do well or even become dominant among competing technologies in some settings, and other technologies fail.

To guide our empirical analysis, we invoke a simple contagion model which suggests that farmers' adoption decisions of a given variety depend on the adoption decisions of network neighbours who are adopters of that variety and neighbours who are adopters of the other varieties. Our model setup is related to other works on technology adoption and consumer market shares (Acemoglu et al., 2011; Arthur, 1989; Kornish, 2006). However, as an extension of these previous frameworks, we allow the status quo-technology to affect farmers' adoption decisions rather than assuming it is an obsolete option with its value normalised to zero. This makes the adoption of the traditional variety in a farmer's neighbourhood an argument in the value function of farmers' adoption decisions in our framework. We then employ spatial econometric techniques similar to Lee (2007), Lin (2010) and Bramoullé et al. (2009) to examine the impacts of social networks on farmers' adoption decisions of two improved soybean varieties in Ghana, using unique and detailed observational data.

Our analysis is novel in the following respects. First, by incorporating endogenous effects, contextual effects and unobserved correlated fixed effects, we are able to delineate the effects due to behavioural decisions, average neighbours' characteristics and those due to unobserved common characteristics. The consideration of all three effects is important, as their unbundling helps identify the effects of behavioural decisions, which is the most important aspect of these network effects in designing and targeting innovation policies more effectively (Manski, 1993 p. 533). Second, we examine cross-variety dependence to show how farmers' adoption of the improved varieties are related to their neighbours' adoption decisions. With this, we are able to circumvent the interpretation problem of the estimated parameters that is usually associated with the approach of capturing interdependence among alternatives in the variance–covariance structure[2] (Autant-Bernard et al., 2008; LeSage & Pace, 2009; Wang et al., 2014).

The remainder of the paper is structured as follows. The next section describes the context and data. In Section 3, we present the conceptual framework that we use to guide the empirical analysis. We present the empirical framework and estimation in Section 4. In Section 5, we report and discuss the results, and conclude in Section 6.

2 | CONTEXT AND DATA

In this section we present the context of our empirical study and the data about social and locational dimensions of the underlying social network. We also present the descriptive statistics of the collected agronomic and socioeconomic data.

2.1 | Context

Soybean is a crop that is mainly cultivated in the northern part of Ghana (Northern, Upper East and Upper West regions), with the Northern region accounting for 65.72% of the total area cultivated to the crop in Ghana. It is a commercial crop that has the potential to raise farmers' incomes and improve their nutritional status. It is also a versatile crop that supports livestock rearing and fisheries and provides raw materials for local industries. However, it has not yet been fully accepted by farmers, because of the perceived cropping and handling difficulties (Plahar, 2006). Also, available evidence suggests that average yields are as low as 0.8 MT/ha, even though there is the potential to achieve

[2]Typically, in order to identify the multinomial probit model, the first diagonal element of the covariance matrix is set to unity, which makes the interpretation of the dependence among alternatives problematic when captured in the variance–covariance structure (Autant-Bernard et al., 2008; Chakir & Parent, 2009).

yields as high as 2.5 MT/ha, with improved varieties of seeds and appropriate agronomic practices (Gage et al., 2012).

The Council for Scientific and Industrial Research (CSIR) and Savannah Agricultural Research Institute (SARI) have developed and introduced a number of innovations including improved seed varieties and inoculant to promote the cultivation and output of the crop. Two of the improved varieties, namely *Jenguma* and *Afayak*, have both been in cultivation since 2014, in addition to the traditional variety (*Salintuya*). These improved varieties were first introduced to farmers at demonstration sites in the various districts by SARI, and following adoption of some farmers, seeds were subsequently made available to these farmers and to extension offices of the Ministry of Food and Agriculture (MoFA, 2010) to promote farmers' access to the seeds and information about planting (CSIR-SARI, 2013). These avenues remain the main sources of information about the cultivation and yield potentials of these varieties.

The improved varieties have a yield potential of over 2.0 MT/ha and are resistant to pod-shattering, earliness in maturity (i.e., about 35 days less compared to the traditional variety) and to other agricultural stress such as pests, diseases, low phosphorous soil and climatic variabilities (CSIR-SARI, 2013). In addition, planting the improved varieties does not require any special complementary inputs that are different from the inputs required by the traditional variety.[3] These notwithstanding, studies show that the use of improved soy seed is quite low, with estimates ranging between 16% and 33% (SIL, 2015) of soybean farmers. The indigenous, late maturing and shattering variety is still in wide use, and CGIAR (2009) reported that this variety constituted more than 50% of all soybean varieties under cultivation in Ghana. This suggests the need to understand what might explain farmers' adoption of a particular variety in a context of multiple improved varieties. This will be useful in explaining the underlying drivers of varieties emerging as dominant or marginal in the farmers' villages.

2.2 | Data

2.2.1 | Social networks

The data used in this study were collected from 483 farm households across 5 districts in 25 villages in the Northern region of Ghana, between July and September 2017. The survey design employed a multistage random sampling technique to first purposively select soybean growing districts, based on intensity of soybean production[4] and then randomly select villages and households, proportionate to the number of households in each district. Finally, random matching within sample was used, whereby in each village (i.e., a village represents a social network or group), 20 farm households were randomly selected and each household was matched with 5 other farm households also randomly drawn from the village sample. For each match, conditioned on knowing the matched household, we collected detailed information about the relationship between them. To identify existing links in the network, we used both social and locational indicators in the definition of a farmer's neighbours (Banerjee et al., 2013).

Table 1 presents these social and locational dimensions of social network contacts. Each farmer knows on average 3.13 of the 5 farmers randomly matched to him.[5] Also, the average farmer has 1.77 agricultural information contacts, 2.17 relatives, 1.18 friends, and exchanged labour with 1.73 of the

[3]The high and excess demand for soybean over its supply, especially by the poultry sector, in Ghana (Plahar, 2006), and the high integration of the soybean market into the international market (Goldsmith, 2017), suggest marketability of soybean may not be the main barrier to adoption given that all three varieties face similar market conditions. In addition, Table A1 in the Online Appendix shows no systematic difference in market access across farmers' adoption status.

[4]This was done in consultation with the Ministry of Food and Agriculture (MoFA) Regional and Districts Offices and Resilience in Northern Ghana (RING)

[5]We use the masculine gender because the majority (60%) of the farmers in the sample are male.

TABLE 1 Social network information

Network connections and information	Mean	SD	Min	Max
Number of random matched known	3.13	1.15	0	5
Conditional on knowing the matched				
Social dimension of contact				
Number of agricultural information contacts	1.77	1.79	0	5
Number of neighbours who are relatives	2.17	1.67	0	5
Number of neighbours who are friends	1.18	1.56	0	5
Number of neighbours with same religion	0.64	1.07	0	5
Number of neighbours ever exchanged labour	1.73	1.86	0	5
Number of neighbours ever exchanged credit	0.69	1.35	0	5
Number of neighbours ever exchanged land	0.33	0.95	0	5
Locational dimension of contact				
Number ever visited	2.18	1.64	0	5
Number of farm neighbours	0.87	1.20	0	5
Number of residential neighbours	0.67	0.96	0	5
Social links (social ties)				
Number of social contacts	3.12	1.25	0	5
Degree[a]	3.73	1.51	1	8
Network transitivity[b]	0.46	0.09	0.18	0.60
Proportion of *Jenguma* adopters in neighbourhood (unconditional)[c]	0.42	0.36	0	1
Proportion of *Afayak* adopters in neighbourhood (unconditional)[c]	0.29	0.31	0	1

Note: SD denotes standard deviation and Min and Max are minimum and maximum values respectively.

[a]The degree statistic was calculated based on the constructed networks. The construction of the networks was done based on undirected links where two farmers, such as i and j, were considered as having a link if either i or j or both mentioned the other as someone they have any of the relationship dimensions in the table with. Hence, the network may have more entries of ones compared to the number of social contacts which is based on links stated by only farmer i. It explains the slightly higher degree statistic compared to the number of social ties.

[b]Figures A1.1–A1.2 present some of the networks and their respective transitivities.

[c]The word 'unconditional' refers to the proportion of adopting neighbours, j, of each variety that is not conditioned on the variety adopted by the farmer, i.

known matched farmers. The farmer, on average, has visited 2.18 of the contacts at least once, and has 0.87 or 0.67 of the contacts as farm or residential neighbours, respectively.

