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Village networks and entrepreneurial farming in Uganda

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ABSTRACT

The transition from semi-subsistence farming to more entrepreneurial farming by the adoption of new crops or improved seeds is important for poverty reduction in developing countries. In rural societies, farmers' propensity to experiment with new technologies is influenced by their access to information and support, provided by networks of friends and relatives. Considering that the same connection can share both information and support, we study the separate effects as well as the interaction of both network functions. Using two waves of data from a sample of Ugandan farmers, we find that the propensity to adopt new crops or improved seeds increases with the number of friends or relatives who adopted new crops or improved seeds before. The effect on the adoption of new crops is stronger if the same friends or relatives also provide support in the form of gifts or loans. At the same time, we find a positive effect of support that is conditional on friends or relatives having adopted new crops before.

1. Introduction

One of the most effective ways to achieve mass poverty reduction in sub-Saharan Africa is to raise agricultural productivity through farmers adopting more profitable crops (World Bank, 2008). In particular, the transition from semi-subsistence farming to more entrepreneurial farming by the adoption of new crops or improved seeds is a promising route out of poverty. Many semi-subsistence farmers, however, are trapped in low-risk, low return agriculture as they face one or both of the following barriers. A first barrier is limited access to insurance or finance. A larger investment is typically required for modern than for traditional agriculture. This might not only require some form of finance. Farmers may also avoid prospects that entail larger losses in the case of harvest failure, unless they have access to some form of insurance (Eswaran & Kotwal, 1990; D'Exelle & Bastiaensen, 2000; Dercon & Christiaensen, 2011). A second barrier is limited access to information about the crops that have promising returns given local climate and market conditions, including the technical information required to ensure that these potential returns are achieved.

Here we consider that the strength of both barriers depends on the number of social relations, which influences a person's access to support in the form of finance or insurance, as well as information about new agricultural technologies. More connected people would receive more information about new agricultural technologies, and would have more opportunities to rely on support to finance the investment or to share the investment risks.

While recent research has focused on how information diffusion via social networks influences the uptake of new agricultural technologies (Bandiera & Rasul, 2006; Conley & Udry, 2010; Krishnan & Patnam, 2013; Maertens, 2017; Vasilaky & Leonard, 2018; BenYishay & Mobarak, 2019; Carter, Laajaj, & Yang, 2021), the influence of social networks through the informal support they provide has not received much attention to explain heterogeneity in the adoption of new technologies in the sector agriculture. This is the first research gap that we aim to fill.

While doing so, it is important to disentangle both network effects. To do so, we need to recognize that the same social relation can be used to provide both information and support (in the form of finance or insurance), and both functions can interact with one another. Connections with farmers who have tried new crops before could provide access to important information that increases the propensity to adopt new crops, and this effect might be stronger if these farmers also provide support in the form of a gift or loan. At the same time, they might also be more willing to provide such support as they have a better understanding of the need for support to finance or insure the investment. Both functions might also interact negatively. If farmers who belong to the same network adopt the same crop, risks might become correlated, which lowers the insurance capacity of the network. Farmers

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might then anticipate that their friends/relatives might be less able to provide support if the investment fails, which would weaken the effect on their propensity to adopt the new crop. To the best of our knowledge, a study of the interaction of these two network functions has not been done before, and is our second main contribution.

To study the effect of both network functions and their interaction, we interviewed farmers from 28 villages in rural Uganda. In a first interview, we collected data on their friendship and kinship relations in their village, as well as the adoption of new crops and the use of improved seeds in previous years. Two years later, we interviewed the same farmers again about the adoption of new crops and the use of improved seeds since the last interview. Combining these data sets, we use regression analysis to estimate how the farmers' likelihood of using new crops or improved seeds after the baseline responds to:

(1) the number of friends/relatives who adopted new crops or improved seeds before the baseline and whether its effect depends on the support exchanged in the form of gifts or loans; and
(2) the number of friends/relatives who exchange support in the form of gifts or loans, and whether this effect depends on the adoption of new crops or improved seeds by these friends/relatives before the baseline.

The identification of these network effects is complicated by two issues. First, assortative matching makes that friends tend to be similar on observable or unobservable characteristics that might influence adoption behavior. This would give rise to a spurious correlation in adoption behavior among them, rather than a causal network effect. To filter out these so-called 'correlated effects', we use network fixed effects, using a within transformation similar to fixed effects panel data models. Second, the effect of the size of a farmer's network might be confounded by observable and unobservable characteristics that influence the propensity to adopt new crops or improved seeds. Not controlling for these characteristics will bias the estimates of the network effects through omitted variable bias. To deal with this issue, we will use a set of controls, combined with a control function.

Our results can be summarized as follows. First, farmers are more likely to experiment with new crops or improved seeds the more friends/relatives they have who did so before. Second, the effect on the adoption of new crops is stronger if the friends/relatives also exchange support (in the form of a gift or a loan). Third, the effect of support among friends/relatives is conditional on these friends/relatives having experimented with new crops before. These results are robust to tests that look into possible biases caused by influential observations or measurement error due to incomplete sampling of the village networks.

There is a large literature that looks at the importance of social networks in small-scale societies in developing countries. Two important strands can be distinguished, which we bring together in our study. First, there is the literature that focuses on the access to resources social networks provide, such as finance (Kinnan & Townsend, 2012), labor (Krishnan & Sciubba, 2009), access to markets (Fafchamps & Minten, 2002) and insurance (De Weerdt & Dercon, 2006; Fafchamps & Lund, 2003; Fafchamps & Gubert, 2007). Second, another strand of literature studies the role of information shared by networks, and how it influences the adoption of new technologies among farmers. These studies look at how farmers' decision to adopt a new technology is influenced by information they receive from others who have used the new technology before (see e.g. Bandiera & Rasul (2006), Conley & Udry (2010), Krishnan & Patnam (2013), Maertens (2017), Vasilaky & Leonard (2018), BenYishay & Mobarak (2019), Carter et al. (2021)).

In this article, we bring together the foci of these two strands of literature. Social networks provide access to resources (in our case, in the form of gifts or loans shared among farmers) and information: we distinguish these functions and consider the operation of both as well as their interaction. In this way, we detect subtle network effects that would have otherwise remained undetected.

2. Research design

In this section, we present the research setting. We also develop the hypotheses that we will test in the empirical section. Thereafter, we present more details about the data collection.

2.1. Setting

For this study, we selected the Sironko district, which is located in eastern Uganda. It is a densely populated area where around 90% of the population lives in rural areas and most households' economic livelihoods depend on farming (Ministry of Water & Environment, 2010). In this region, traditional farmers grow maize intercropped with beans with a minimal reliance on purchased inputs such as fertiliser and pesticides (Verschoor, D'Exelle, & Perez-Viana, 2016). These crops are for feeding the farmer's household, with the surplus being sold. In a representative sample for the area, 93% grow maize and 97% grow beans (Balungira, D'Exelle, Perez-Viana, & and Verschoor, 2016).[1]

An entrepreneurial orientation in the study area normally takes the form of purchasing inputs for the growing of maize and beans, or experimenting with new crops such as coffee, tomatoes, onions and cabbages, which are grown for the market rather than for subsistence and usually grown in addition to maize and beans. The adoption of new crops can therefore be equated with cash crops in the study area: maize and beans are very unlikely to be new crops (they are traditional in the area and almost universally grown), and all other crops are cash crops. However, the use of improved seeds is predominately for maize, which as mentioned is almost universally grown in the study area (Verschoor et al., 2016).

At the time of purchase of inputs, farmers in the study area are liquidity constrained (Dehmel et al., 2021): improved maize seed compared to local maize seed requires a cash outlay that is three times larger and that many farmers struggle to meet because of liquidity constraints. The same is true a fortiori for cash crops, such as tomatoes and cabbages. Village savings and loans associations (VSLAs) are common, as are microfinance organisations, but the risk entailed in the loans provided by these institutions (a harvest failure would mean defaulting on the loan with potentially disastrous consequences), makes that only the wealthiest community members make use of these for financing the purchase of agricultural inputs (Osborne et al., 2022). As a result, local support networks are commonly used, as they not only provide an accesible form of finance; they also provide insurance, which VSLAs and microfinance do not offer.