We define the farmer's neighbours as those among the 5 farmers randomly assigned to them, that they share any of these social and locational contacts with (i.e., the union of these contacts). When we take the union of these social and locational contact dimensions, an average farmer has 3.12 social ties (Table 1). We use the social and locational contacts to construct our social network matrix with entries, w_{ij}, being equal to one if the respondent i had any of these relationships with a matched farmer j (i.e., i and j are neighbours), and zero otherwise (i.e., i and j are not neighbours). The resulting social network matrix, W, is a 483×483 block-diagonal matrix, along village networks. Based on the matrix, W, the average farmer has 3.73 neighbours in the social network and a maximum of 8 neighbours as indicative by the term degree in Table 1. The table also shows that an average farmer has 42% and 29% adopting network members of *Jenguma* and *Afayak* varieties, respectively.

2.2.2 | Descriptive statistics

We also elicited detailed information on the household and farm level characteristics. Table 2 shows definition, measurement and descriptive statistics of variables for the surveyed households and of

TABLE 2 Variable description, measurement and descriptive statistics

Variable	Definition	Own (X) characteristics Mean	SD	Neighbours' (WX) characteristics Mean	SD
Independent variables					
Age of farmer	Age of farmer (years)	44.00	12.01	43.93	7.15
Gender of farmer	1 if male; 0 otherwise	0.59	0.49	0.58	0.33
Farmer's education	No. of years in school	1.11	3.08	1.11	1.81
Farmer's experience	No. of years in farming	12.67	2.72	12.71	2.01
Household size	Household size (No. of members)	5.72	2.09	5.72	1.48
Household landholding	Total land size of household (in hectares)	2.59	1.56	2.63	1.12
Credit constraint	1 if farmer indicated did not obtain sufficient credit or not successful in applying for credit; 0 otherwise	0.55	0.49	0.55	0.34
Risk of food insecurity	Risk of food insecurity (No. of months household was food inadequate)	0.94	1.39	0.93	0.94
Extension contact	1 if ever had extension contact; 0 otherwise	0.54	0.92	0.56	0.69
NGO/Res contact	1 if ever had contact with non-governmental/research organisation; 0 otherwise	0.28	0.45	0.29	0.33
Association membership	No. of village-based associations a farmer is a member	1.09	1.29	1.08	0.89
Electronic device	1 if own phone, radio and/or television; 0 otherwise	0.82	0.39	0.82	0.26
Soil quality	4 = fertile; 3 = moderately fertile; 2 = less fertile; and 1 = infertile	2.96	0.97	2.97	0.69
Soybean seed price	Soybean price in GHS/kg	1.06	0.19	1.06	0.14
Dependent variable					
Jenguma	Adopters of *Jenguma* variety (1 if adopted *Jenguma*; 0 otherwise)	0.42	0.49	0.87^{+}	0.21
Afayak	Adopters of *Afayak* variety (1 if adopted *Afayak*; 0 otherwise)	0.26	0.44	0.82^{+}	0.24
Salintuya	Adopters of *Salintuya* variety (1 if adopted *Salintuya*; 0 otherwise)	0.32	0.47	0.85^{+}	0.26
Instruments					
Village born	1 if farmer was born in village	0.69	0.46		
Parent authority	1 if any parent of the farmer had an authority in village	0.13	0.34		
W^2Adopt	Proportion of adopting neighbours of neighbours	0.21	0.40		
Extension distance	Distance to the extension office (in kilometres)	9.89	9.14		

TABLE 2 (Continued)

Variable	Definition	Own (X) characteristics Mean	SD	Neighbours' (WX) characteristics Mean	SD
NGO distance	Distance to the nearest agric. Research or non-governmental organisation (in kilometres)	14.56	11.79		
Finance distance	Distance to the nearest financial institution (in kilometres)	9.26	6.88		

Note: SD denotes standard deviation. + implies that the proportion of adopting neighbours (*j*'s) of each variety is conditional on the farmer (*i*) adopting that variety. That is why the proportion of adopting neighbours of each variety in this table is higher than the unconditional proportions in Table 1. Figure A4 of Online Appendix A illustrates the proportion of uptake of varieties by villages.

their neighbours. The majority of farmers in the sample are male. The average education attained by the surveyed farmers is low, about 1.11 years, but with an average experience of about 12.7 years of farming. In addition, the majority (55%) of the farmers and (56%) of their neighbours ever had contact with extension agents, whereas only 28% of farmers and 30% of their neighbours ever had contact with research and non-governmental organisations. Table 2 further shows that the majority of the farmers and their neighbours, 55%, are credit-constrained. The proportion of credit-constrained farmers is significantly lower for *Jenguma* producers (Table A1 Panel B, Online Appendix A).

Furthermore, about 42% and 26% of the households were adopters of *Jenguma* and *Afayak*, respectively, whereas 32% cultivated *Salintuya*.[6] Table 2 also shows a strong association between a farmer's adoption of an improved variety and the proportion of neighbours who adopted that variety. In particular farmers who adopted *Jenguma* have up to 87% of their neighbours also adopting *Jenguma*. At the same time, about 82% of neighbours of *Afayak* adopters are themselves adopters of *Afayak*, and farmers who are cultivating the traditional variety have about 85% of their neighbours also producing the traditional variety. This suggests that farmers exchange information about soybean, and/or imitate their neighbours' cultivation choices.

3 | CONCEPTUAL FRAMEWORK

In our study, the technologies under consideration are the two improved soybean varieties and the traditional variety as the default option. The farmer's decision problem is to maximise the expected net benefit from adoption, by selecting the strategy that offers the highest payoffs. The alternative strategies are characterised by the payoffs from (i) adopting variety 1, (ii) adopting variety 2 and (iii) from maintaining the traditional variety 0. Adoption decisions not only depend on the farmer's subjective expected current stand-alone net benefits of an improved variety, but also on the perceived reliability of these expectations. The relative and absolute numbers of adopting and non-adopting neighbours of both modern varieties allow farmers to learn about their neighbours' private beliefs and to form their subjective expectations. Alternatively, farmers may prefer to wait rather than adopting. A farmer's potential benefit from waiting is given by (i) the uncertainty of the expected net benefits of modern varieties declines over time, as more neighbours try them and (ii) later adoption facilitates 'learning from others', given a number of adopters. The higher the share of neighbours that have adopted one of the improved varieties compared to the share of neighbours that adopted the other variety, the higher is the likelihood that a farmer adopts this variety. Yet, the farmer's likelihood of adoption is conditional

[6] Very few households were found to be using more than one variety (i.e., either the two improved or an improved and the traditional variety), which constituted 17 (i.e., 3.4%) out of the total sample of 500 households. This category was dropped in the analysis which resulted in a sample size of 483.

in the sense that it not only depends on the share of neighbours but also on the absolute number of neighbours that have adopted this improved variety.

The distinction between the relative and absolute numbers of adopters is useful as it allows the contextualisation of the relative and absolute influence neighbours' decisions have on the farmer adoption decision. For example, even if the relative number of adopters for one variety is high, adoption may not take place because the absolute number of neighbours that adopted this variety in the past is small. Hence, the overall likelihood of adoption is small as well. Similarly, if the relative number of adopters for one of the improved varieties is small, but the absolute number of neighbours that adopted this improved variety is large, the overall likelihood of adoption may be large as well. Thus, a farmer's likelihood of adoption increases with the number and/or proportion of adopting neighbours of that variety. However, farmers are less likely to switch from the traditional variety if none of the two improved varieties is dominant, that is, if the proportions of adopting neighbours of the two improved varieties are both low, high or similar.

4 | EMPIRICAL FRAMEWORK

We first present the base model and discuss the identification concerns and strategies we use in the empirical analysis in Section 4.1, and then outline the empirical estimation in Section 4.2.

4.1 | The model and identification

The empirical literature has identified three types of behavioural effects that can arise from social interactions: endogenous effects; exogenous/contextual effects; and correlated effects (Manski, 1993; Moffitt, 2001). To motivate our discussion on these effects, let us define m_g as the number of individuals in a reference group g with $g = 1, \ldots, G$, and G as the total number of groups (villages) in the sample. Consider the following linear regression in which y is a scalar outcome (i.e., adoption) and $\boldsymbol{x}$ are observed exogenous attributes that affect y. Adoption is defined by:

$$y = \rho E\left(y \middle| m_g\right) + \boldsymbol{x}'\beta_1 + E\left(\boldsymbol{x} \middle| m_g\right)'\beta_2 + u, \tag{1}$$

where $E\left(y \middle| m_g\right)$ is the mean of the outcome among those individuals, m_g, in the reference group, g; $E\left(\boldsymbol{x} \middle| m_g\right)$ is the mean of exogenous characteristics among those individuals in the reference group; and the ρ and β's are parameters to be estimated with u as the error term. The parameter ρ denotes the endogenous network effect, whereas β_2 defines the exogenous/contextual effects. Manski (1993) showed that specification (1), called the linear-in-means model, suffers from the 'reflection problem', which is the difficulty in differentiating between endogenous (behavioural) and exogenous (contextual) factors, since expressing the endogenous effects $E\left(y \middle| m_g\right)$ as the average behaviour or outcome of the group makes it a linear function of the mean characteristic of the group $E\left(\boldsymbol{x} \middle| m_g\right)$ in model (1). This confounds and confuses the two effects, and the inherent implications associated with each may be misleading, as they have been identified to have effects different in nature and in policy conclusions (Lin, 2010; Manski, 1993).