2.2. Hypotheses

As described above, in our study area, semi-subsistence farmers growing traditional staple crops might face the option to adopt new crops and improved seeds. Doing so, potentially increases the expected income, but it also leads to a greater variance of income than these traditional crops (Verschoor et al., 2016). Whether to adopt new crops and improved seeds, might crucially

[1] In our sample, these figures are 91% and 94%, respectively (see Table A.1 in Appendix A).

depend on access to information and support from other farmers in the village.

We assume that sharing of information and support is mediated by social relations with other farmers who live in the same village. More formally, we assume that the village has N farmers who are connected through a network represented by an N x N matrix A, with entries a_{ij} equal to one if farmer i has a social tie with j, zero otherwise. The network of social ties of farmer i is then defined by row a_i of the matrix, and the size of this network is $C_i = \sum_{j \neq i} a_{ij}$.

We will focus on social ties of friends or relatives. We assume that a farmer's network of friends/relatives can have two functions that are important for the adoption of new crops or improved seeds: the sharing of information and support. The approach to use friends/relatives to study social learning or information sharing in social networks is commonly accepted (e.g., see Bandiera & Rasul (2006)), and it has been documented that support is common among friends or relatives (see p. 103 Fafchamps (2003)). To look in detail at both network functions, we distinguish the following networks.

1. $C_i^{I(1)} = \sum_{j \neq i} (a_{ij} | I = 1)$: the number of friends/relatives of farmer i who adopted new crops or improved seeds before.
2. $C_i^{S(1)} = \sum_{j \neq i} (a_{ij} | S = 1)$: the number of friends/relatives of farmer i with whom they exchange support.

Friends/relatives who adopted new crops before share information that allows a farmer to identify the crops that have promising returns given local climate and market conditions, and often also includes the technical information required to ensure that these potential returns are achieved. The more information farmers receive from friends/relatives, the more likely it becomes that they find a crop that is sufficiently profitable. In other words, we expect that the amount of information a farmer i receives increases with the size of their network $C_i^{I(1)}$. Therefore, the larger this network, the higher the likelihood that a new crop or improved seeds are adopted, as stated in Hypothesis 1.[2,3]

Hypothesis 1: The likelihood that farmer i adopts a new crop or improved seeds increases with $C_i^{I(1)}$.

The adoption of a new crop requires an investment that often comes with substantial risks. To undertake the investment, cash-constrained farmers might need support to finance the investment, and risk-averse farmers whose subsistence needs may not be met because of downside risk may need insurance. In the absence of finance or insurance markets in rural areas, farmers rely on support from friends or relatives to obtain the necessary finance or insurance. In other words, we expect that the support a farmer i could receive increases with the size of their network $C_i^{S(1)}$. Therefore, the larger this network, the higher the likelihood that new crops or improved seeds are adopted, as stated in Hypothesis 2.

Hypothesis 2: The likelihood that farmer i adopts a new crop or improved seeds increases with $C_i^{S(1)}$

Up until now, we ignored the potential interaction between the information and support sharing functions of a farmer's networks. The same friend/relative can share both information and support, and whether they do might matter for their effect on a farmer's propensity to adopt a new crop or improved seeds. To look in detail at the interaction of both network functions, we distinguish the following networks.

1. $C_i^{I(1)S(0)} = \sum_{j \neq i} (a_{ij} | I = 1, S = 0)$: the number of friends/relatives of farmer i who adopted new crops or improved seeds before and with whom no support is exchanged.
2. $C_i^{I(1)S(1)} = \sum_{j \neq i} (a_{ij} | I = 1, S = 1)$: the number of friends/relatives of farmer i who adopted new crops or improved seeds before and with whom support is exchanged.
3. $C_i^{I(0)S(1)} = \sum_{j \neq i} (a_{ij} | I = 0, S = 1)$: the number of friends/relatives of farmer i who did not adopt new crops or improved seeds before and with whom support is exchanged.

One might argue that there could be a positive interaction between both network functions. For example, a friend/relative who adopted a new crop before might better understand the need for support to finance or insure the investment, and therefore be more inclined to provide support when needed. It might also be that both functions interact negatively. If farmers who belong to the same network adopt the same crop, risks become correlated, which lowers the insurance capacity of the network. The farmer might then anticipate that the friends/relatives might be less able to provide support if the investment fails, which would weaken the effect on their propensity to adopt the new crop.

In the end, it will be an empirical matter. For the purpose of the hypothesis, we will assume that both functions are complementary. More specifically, the positive effect of a friend/relative who provides support will be stronger if the friend/relative also introduced crops or improved seeds before, and the positive effect of a friend/relative who introduced crops or improved seeds before is stronger if they also provide support. We summarize this as Hypothesis 3.

Hypothesis 3: The positive effect of $C_i^{I(1)S(1)}$ on the likelihood that farmer i adopts a new crop or improved seeds is stronger than the positive effects of $C_i^{I(1)S(0)}$ and $C_i^{I(0)S(1)}$.

2.3. Data collection

To select the participants in our study, we used a multi-stage cluster sampling procedure. In each of the 28 selected villages, we took a census from which we randomly selected households. In a next step, we randomly selected one adult member in each selected household. At that moment, we also took a photograph of each of the selected respondents, which we would use to facilitate the identification of co-villagers when we ask respondents to identify friendship and kinship relations.

The respondents were interviewed twice. In the first interview we captured data on important investment decisions made, including whether they adopted any new crops or improved seeds in the past years. We also collected data on important socio-economic characteristics (age, education, household size, etc.) and the social ties with each of the other people in the (village) sample. For the latter, we used cards with the name and photograph of each of the sampled respondents. To avoid reporting bias, we randomized the order in which the cards were presented to each respondent. For each card, the interviewees were first asked whether they knew the other person. If the answer was affirmative we asked

[2] Note that we ignore whether all farmers in the network of farmer i adopted the same crop. We do so, as it is not a priori clear for a given network size, which of the informational benefits are greater: a larger number of farmers adopting the same new crop, or a larger number of new crops being adopted. In the two extreme cases, if all farmers in one's network adopted a *different* crop, a larger network increases the information about the existence of new crops that are potentially productive in the village. If all farmers in one's network adopted the *same* crop, a larger network leads to more accurate information about how to make a crop most productive. In sum, the size of a farmer's network increases the amount of useful information in terms of the crops that have potential and/or on how to make them most productive, and hence increases the likelihood that a new crop is adopted.

[3] We assume that farmers ignore the effect their adoption decision would have on the amount of information others would have access to in the future. This rules out the possibility of strategic delay in innovation (on this see e.g. Bandiera & Rasul (2006)). The latter is most relevant when a crop is adopted *for the first time in a village*, which is not the focus of our study.

for details on the content of the relation, including whether they were friends or relatives, or exchanged support.[4] Two years later, we interviewed the same respondents again, and asked them whether they had adopted any new crop or used improved seeds in the last two years. The answer to this question is used to construct the main dependent variable in our analysis. Interviews and data collection were assisted with portable electronic devices.

3. Data

In this section, we present descriptive statistics. We first look at correlations between socio-economic characteristics of the respondents and their adoption of new crops or improved seeds. In a next step, we present descriptives on social network ties. Finally, we look at descriptives on the size of the respondents' networks, including how it correlates with the use of new crops and improved seeds.

3.1. Agricultural crops

In the first interview, we collected detailed information about the crops that farmers in our sample cultivated. For an overview of the crops cultivated and crop-specific investments, we refer to Table A.1 in Appendix A. We find that staple crops (maize, beans), coffee and cooking bananas are most commonly cultivated. We also observe that a large variety of cash crops are used in the area. Table A.1 shows that in each village there is a large variety of crops used, which is in line with evidence we collected from interviews with local key-informants that in each village a variety of new crops is experimented with.

Two years later, we interviewed the same farmers again, and asked them whether they had adopted any new crops or improved seeds in the last two years. 53.9% of them confirmed that they had used new crops. While this percentage may seem high, key informant interviews in the study area confirm that experimentation with new crops is very common (see Verschoor et al. (2016), pp. 138–139). 80.3% of the farmers used improved seeds.