Another important confounder of the behavioural effects is the argument by Moffitt (2001) that unobserved factors in u, noted earlier as correlated effects, may also be a source of correlation among individuals in a given group (see also Calvo-Armengol et al., 2009; Lee et al., 2010). Moffitt (2001) distinguished between correlations due to similarities or preferences that drive a group of individuals to group together, and those that are attributable to similar environmental characteristics, suggesting that any social impact could be a reflection of omitted variables, or a spurious effect. Accordingly, we use a spatial autoregressive (SAR) model, where the disturbance in Equation (1) is decomposed into network fixed effects, α_g (which defines unobserved characteristics that are similar for all network members in a network), and innovations, ε_{kg}, to account for endogenous, contextual and group fixed effects in a network interaction setting as follows:

$$Y_{kg} = \rho_0 W_{kg} Y_{kg} + X_{kg}\beta_1 + W_{kg}X_{kg}B_2 + l_{m_g}\alpha_{g0} + \varepsilon_{kg}, \tag{2}$$

where $g = 1, \ldots, G$ and G is the total number of groups (villages) in the sample; m_g is the number of members in the g th group; and $k = \sum_{g=1}^{G} m_g$ is the total number of observations. The term $Y_{kg} = \left(y_{1g}, \ldots, y_{m_g,g}\right)'$ is an m_g dimensional vector of y_{ig}, with y_{ig} as the adoption decision of the ith member in group g and X_{kg} is an $m_g \times r$ dimensional matrix of exogenous characteristics. W_{kg} is a non-stochastic $m_g \times m_g$ network weights matrix with zero diagonal elements, and the W_{kg} specification captures the network structure of the macro group g. l_{m_g} is an m_g vector of ones, with the coefficients α_{g0} capturing group fixed effects. The term $\varepsilon_{kg} = \left(\varepsilon_{kg,1}, \ldots, \varepsilon_{kg,m_g}\right)'$ is an m_g dimensional vector of errors, where $\varepsilon_{kg,i}$'s are assumed to be i.i.d., with $\mathrm{Var}(\varepsilon_{kg}) = \sigma_0^2 I_{m_g}$.

Studies by Bramoullé et al. (2009), Calvo-Armengol et al. (2009) and Lee et al. (2010) demonstrate that the SAR model in our setting is identified by accounting for group fixed effects, because each group g can have any arbitrary structure, making the interaction patterns sufficiently different across networks, and this is reflected in the different structure of each network's weight matrix. Given that we define networks at the village level, we account for group fixed effects with village dummies of all the 25 sampled villages. The intuition is that farmers in the same village face similar environmental and institutional conditions and, thus, the inclusion of these village fixed effects is expected to account for any unobserved conditions that may affect the behaviour and outcomes of farmers in the same village/network (Lee, 2007).

Whereas the network fixed effects can account for correlated unobservables at the group/network level, they do not account for endogenous network formation, or correlated unobservables between individuals in the same group, which may result in endogeneity problems (Moffitt, 2001). For this reason, we use the control function approach, suggested by Brock and Durlauf (2001), to account for the potential endogeneity of link formation and neighbours' adoption. Specifically, we use farmers' birth status (i.e., whether the farmer was born in the village) and the authority of farmers' parents (i.e., whether any of the farmer's parents ever had an authority in the traditional chieftaincy structure in the village) as instruments for network links, and the proportion of adopting neighbours of neighbours as an instrument for neighbours' adoption (see Table 2 for the descriptive statistics).

The reasoning behind the use of farmers' birth status as an instrument is that farmers who are born in the village are expected to have deeply rooted and well-connected social ties, which have evolved over time, with other members of the village. Non-natives seldom move to or settle in these villages, making out-migration to urban areas more likely than in-migration. The second instrument is the authority of farmers' parents in the traditional chieftaincy structure in the village. We believe this is a relevant instrument because the traditional authority of the parents affects the farmer by increasing the farmer's contact with people who contact the parents and may increase the popularity of the farmer in the village. Thus, farmers who were born in the village or have parents with authority in the traditional chieftaincy structure are expected to have more social connections and links than other village members.

However, we do not expect a farmer's birth status or the status of the parent in the village to directly affect his decision to adopt any of the improved varieties except through other means, such as the interactions with other farmers.[7] We then use these instruments together with other control variables

[7]One issue that might threaten the use of these two variables as instruments is when privileges due to parents' authority lead to higher access to production opportunities and resources which then affect adoption through access to land, other resources and information. For this reason, we control for household landholding, credit, and other sources of information on farming in all specifications.

to estimate a first-stage conditional edge independence model of network formation (Fafchamps & Gubert, 2007), retrieve the predicted residuals and insert them into our adoption Equation (2) as a control function to account for endogeneity of link formation within networks.

We next considered the potential endogeneity of neighbours' adoption. In order to account for this, we follow the approaches of Bramoullé et al. (2009)[8] and Di Giorgi et al. (2020) and use the proportion of adopting neighbours of neighbours as an instrument for neighbours' adoption. The intuition is that the behaviour and characteristics of a farmer's neighbours of neighbours are correlated with the behaviour of the farmer's neighbours, but do not directly affect the behaviour of the farmer. Thus, it satisfies the exclusion restriction of being an exogenous instrument for the adoption decisions of the farmer's neighbours. When farmers are neighbours, they are more likely to interact and exchange information and resources, which can increase the likelihood that they influence the behaviour and decisions of each other. Consequently, when a farmer has a neighbour, whose neighbours received new and more information about the improved variety, then the farmer can access this information indirectly through his neighbour.

Using these instruments together with other controls, we estimate a first-stage model of neighbours' adoption, retrieve the predicted residuals and insert them into the household adoption model. The inclusion of the residuals controls for the endogeneity of neighbours' adoption by accounting for the correlation between the endogenous peer effects and the unobservables that affect farmers' adoption decisions (Wooldridge, 2015). The network formation model and the first-stage estimates are shown in Online Appendix B.

4.2 | Empirical estimation: Spatial autoregressive multinomial probit

We specify farmers' adoption decisions in a spatial autoregressive multinomial probit model of the adoption of two improved soybean varieties (*Jenguma* and *Afayak*) in relation to a conventional variety (*Salintuya*).

The spatial autoregressive multinomial probit (SAR MNP) model is based on the random utility framework, which is expressed as a system of G seemingly unrelated regression models, with each latent choice considered as an equation (LeSage & Pace, 2009; Wang et al., 2014). Thus, we denote the model as $kV \times 1$ vector of latent outcomes $\overline{\boldsymbol{Y}}^* = \left(Y_1^{*\prime}, Y_2^{*\prime}, \ldots, Y_k^{*\prime}\right)$ and each of the $V \times 1$ vectors $Y_i^* = \left(Y_{i1}^*, \ldots, Y_{iV}^*\right)'$ is expressed as a continuous SAR model. Given this formulation and following Section 4.1, we express our estimation model as:

$$\overline{\boldsymbol{Y}}^* = \rho_1 \widetilde{W} \overline{Y}^*_{v=1} + \rho_2 \widetilde{W} \overline{Y}^*_{v=2} + \overline{X} \beta_1 + \widetilde{W} \overline{X} \beta_2 + l_{m_g} \alpha + \overline{\boldsymbol{e}}, \tag{3}$$

where $V = 1, 2$ represents the improved varieties, ρ_1 and ρ_2 are the endogenous effects of variety 1 and 2, respectively, on the adoption of all varieties. For example, in the equation of variety 2, ρ_1 is the cross effect of variety 1 and ρ_2 is the own effect of variety 2. The vector X, like the $kV \times 1$ matrix, is stacked based on the respective observed choices V to obtain $\overline{X}$ which represents $kV \times rV$ matrix of explanatory variables associated with each choice.