Table 1 compares important socio-economic characteristics (as measured at baseline) between producers who adopted new crops or improved seeds in the two years between both interviews and those who did not. We observe a strong gender bias, with a significantly lower proportion of men in the non-investors groups than in the investors group. Household wealth, household size and education correlate positively with the use of new crops and improved seeds. Age correlates negatively with the adoption of new crops but not with the use of improved seeds. This suggests that the younger generation is more entrepreneurial, while the use of improved seeds is already widespread. We do not find any influence of risk preferences, which we elicited with a hypothetical choice experiment.[5] The use of new crops and improved seeds in the last two years is also positively associated with whether one received agricultural advice from an organization before the baseline, and whether one adopted new crops or improved seeds before the baseline (see the variable 'invested before'). Finally, farmers who adopted new crops or improved seeds had on average more (cash) crops at baseline than the group who did not adopt new crops or improved seeds.

3.2. Social ties

One of the main contributions of our study is to disentangle network effects that work via the access networks provide to information about new crops and improved seeds, and the support they offer. The justification for such analysis is based on the assumption that both information sharing and the provision of support make use of the same social ties.

It is commonly accepted to focus on friends or relatives when studying information sharing in social networks (see the literature cited in the introduction). To verify that friends or relatives also commonly share support, we look at the overlap between friendship ties (in which the respondent ('ego') calls the other person ('alter') a friend), kinship ties (in which ego calls alter a relative) and support ties (in which ego gave/received a gift or loan to/from alter in the 12 months before the interview). Table 2 shows the percentage of overlap, measured at the dyad level, between these three types of social ties. The percentages need to be read from the row relations to the column relations. In other words, rows indicate the denominator of the proportions/percentages, while columns indicate the numerator. The percentages presented in the table show that loans or gifts are mainly given among friends and to a lower extent among relatives. In 77–78% and 54% of the dyads where a loan or gift is given or received, ego calls alter a friend or a relative, respectively. This insight supports our approach of focusing on friends/relatives, when studying the effect of support.

We also observe a high overlap between the two directions in which gifts/loans are given: in 72.87% of the dyads in which ego reported to have given a gift or loan to alter, did ego also report that they received a gift or loan from the same alter. Similarly, in 73.78% of the dyads in which ego reported having received a gift or loan from alter, did ego also report having given a gift or loan to the same alter. These observations confirm that support is highly symmetric, which is in line with the reciprocal nature of local support arrangements.

3.3. Network size

As explained before, we expect a farmer's social networks to exert an important influence on their investment decisions, via the information and support that friends or relatives provide. We use the size of one's so-called *ego-network*, calculated as $C_i = \sum_{j \neq i} a_{ij}$, with a_{ij} being equal to 1 if i and j have a social tie. We focus on social ties of friends or relatives. For the definition of these ties, we assume that such a tie exists if *both* persons identify such a relation, when asked during the baseline. These are so-called AND-ties. To obtain an idea of the variation of the network size within and between the villages in our sample, Fig. 1 plots the entire village networks of ties of friends/relatives for each of the 28 villages. We observe substantial variation in the size of the farmers' ego-networks both within and between villages.

To distinguish the two network mechanisms that provide access to information and support, we add the following conditions to the AND-ties of friends/relatives. First, to identify ties that provide access to information we add the condition that node j adopted new crops or improved seeds before the baseline. Second, to study the effect of support, we add the condition that node i reports having given or received a loan or gift to/from alter in the 12 months before the baseline.

This leads to the different network sizes presented in Table 3. Note that these correspond to the network sizes used in the con-

[4] We also captured whether they were neighbours, got along well, belonged to the same social group (e.g., saving groups, burial society, farmers' group, microfinance group, etc.), and went to the same church or mosque. Given the focus of our analysis, however, this information is not used in this paper.

[5] We used a hypothetical investment question, adapted from Dohmen et al. (2005), about their willingness to invest $x \in \{0, 20,000, 40,000, 60,000, 80,000, 100,000\}$ in an asset that yields a return of 100 percent if successful and minus 50 percent if a failure, with equal probability. Subjects chose one of six decision cards on which the two outcomes of a possible choice were clearly displayed. We use the amount invested (divided by 10,000) as a measure of risk preferences.

Table 1
Descriptive statistics by adoption of new crops and improved seeds.