The observed response values, Y, of the latent outcomes are such that $Y_i = v$, if $Y_{i,v}^* = \max\left[Y_{i,1}^*, \ldots, Y_{i,V}^*\right] > 0$, and 0 if $Y_{i,v}^* \leq 0$, $\forall V = 1, 2$. The stacked V observations also require the network weight matrix to be re-cast in order to generate the interaction lags of $Y_{i,V}^*$ and to ensure conform-

[8]Unlike Manski's linear-in-means model, which assumes that all individuals of a group are affected by all members of the group. However, for the majority of social networks, individuals are influenced by their direct connections or neighbours, and this makes the influence of members uneven in the network (Bramoullé et al., 2009). This makes it possible to identify the endogenous effects from the exogenous effects by exploiting the network structure. For example, in a case of three individuals, i, j and k, that form a non-closed triad such that i and j are connected and j and k are connected but i and k are not connected, the characteristics of k can be used as an instrument to identify the effect of j on i (Bramoullé et al., 2009; Di Giorgi et al., 2020).

ability. This involves repeating each row of the $k \times k$ weight matrix V times to yield a matrix expressed as $I_V \otimes W = \widetilde{W}$, where I_V is a $V \times V$ identity matrix and W is the $k \times k$ social network matrix described in Section 2.2. Typically, the error terms are denoted by $\overline{\boldsymbol{e}} = (e_1, e_2, \ldots, e_k)'$ with $e_i = \left(e_{i,1}, \ldots, e_{i,V}\right)'$. The covariance matrix of $\overline{\boldsymbol{e}}$ is expressed as $I_k \otimes \sum$, with the $V \times V$ matrix $\sum$ representing the cross-varietal covariance matrix for the error terms across varieties. This is the cross-variety covariance, which is assumed to be identical and independent across individuals, but not varieties. However, modelling the cross-variety dependence in the mean part of the model implies restricting $\sum = I_V$, as suggested by LeSage and Pace (2009).

The challenges to the estimation of Equation (3) are the issues of the multidimensional integrals, correlations in the error terms and the complexity of the spatial dependence (Fleming, 2004; Kelejian & Prucha, 1999). We use the Markov Chain Monte Carlo (MCMC) sampling, as it is mostly applied in such settings, where the higher dimensional integrals are respecified into a sequence of draws with sometimes known conditional distribution (Wang et al., 2014). Given that $Y^*_{i,v}$ is not observable, we apply a Bayesian estimation approach to elicit the conditional posterior distributions $p\left(\rho \mid \bar{Y}^*, \beta, \Sigma\right)$ and $p\left(\beta \mid \bar{Y}^*,\ R, \Sigma\right)$. The Bayesian estimation approach is briefly presented in Online Appendix C.

5 | EMPIRICAL RESULTS

The Bayesian estimates of the parameters and diagnostics of the spatial autoregressive multinomial probit model are reported in Figure A2 (online) and in Table 3. The trace plots in Figure A2 exhibit a stationary trend in the draws, and the Geweke diagnostics in Table A2 show that all the variables have test statistics lower than the critical value of 2.71 (values in squared brackets) (Geweke, 1991). These are suggestive that the MCMC chains evolve to a convergent series of distribution, and thus meet the convergence criterion. We also check the estimates by increasing the number of draws and the burn-in from 5000 and 2000 in Tables 4 to 45,000 and 5000 (column 1 in Table A3), respectively, which shows that the estimates are similar in magnitudes, direction and significance to those reported in Table 3. The estimates of the residuals of the network formation and neighbours' adoption models are generally not statistically significant in all specifications, suggesting that the results are not driven by endogenous network formation or other correlated unobservables between individuals in the same group (see Table 3).

5.1 | Effects of absolute number and proportion of adopting neighbours

Table 4 presents estimates of marginal effects of endogenous own and cross-varietal effects on adoption of *Jenguma* and *Afayak*, using the absolute numbers of adopting neighbours (in Panel A) and the proportion of adopting neighbours (in Panel B) as measures of endogenous effects respectively, in Equation (3). The endogenous own varietal effects examine the effects of having *Jenguma* or *Afayak* adopting neighbours on adoption of *Jenguma* or *Afayak*, respectively, while the endogenous cross-varietal effects consider the effects of having *Afayak* or *Jenguma* adopting neighbours on the adoption of *Jenguma* or *Afayak*, respectively.

In terms of absolute numbers in own effects, a 10% increase in the number of adopting neighbours of *Jenguma* or *Afayak* is associated with a 1.3 or 2.6 percentage points increase in the probability of adopting *Jenguma* or *Afayak*, while decreasing the probability of adopting the traditional variety (i.e., *Salintuya*) by 2.6 and 2.9, respectively (Panel A in Table 4). These effects are all statistically significant at least at the 5% level. Also, having neighbours adopting a cross-variety, that is a 10% increase in the number of *Afayak* or *Jenguma* adopting neighbours, leads to a 0.03 and 0.04 percentage points decrease in the probability of adopting *Jenguma* or *Afayak*, respectively, *albeit* not statistically significant.

TABLE 3 SAR MNP estimates based on the proportion of adopters in farmer's neighbourhood (influence of non-adopting neighbours is taken into account)

Variables	*Jenguma*		*Afayak*	
	Estimates	SD	Estimates	SD
Endogenous effects				
Prop. Neighbadopt_*Jenguma*	0.231†	0.024	−0.053†	0.017
Prop. Neighbadopt_*Afayak*	−0.052†	0.018	0.340†	0.016
Own characteristics				
Age of farmer	7.6E-5	0.001	0.001	0.001
Gender of farmer	−0.029	0.022	0.016	0.024
Farmer's education	0.002	0.002	0.014†	0.004
Farmer's experience	−0.011†	0.004	−0.013†	0.003
Household size	0.003	0.004	−0.009†	0.005
Household landholding	0.057†	0.006	0.022†	0.007
Credit constraint	−0.142	0.084	0.013	0.028
Risk of food insecurity	0.001	0.008	−0.003	0.007
Extension contact	0.050†	0.022	0.100†	0.019
NGO/Res contact	0.039	0.063	0.057†	0.031
Association membership	−0.043†	0.011	0.017†	0.010
Electronic device	0.015	0.023	−0.019	0.025
Soil quality	0.062†	0.011	−0.011	0.010
Soybean seed price	−0.155†	0.075	−0.083	0.075
Contextual effects				
WAge of farmer	0.138	0.118	0.118	0.110
WGender of farmer	0.001	0.001	0.002†	0.001
WFarmer's education	0.017	0.021	0.004	0.027
WFarmer's experience	−0.001	0.003	−0.012†	0.005
WHousehold size	−0.002	0.003	2.0E-4	0.003
WHousehold landholding	0.001	0.005	0.013†	0.005
WCredit constraint	−0.020†	0.006	0.001	0.007
WRisk of food insecurity	0.138†	0.031	0.040	0.030
WExtension contact	0.005	0.008	0.003	0.008
WNGO/Res contact	0.014	0.016	0.024	0.018
WAssociation membership	−0.077†	0.027	−0.069†	0.032
WElectronic device	−0.018†	0.009	0.012	0.010
WSoil quality	0.063†	0.026	−0.012	0.026
WSoybean seed price	−0.019†	0.011	−0.001	0.010
Credit constraint residual	0.021	0.051	0.021	0.016
Extension contact residual	0.006	0.014	−0.010	0.013
NGO/Res contact residual	0.001	0.039	−0.020	0.018
Link formation residual	0.029	0.052	−0.051	0.059
Neighbour adoption residual	0.050	0.065	0.030	0.070

TABLE 3 (Continued)

Variables	*Jenguma*		*Afayak*	
	Estimates	**SD**	**Estimates**	**SD**
Constant	0.356†	0.171	0.319†	0.127
Network fixed effects	Yes		Yes	

Note: Pseudo -R^2 = 0.8390; DIC = 1171.30; Mean Log-likelihood = −976.07; n = 483; of draws = 5000 and burnin = 2000. SD denotes standard deviation. The estimates were obtained from the standardised social weight matrix. Thus, the endogenous and cross-variety effects indicate the effects of an increase in the proportion of adopters of each variety on the probability of adoption. The Prop. Neighbadopt_*Jenguma* is the own effect of *Jenguma* under the *Jenguma* equation but shows the cross-variety effect of *Jenguma* in the *Afayak* equation. Likewise, the Prop. Neighbadopt_*Afayak*, is the own effect of *Afayak* under the *Afayak* equation but also shows the cross-variety effect of *Afayak* in the *Jenguma* equation. The † denote significance at the 5% level. Table A4 of Online Appendix A considers group fixed effects.

TABLE 4 Marginal effects of SAR MNP estimates based on the absolute number and the proportion of adopters

Adopting neighbours	*Salintuya*			*Jenguma*			*Afayak*		
	Lower 0.05	**Posterior mean**	**Upper 0.95**	**Lower 0.05**	**Posterior mean**	**Upper 0.95**	**Lower 0.05**	**Posterior mean**	**Upper 0.95**
Panel A: Number of adopting neighbours									
Endogenous effects									
No. Neighbadopt_*Jenguma*	−0.321	−0.264†	−0.209	0.132	0.132†	0.132	−0.015	0.004	0.022
No. Neighbadopt_*Afayak*	−0.345	−0.288†	−0.233	−0.016	0.003	0.021	0.204	0.257†	0.311
Panel B: Prop. of adopting neighbours									
Endogenous effects									
Prop. Neighbadopt_ *Jenguma*	−0.661	−0.545†	−0.443	0.327	0.442†	0.567	−0.035	−0.004	0.028
Prop. Neighbadopt_ *Afayak*	−0.677	−0.562†	−0.454	−0.043	−0.008	0.028	0.433	0.539†	0.647
Own characteristics		Yes			Yes			Yes	
Contextual effects		Yes			Yes			Yes	
Network FEs		Yes			Yes			Yes	
Credit constraint residual		Yes			Yes			Yes	
Extension contact residual		Yes			Yes			Yes	
NGO/Res contact residual		Yes			Yes			Yes	
Link formation residual		Yes			Yes			Yes	
Neighbour adoption residual		Yes			Yes			Yes	

Note: For Panel A: Pseudo R^2 = 0.8207; DIC = 2794.90; and Mean Log-likelihood = −2329.10. The endogenous and cross-variety effects indicate the effects of an increase in the number of adopters of each variety on the probability of adoption. In Panel B: Pseudo-R^2 = 0.8390; DIC = 1171.30; Mean Log-likelihood = −976.07. The estimates were obtained from the standardised social weight matrix. Thus, the endogenous and cross-variety effects indicate the effects of an increase in the proportion of adopters of each variety on the probability of adoption. The Prop. Neighbadopt_*Jenguma* is the own effect of Jenguma under the *Jenguma* equation but shows the cross-variety effect of *Jenguma* in the *Afayak* equation. Likewise, the Prop. Neighbadopt_*Afayak*, is the own effect of *Afayak* under the *Afayak* equation but also shows the cross-variety effect of *Afayak* in the *Jenguma* equation. n = 483; of draws = 5000 and burnin = 2000. The † denote significance at the 5% level.

Given that farmers could be more concerned with the proportions and not the absolute number of adopters in their network, as it gives an indication of the skewness of the neighbourhood in terms of adoption, we present the estimates of these endogenous effects in Panel B of Table 4. The effects are similar to the effects in Panel A in terms of direction and significance levels of these effects but differ in the magnitude of the coefficients. In particular, a 10% increase in the proportion of a farmer's neighbours adopting *Jenguma* or *Afayak* increases the probability of the farmer adopting *Jenguma* or *Afayak* by 4.4 or 5.4 percentage points, respectively. However, the probability of adopting the traditional variety decreases by 5.4 or 5.6 percentage points with a 10% increase in the proportion of adopting neighbours of *Jenguma* or *Afayak*, respectively. These are also statistically significant at the 5% significance level. The marginal effects of the cross-varieties are also negative, suggesting that a farmer's probability of adopting a given variety, say *Jenguma (Afayak)*, decreases by 0.08 (0.04) percentage points with a 10% increase in the proportion of adopting neighbours of *Afayak* (*Jenguma*), although these are not statistically significant.

These findings generally suggest contagion effects, where farmers adopt the behaviour of their neighbours in the network. The endogenous own and cross-variety effects taken together imply substitutability between the new varieties. This is consistent with the argument by Niehaus (2011) that an agent's marginal valuation of the knowledge obtained from different neighbours is evaluated in relative terms if different kinds of knowledge is substitutable in the social learning process.

5.2 | Effects of the relative number of adopting neighbours

The number of adopters that needs to be attained before generating a significant relationship between the share of adopters and the likelihood of adoption is not evident from the above estimates. Hence, we consider three ranges of adopting neighbours of each variety in order to shed some light on this relationship. The results are presented in Table 5, where we report estimates of specifications that include different ranges of *Jenguma* and *Afayak* adopting neighbours.

These ranges are dummies with the reference (or base) category as having no adopting member of any of the improved varieties among the farmer's neighbours. The results show that relative to a farmer without an adopting neighbour of any of the improved varieties, the probability of growing the traditional variety (*Salintuya*) decreases by 0.25 or 0.18 percentage points for farmers with a *low share of neighbours'* adoption (at most 25%) of *Jenguma* or *Afayak*, respectively, and these are statistically significant at the 5% level. Also, the likelihood of growing the traditional variety further decreases when the share of adopters of the improved varieties consists of between 26% and 75% (*intermediate share of neighbours*), and above 75% (*high share of neighbours*) of adopters in the farmer's neighbourhood. Specifically, the probability of growing the traditional variety decreases significantly by 0.48 (0.41) or 0.82 (0.81), when the share of adopting neighbours of *Jenguma* (*Afayak*) is between 26% and 75%, or above 75%, respectively, relative to a farmer with no adopting neighbours of either of the improved varieties. This inclination of switching from *Salintuya*, is expected in cases where the traditional variety is relatively inferior, given the growing and environmental conditions. [9]

We now turn to the adoption of *Jenguma* and *Afayak* (Table 5). The probability of adopting *Jenguma* or *Afayak* when at most 25% of a farmer's neighbours adopt *Jenguma* or *Afayak* decreases by 0.04 or 0.14, respectively, relative to farmers without any adopting neighbours of the improved variety, with the coefficient of *Afayak* being statistically significant at the 5% significance level. Thus, having at most 25% of neighbours adopting *Jenguma* or *Afayak* is not generally sufficient to persuade the farmer to adopt that variety, and in fact this significantly decreases the probability of adopting *Afayak*. However, in terms of cross-varietal effects, a farmer with at most 25% of the neighbours adopting *Afayak* is associated with a 0.15 increase in the probability of adopting *Jenguma* compared to those with no adopting neighbours of the improved varieties. Similarly, relative to a farmer with no adopting neighbours of the improved varieties, the probability of adopting *Afayak* increases by 0.18 when a farmer has at most 25% of the neighbours adopting *Jenguma*.

[9] This is also the case in our study setting because of the high susceptibility of the traditional variety to environmental stress, which is quite unfavourable for this variety.

TABLE 5 SAR MNP estimates of distribution in proportion of adopter in farmer's neighbourhood

Prop. Of adopting neighbours	*Salintuya*			*Jenguma*			*Afayak*		
	Lower 0.05	**Posterior mean**	**Upper 0.95**	**Lower 0.05**	**Posterior mean**	**Upper 0.95**	**Lower 0.05**	**Posterior mean**	**Upper 0.95**
High Neighbour_ *Jenguma*	−0.867	−0.822†	−0.669	0.236	0.386†	0.536	−0.074	−0.003	0.067
Intermediate Neighbour_ *Jenguma*	−0.513	−0.479†	−0.367	0.067	0.173†	0.280	−0.062	0.015	0.097
Low Neighbour_ *Jenguma*	−0.288	−0.255†	−0.151	−0.129	−0.039	0.052	0.079	0.176†	0.274
High Neighbour_*Afayak*	−0.859	−0.809†	−0.660	−0.134	−0.058	0.013	0.517	0.677†	0.841
Intermediate Neighbour_*Afayak*	−0.446	−0.413†	−0.298	−0.091	−0.015	0.062	0.178	0.291†	0.413
Low Neighbour *Afayak*	−0.221	−0.180†	−0.063	0.063	0.152†	0.250	−0.252	−0.145†	−0.038
Own characteristics		Yes			Yes			Yes	
Contextual effects		Yes			Yes			Yes	
Network FEs		Yes			Yes			Yes	
Credit constraint residual		Yes			Yes			Yes	
Extension contact residual		Yes			Yes			Yes	
NGO/Res contact residual		Yes			Yes			Yes	
Link formation residual		Yes			Yes			Yes	
Neighbour adoption residual		Yes			Yes			Yes	
Pseudo R^2	0.866								
DIC	1269.3								
Mean Log-likelihood	−1057.7								

Note: $n = 483$; of draws = 5000 and burnin = 2000. SD denotes standard deviation. The estimates in this table were also obtained from the standardised social weight matrix. The quartiles denote the distribution of adopting neighbours of each improved variety. The *low*, *intermediate* and *high* neighbour were defined as having a proportion of adopting neighbours of an improved variety falling in 0.0 to 0.25, 0.26 to 0.75 and 0.76 to 1.0, respectively. The estimates show that having adopting neighbours of an improved variety (e.g., *Jenguma*) in the low range reduces the likelihood of adopting the traditional (*Salintuya*) and that improved variety (i.e., *Jenguma*), but increases the likelihood of adopting the other improved variety (i.e., *Afayak*). However, having adopting neighbours of *Jenguma* in the intermediate and high ranges increases the likelihood of adopting *Jenguma* but reduces the likelihood of adopting the other improved (i.e., *Afayak*) and the traditional varieties. The †denote significance at the 5% level.

These effects are statistically significant, but the difference in their magnitudes across varieties is not significantly different from zero ($p > 0.3$). We also observe that the probability of adopting an improved variety increases as the share of adopting neighbours increases beyond 26%. Still, in Table 5, the probability of adopting *Jenguma* increases by 0.17 and 0.39, when the share of a farmer's neighbours adopting *Jenguma* is within the 26% and 75% and above the 75% ranges, respectively, compared to a farmer without adopting neighbours of the improved varieties. For *Afayak*, a farmer with 26% to 75% or above 75% of the neighbours adopting *Afayak* in his network is associated with a 0.29 or 0.68 increase in the probability of adopting *Afayak* relative to a farmer without adopting neighbours of the improved varieties. These effects are statistically significantly different from zero. Also, the effects of the above 75% range of adopting neighbours are significantly higher than the effects of the 26% and 75% range of adopting neighbours for each of the two varieties ($p < 0.01$).

However, we also find that the cross-variety effects lose their significance, and the probability of adopting a given improved variety decreases as more neighbours adopt the other improved variety. For instance, in the case of neighbour adoption of *Jenguma*, the cross-variety effects suggest a decrease in the probability of adopting *Afayak* by 0.003 when a farmer has above 75% of adopting neighbours adopting *Jenguma*. Similarly, for neighbour adoption of *Afayak*, the cross-variety effects suggest a decrease in the probability of adopting *Jenguma* by 0.015 and 0.06 when a farmer has between 26% and 75%, and above 75% of adopting neighbours adopting *Afayak*, respectively, *albeit* not statistically significant at the 5% significance level. These estimates suggest self-reinforcement in the adoption process, as suggested in the conceptual framework, where a farmer is less likely to adopt a given variety when the proportion of adopting neighbours of that variety is low, and more likely as the proportion of adopting neighbours' increases (see also Kornish, 2006). Although the observation that a farmer's probability of adopting an improved variety decreases at low levels of adopting neighbours may seem unexpected on the face value, it suggests a threshold in farmers' response to neighbours' adoption. In particular, when the neighbours' adoption of a given variety does not exceed a certain threshold, farmers will be less likely to adopt that variety until neighbours' adoption reaches this threshold (Acemoglu et al., 2011).[10]

Finally, the estimates also show that adoption behaviour in respect of the two improved varieties converges towards the variety that leads in the neighbour's adoption rate, and will persist in its lead if the proportion of adopting neighbours of this variety translates to a higher adoption probability of the farmer than the proportion of the adopting neighbours of the competing variety. [11] Such skewed conditions could lead to a 'lock-in' on the lead variety in the neighbourhood and in the network. This result is consistent with the argument (Arthur, 1989) that agents' choice of technologies among competing technologies will lock in on the technology that by chance and historical events leads to adoption by neighbours, and that this could continue to the extent that reversal of such patterns of adoption will be difficult even with policy intervention.

5.3 | Differences in the share of adopting neighbours of varieties

Our conceptual framework suggests that the expected net benefits from adopting the improved variety with more adopting neighbours will be higher compared to low adopting neighbours.[12] In this section, we estimate the effects of the difference in the share of neighbours adopting *Jenguma* and *Afayak* on the probability of adopting these two varieties and present the results in Table 6. This analysis is also significant because it allows us to show the likelihood of adoption when a farmer has an equal proportion of adopting neighbours of each improved variety in the neighbourhood.

We find that, relative to a farmer without an adopting neighbour of any of the improved varieties, the probability of adopting *Jenguma* (*Afayak*) increases by 0.06 (0.18) when the difference in the share of adopting neighbours between *Jenguma* (*Afayak*) and *Afayak* (*Jenguma*), is *moderately higher* (i.e., $0 < \text{difference} \leq 0.5$) for *Jenguma* (*Afayak*), but statistically significant only for the adoption of

[10]So, when peer involvement is below a farmer's threshold, the farmer is most probably going to defer adoption until their threshold is met. Under such low levels, it is possible to observe a decreasing probability of adoption relative to a farmer without an adopting neighbour of either improved variety because the farmer cannot get the benefits of waiting and learning from the neighbours. If there are no adopting neighbours at all in the farmer's network, strategic delay is less attractive and the farmer may decide to learn by doing. In this situation, the probability of adoption decreases with low adopting neighbours compared to a farmer with no adopting neighbours at all.

[11]Our interpretation of the convergence process needs to be taken with caution as this is a snapshot of adoption behaviour in these social networks (villages) and not over time. This is a potential area for future empirical research by examining the dynamics and the equilibria state of adoption in these networks over time.

[12]The reported distribution of adopting neighbours over the different ranges of adoption is presented in Figure A3 of Online Appendix A.

TABLE 6 SAR MNP estimates of differences in proportion of adopters of improved varieties in farmer's neighbourhood

Difference in adopting neighbours	*Salintuya*			*Jenguma*			*Afayak*		
	Lower 0.05	**Posterior mean**	**Upper 0.95**	**Lower 0.05**	**Posterior mean**	**Upper 0.95**	**Lower 0.05**	**Posterior mean**	**Upper 0.95**
Panel A									
Very high *Jenguma*	−0.502	−0.397†	−0.295	0.227	0.329†	0.436	−0.140	−0.075†	−0.011
Moderately high *Jenguma*	−0.109	−0.008	0.091	−0.021	0.058†	0.141	−0.152	−0.074†	−0.011
Very high *Afayak*	−0.531	−0.421†	−0.312	−0.136	−0.066†	−0.001	0.466	0.579†	0.697
Moderately high *Afayak*	−0.237	−0.122†	−0.008	−0.110	−0.025	0.058	0.085	0.183†	0.284
Equal	−0.088	0.091	0.270	−0.157	−0.024	0.112	−0.202	−0.053	0.090
Panel B									
Very high *Jenguma*	−0.485	−0.374†	−0.266	0.209	0.322†	0.436	−0.145	−0.078†	−0.012
Moderately high *Jenguma*	−0.112	−0.009	0.091	−0.017	0.059	0.139	−0.158	−0.075	0.003
Very high *Afayak*	−0.523	−0.403†	−0.292	−0.135	−0.068	0.002	0.459	0.579†	0.701
Moderately high *Afayak*	−0.245	−0.124†	−0.009	−0.104	−0.018	0.066	0.080	0.182†	0.278
Both >0.25	−0.057	0.068	0.193	−0.121	−0.029	0.065	−0.100	−0.004	0.097
Both <0.25	−0.061	0.083	0.226	−0.079	0.028	0.134	−0.174	−0.054	0.062
Own characteristics		Yes			Yes			Yes	
Contextual effects		Yes			Yes			Yes	
Network FEs		Yes			Yes			Yes	
Credit constraint residual		Yes			Yes			Yes	
Extension contact residual		Yes			Yes			Yes	
NGO/Res contact residual		Yes			Yes			Yes	
Link formation residual		Yes			Yes			Yes	
Neighbour adoption residual		Yes			Yes			Yes	
Pseudo R^2	0.866								
DIC	1269.3								
Mean Log-likelihood	−1057.7								

Note: $n = 483$; of draws = 5000 and burnin = 2000. SD denotes standard deviation. The estimates in this table were also obtained from the standardised social weight matrix. The *very high Jenguma* or *Afayak* denotes when the difference between the proportions of *Jenguma* and *Afayak* adopters is greater than 0.5 for *Jenguma* or *Afayak*, respectively. Also, the *moderately high Jenguma* or *Afayak* denotes when the difference between the proportions of *Jenguma* and *Afayak* adopting neighbours is greater than 0 but less than or equal to 0.5 for *Jenguma* or *Afayak*, respectively. Equal means the proportion of adopting neighbours of *Jenguma* and *Afayak* are equal. Both >0.25 and both <0.25 denote both the proportion of *Jenguma* and *Afayak* adopting neighbours are greater and less than 0.25, respectively. The base category is those without any adopting neighbours of the improved varieties and consist of 18.6% of the sample. The values in parentheses are standard deviations. The † denote significance at the 5% level.

Afayak. However, the probability of adopting *Jenguma* (*Afayak*) decreases when the difference in the share of adopting neighbours between *Jenguma* (*Afayak*) and *Afayak* (*Jenguma*) is *moderately higher* for *Afayak* (*Jenguma*). Specifically, relative to farmers with no adopting neighbours of any of the improved varieties, a farmer's probability of adopting *Jenguma* (*Afayak*) decreases by 0.02 (0.07), if the share of neighbours adopting *Afayak* (*Jenguma*) is *moderately higher* (i.e., $0 < \text{difference} \leq 0.5$) than the share of neighbours adopting *Jenguma* (*Afayak*). Although this is statistically significant only for adoption of *Afayak*, the difference in magnitudes of the coefficients across varieties are statistically (weakly) different from zero ($p = 0.07$).

We observe a similar pattern, and even stronger and statistically significant own and cross-varietal effects on adoption, when the difference in the share of adopters between the two improved varieties is *very high* (i.e., difference > 0.5). In particular, a farmer with a very high share of adopting neighbours of *Jenguma* (*Afayak*) over *Afayak* (*Jenguma*) is associated with a 0.33 (0.58) increase in the probability of adopting *Jenguma* (*Afayak*) relative to a farmer with no adopting neighbours of these new varieties. Also, the probability of adopting *Jenguma* (*Afayak*) decreases by 0.07 (0.07) when the difference in the share of adopting neighbours between *Jenguma* (*Afayak*) and *Afayak* (*Jenguma*) is *very high* for *Afayak* (*Jenguma*).

In order to shed more light on what happens when the share of adopters of the improved varieties in a farmer's neighbourhood are equal, we examine this effect in Panel A, and the effects of having both shares of adopting neighbours being higher than 0.25 and lower than 0.25 in Panel B. For both panels, the reference category is still farmers without any adopting neighbours of the improved varieties. Interestingly, the results in Panel A show that the probability of adopting either *Jenguma* or *Afayak* decreases when the shares of adopting neighbours of the two improved varieties are equal, although not statistically significant in all cases. Panel B further shows that, relative to a farmer without adopting neighbours, the probability of a farmer adopting *Jenguma* (*Afayak*) increases (decreases), if the shares of adopting neighbours of both improved varieties are higher than 0.25 or lower than 0.25, *albeit* not statistically significant in all cases.

Given that the Bayesian estimates rely on a number of assumptions, discussed in Online Appendix D, which may affect the sensitivities of the draws and the consistency of the computed point estimates, we present binary non-parametric estimates of the effects of neighbours' adoption on own adoption in Figure A5 of the Online Appendix. We present estimates of the farmers' adoption of the improved varieties when the shares of adopters of the improved varieties in the farmer's network are equal (Figures A5.1 and A5.2), are greater than 25% (Figures A5.3 and A5.4) and less than 25% (Figures A5.5 and A5.6). Interestingly and consistent with the estimates in Table 6, we see that the probability of adoption for all cases is not statistically different from zero across the distribution of adopting neighbours within these ranges of adopting neighbours of both improved varieties.

Conversely, the probability of growing the traditional variety (*Salintuya*) increases, if the shares of adopting neighbours of the improved varieties are equal (Panel A) or if the share of adopting neighbours of both improved varieties are higher, or lower than 0.25, although the effects are also not statistically significant (Panel B). This suggests that farmers are not significantly more likely to adopt any of the improved varieties compared to farmers without adopting neighbours, if the share of adopters of these improved varieties are equal. However, the probability of growing the traditional variety (*Salintuya*) decreases when the difference in share of adopting neighbours between the improved varieties becomes higher in favour of any of the improved varieties. We also see that the magnitudes of the effects of *Afayak* adopting neighbours are mostly higher than the effects of *Jenguma* adopting neighbours, although these differences are not statistically significant ($p > 0.1$) in all cases.

5.4 | Effects of other controls

Table 7 documents the marginal effects of our controls for all the three varieties. For each variety, the table presents the direct and indirect (spillover) effects of each variable. We find that a 10% standard deviation (SD) increase in education covariate of all soybean adopters is estimated to significantly increase *Afayak* adoption probability by 0.17 percentage points, while decreasing the probability of using *Salintuya* by 0.12 percentage points, at the 5% significance level. The spillover effects of education of a farmer is estimated to increase the probabilities of his neighbours adopting *Afayak* by 0.04 percentage points when there is a 10% standard deviation increase. The effect of education generally emphasises the importance of human capital in learning about new technologies (Foster & Rosenzweig, 2010).

TABLE 7 SAR MNP marginal effects of other controls

Variables	*Salintuya*		*Jenguma*		*Afayak*	
	Direct	**Indirect**	**Direct**	**Indirect**	**Direct**	**Indirect**
Own characteristics						
Age of farmer	−0.001	−1.60E-04	8.1E-05	1.70E-05	0.001	1.8E-04
Gender of farmer	−0.029	−0.006	−0.031	−0.006	0.019	0.004
Farmer's education	−0.012†	−0.003†	0.002	0.001	0.017†	0.004†
Farmer's experience	0.032†	0.007†	−0.012†	−0.003†	−0.017†	−0.004†
Household size	0.005	0.001	0.003	0.001	−0.011†	−0.002†
Household landholding	−0.019†	−0.004†	0.061†	0.013†	0.027†	0.006†
Credit constraint	0.024	0.005	−0.152†	−0.032†	0.017	0.004
Risk of food insecurity	−0.003	−0.001	0.001	2.60E-04	−0.004	−0.001
Extension contact	−0.085†	−0.019†	0.054†	0.011†	0.123†	0.029†
NGO/Res contact	−0.090	−0.020	0.041	0.009	0.070†	0.016†
Association membership	0.049†	0.011†	−0.046†	−0.009†	0.021†	0.005†
Electronic device	−0.017	−0.004	0.017	0.003	−0.024	−0.005
Soil quality	−0.067†	−0.015†	0.067†	0.014†	−0.014	−0.003
Soybean seed price	0.280†	0.063†	−0.166†	−0.035†	−0.102	−0.024
Contextual effects						
WAge of farmer	−0.658†	−0.149†	0.147	0.031	0.144	0.034
WGender of farmer	0.001	1.60E-04	4.70E-04	1.00E-04	0.003†	0.001†
WFarmer's education	−0.035	−0.007	0.018	0.003	0.005	0.001
WFarmer's experience	0.011	0.003	−0.002	−4.40E-04	−0.015†	−0.004†
WHousehold size	0.008	0.002	−0.003	−0.001	2.40E-04	5.90E-05
WHousehold landholding	−0.010	−0.002	0.002	4.40E-04	0.016	0.004
WCredit constraint	0.021	0.004	−0.022	−0.005	0.001	1.20E-04
WRisk of food insecurity	−0.168	−0.038	0.148	0.031	0.049	0.011
WExtension contact	−0.002	−0.001	0.006	0.001	0.004	0.001
WNGO/Res contact	−0.071	−0.016	0.015	0.003	0.030	0.007
WAssociation membership	0.072	0.016	−0.083	−0.017	−0.084	−0.020
WElectronic device	0.027	0.006	−0.019	−0.004	0.015	0.003
WSoil quality	0.053	0.012	0.067	0.014	−0.015	−0.003
WSoybean seed price	0.001	3.90E-04	−0.021	−0.004	−0.002	−3.90E-04

Note: These are the marginal effects of the other covariates and the direct effects of own characteristics indicate the effect of the farmer's characteristics on his adoption decision whereas indirect effects show the effects of the farmer's characteristics on the neighbours. Likewise, the direct contextual effects show the effects of the neighbours on the farmer's adoption decision and the indirect contextual effects are the effects of the neighbours' covariates on their own adoption decisions. The † denote significance at the 5% level.

Conversely, the estimates show that a 10% SD increase in experience of a farmer in farming directly (indirectly) decreases the probability of adopting *Jenguma* or *Afayak* by 0.12 (0.03) or 0.17 (0.04), respectively. An inverse relationship between experience and adoption could be due to two reasons. First, farmers with more experience and information about their environment are less likely to learn about a new technology and update their beliefs due to the experience they already have about the production conditions (Conley & Udry, 2010). Second, given the cost associated with social learning (i.e., through own experimentation or risk of improper learning from peers), experienced farmers may feel less motivated to commit their time and other resources into risking a new technology for adoption.

Also, a SD increase in extension contact increases the direct (spillover) effects of adopting *Jenguma* and *Afayak* by a probability of 0.05 (0.01) and 0.12 (0.03) percentage points, respectively, and decreases the use of *Salintuya* by a probability of 0.08 (0.02) percentage points. Also, an increase in the number of village associations a farmer belongs to increases the probability of adopting *Afayak* while decreasing the probability of adopting *Jenguma*. The effect of the associations on *Jenguma* adoption appears unexpected, but this may be due to a specific type of village association which is relevant in promoting adoption and possibly exists among *Afayak* adopters, but not among *Jenguma* adopters. Although we do not have data on specific types of associations to test this assertion, examination of the data at hand shows that the average number of village associations that *Afayak* and the traditional variety growers belong to is significantly higher than the average number for *Jenguma* (Table A1, Online Appendix A). These results, and the significant effects of NGO/Research agents on adopting *Afayak* could be due to the recent field demonstrations and farmer field-days carried out by the Ministry of Food and Agriculture, Council for Scientific and Industrial Research, and Savannah Agricultural Research Institute.

5.5 | Additional analysis and robustness checks

To check the sensitivity of the estimates, we present estimates in Tables A3 and A4 in Online Appendix A. For brevity, we present only the coefficient estimates and compare these to the estimates in Table 3. We present estimates of alternative specification where we control for squared terms of neighbours' adoption in columns (3)–(4) in Table A3. This is to examine whether the likelihood of adopting a technology decreases with higher adoption rates, as argued in the social learning literature (Bandiera & Rasul, 2006). Expectedly, the estimates confirm the non-linearity of the relationship, since the likelihood of adoption of *Jenguma* or *Afayak* increases with increasing neighbour adoption of *Jenguma or Afayak* at levels, but decreases with higher order (squared terms) neighbour adoption of *Jenguma* or *Afayak*, respectively.

Next, we present a specification of the model where we allowed for spatial dependence in the error terms in columns (5)–(6) as a way of further accounting for correlated effects in link formation (Ward & Pede, 2015). The objective is to show whether our estimates are (in)sensitive to the approach used in accounting for correlated effects and whether the estimates are still driven by correlations in the unobservables. With the exception of some increment in the magnitude of coefficients of the cross-varietal effects, the results remain qualitatively similar to those in Table 3. Relatedly, we further present estimates in columns (7)–(8) of Table A3, where the cross-varietal effects are captured by the variance–covariance structure, instead of the mean part of the model (LeSage & Pace, 2009). The cross-variety correlations are also negative and statistically significant, suggesting that the likelihood of adopting *Jenguma* (*Afayak*) is negatively correlated with the share of adopting neighbours of *Afayak* (*Jenguma*). [13] In addition, all the endogenous estimates have similar patterns as in Table 3, suggesting that our results are robust to these alternative specifications.

To test the sensitivity of our baseline results to the nature of interactions in the network, we control for local transitivity and degree in the specifications, and the results are reported in columns (1)–(2) and columns (3)–(4), respectively, in Table A4. Both network characteristics influence the flow of information and the nature of interaction in the network (Jackson et al., 2017). Generally, the estimates of the own and cross-varietal effects are similar to those in the base models presented in Table 3. However, we caution the reader against an attempt to interpret the estimates of these network effects since these are calculated from a sampled and not from a fully observed network. We next define an

[13] However, these correlations are difficult to interpret because of the identification restriction imposed on the first element of the variance–covariance matrix (Chakir & Parent, 2009).

alternative set of networks based on social relations and geographic neighbours as suggested by Ward and Pede (2015) (columns 5–8 in Table A4).[14] The network of social relations was based on the social dimension of contact whereas the network of geographic relations was based on the locational dimension contacts in Table 1. In effect, we find that the estimates of both networks are very similar to the base estimates in Table 3, with the social relations network showing marginally higher magnitudes in most of the coefficients.[15]

Finally, we present estimates of alternative specification of the network weight matrix in columns (9)–(10) in Table A4. This is meant to check whether the random matching within sample of the five households to each farm household, which truncates the number of links, could severely impact the estimates. As such, farmers who knew all five matched farmers, and/or were neighbours to all five, who were randomly matched to them were dropped in this estimation. The estimates still show evidence of social network effects, and without substantial qualitative differences in most of the estimated endogenous effects compared with Table 3, *albeit* with attenuation bias in the magnitudes. These findings suggest that the social network effects are quite robust to the altered sociomatrix. This is not surprising, because the truncation at five matches is not binding in our sample, since only 4.5% of farmers in the sample mentioned they knew and/or were neighbours to all randomly matched five households (see also Liu et al., 2017).

6 | CONCLUSIONS AND IMPLICATIONS

We examine the impacts of social networks on the adoption of two improved soybean varieties in northern Ghana, using observational data, and find that a farmer's adoption decision of a given improved variety depends on the neighbours' adoption of all varieties in the social network. In aggregate terms, a farmer's adoption decision of a given improved variety is positively influenced by the decisions of adopting neighbours of the same variety, but negatively by the adopting neighbours of the competing variety. However, the interesting aspects of our findings are: For a given new variety, say *Jenguma*, the effect of the neighbours' adoption of that variety (i.e., *Jenguma*) is negative and only becomes positive when at least a quarter of the farmer's neighbours have adopted this variety. When this limit is passed, the effects of cross-varietal adoption by neighbours loses its importance, irrespective of the level of adopting neighbours of the cross-variety in the network.

The second aspect is that, when the relative proportion of adopting neighbours of each of the new varieties are equal, the farmer is not more likely to adopt either of the improved varieties, compared to farmers without adopting neighbours of the improved varieties. This could be due to the fact that, at this stage, farmers are most likely not certain about the expected net benefits from these new varieties and are therefore less likely to adopt. This observation is significant because it partly provides insights into why traditional varieties are still cultivated in some villages, as well as their persistence among farmers in developing countries, as shown in the literature (CGIAR, 2009), even though new varieties are significantly superior in terms of yields and resistance to agro-climatic stress. These findings also suggest the importance of social effects, even under conditions of multiple and competing improved technology settings.

Our findings have some implications for policy. First, the result can help to explain the differential adoption rates of competing technologies and why some technologies become dominant in a particular village, while others end up as subordinate or cease to exist in some circumstances. Our finding of the significance of network and neighbourhood effects suggests the need to consider the performance

[14] We could only reconstruct the social networks along these two groups in order to guarantee that the sample size has sufficient degrees of freedom. Otherwise, we would have obtained many observations without any links that consequently had to be discarded for the econometric analysis. This limitation was due to the use of the *random matching within sample* which truncated the number of neighbours one could have in the network.

[15] The closeness of the estimates between the social relation and geographic networks can be explained by the overlap in these relations because some of the social relations of a respondent correspond to geographic neighbours.

of these improved varieties in terms of adoption vis-à-vis the network and context before designing and implementing public and other private promotional interventions such as demonstration of the benefits and increasing access to seeds for adoption. In particular, there is the need for policy-makers to focus promotion efforts on inducing some adoption in these villages, and demonstrating the relative net benefits and production knowhow of improved varieties introduced to farmers, since these would be a motivation for farmers to adopt. Thus, these measures will stimulate synergic relationship between neighbours' adoption and public-private support efforts by providing government and research institutions (such as CSIR and SARI) a launch pad for effective campaign and training of farmers, as well as increasing access to seed on one hand and propelling higher learning opportunities for adoption through these social networks on the other hand. Such efforts will be instrumental in tackling the lack of information about the production techniques and benefits of the improved varieties (CSIR-SARI, 2013).

This will also improve the effectiveness and efficiency of promoting the improved varieties through reduced costs associated with the introduction and promotion of multiple technologies at the same time, where only one or few will gain acceptance by farmers. Finally, our findings suggest that exposure to external and other sources of information, and to public learning are very important in the adoption of new technologies, particularly in cases where there is the need to induce adoption beyond a threshold required to trigger adoption in the neighbourhood. Hence, interventions to promote soybean farming should also consider measures that enhance the human capital of farmers to reduce challenges of adoption.

ACKNOWLEDGEMENTS

The authors are grateful for the comments and suggestions from three anonymous reviewers and the journal editor. Any remaining errors are theirs. Yazeed Abdul Mumin acknowledges funding from the German Academic Exchange Service (DAAD) and the Government of Ghana, while Renan Goetz acknowledges the support from the Spanish Government, Ministerio de Ciencia e Innovación (MCIN) / Agencia Española de Investigación (AEI) grant PID2020-118268RB, by MCIN/AEI/10.13039/501100011033.

Open access funding enabled and organised by Projekt DEA.

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SUPPORTING INFORMATION

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

How to cite this article: Abdul Mumin, Y., Abdulai, A., & Goetz, R. (2022) The role of social networks in the adoption of competing new technologies in Ghana. *Journal of Agricultural Economics*, 00, 1–24. Available from: https://doi.org/10.1111/1477-9552.12517