	New crops			Improved seeds		
	No (N = 200)	Yes (N = 234)	p-value	No (N = 85)	Yes (N = 348)	p-value
Male	0.420	0.585	0.001	0.329	0.552	0.000
Household wealth	−0.371	0.414	0.001	−0.618	0.213	0.004
Household size (aged 15–69)	2.755	3.107	0.034	2.541	3.046	0.016
Education (years)	4.785	6.145	0.000	4.012	5.882	0.000
Age	42.910	38.299	0.000	41.235	40.256	0.544
Risk preferences	7.170	7.573	0.171	7.271	7.408	0.711
Years lived in the village	28.050	25.919	0.205	27.894	26.647	0.555
Agr. advice from organisation	0.270	0.355	0.058	0.153	0.356	0.000
Invested before	0.490	0.650	0.001	0.682	0.848	0.000
Number of crops	3.300	3.919	0.000	2.953	3.802	0.000
Number of cash crops	0.665	1.111	0.000	0.506	1.003	0.000

Notes: Two-sided p-values reported of t-test and test of proportions, for continuous and dichotomous variables, respectively. All variables measured at baseline. To measure household wealth we created an index equal to the first factor of a principal component analysis of the household's assets, following (Filmer & Pritchett, 2001). Details of twenty-seven asset types were included in the broad categories household's dwelling, durable consumer goods, vehicles, farm buildings and equipment, land, and livestock.

Table 2
Overlap of different types of social ties (in percent).

	Ego calls alter a friend	Ego calls alter a relative	Ego gave gift/loan to alter	Ego received gift/loan from alter
Ego calls alter a friend	–	52.37	28.94	29.08
Ego calls alter a relative	77.71	–	30.38	29.95
Ego gave gift/loan to alter	76.95	54.44	–	72.87
Ego received gift/loan from alter	78.28	54.34	73.78	–

Notes: In the table inclusion runs from the row relations to the column relations for instance, in only 28.94 percent of the friendship ties did ego give a loan or gift to alter, but in 76.95 percent of the dyads in which ego gave a gift or loan to alter, ego called alter his/her friend. Hence, the overlap between any two dimensions does not need to be symmetric.

ceptual section. For example, the number of friends/relatives who adopted new crops before the baseline (labeled 'friends/relatives – information') corresponds to $C_i^{I(1)}$, while the number of friends/relatives who exchange support (labeled 'friends/relatives – support') corresponds to $C_i^{S(1)}$. We assume that a support relation exists if i reports having given or received a loan or gift to/from alter in the 12 months before the baseline. Finally, to study the interaction between the provision of information and support, we use different combinations of both contents, i.e. we use the number of ego's friends/relatives who did (not) invest before and/or who made (not) transfers with ego.

To obtain an idea of the association between the size of one's ego-network and the likelihood to adopt new crops, Table 3 compares the average ego-network size between farmers who adopted new crops or improved seeds in the two years after the baseline and farmers who did not. Looking at the average number of friends or relatives, we do not find any statistically significant difference between the two groups. We do find that farmers who adopted new crops or improved seeds in the two years after the baseline have significantly more friends and relatives who adopted new crops or improved seeds before the baseline. We also observe that the group who adopted new crops has significantly more friends/relatives who they shared gifts or loans with before the baseline (labeled 'friends/relatives – support'). Looking at the interaction between both network functions, we observe that the number of 'friends/relatives – information – support' is significantly higher among farmers who adopted new crops, but the number of 'friends/relatives – information – no support' is not statistically different between both groups.

4. Regressions

In this section, we will use regression analysis to estimate the effects of village networks on the propensity to use new crops or improved seeds. We start by explaining the identification strategy, after which we present the regression results, followed by a set of robustness tests.

4.1. Identification

To identify the different network effects, we use the following econometric specification:

$$Y_i = \beta_0 + C_i.\beta_1 + V_i.\beta_2 + \mu + \epsilon_i \quad (1)$$

with $Y_i = 1$ if farmer i adopted a new crop or improved seeds in the two years *after the baseline*, zero otherwise. C_i is a vector with farmer i's ego-network size(s) *at baseline*, using the different definitions introduced before.[6] ϵ_i the error term. As observations on farmers in the same village are not independent, we cluster standard errors at the village level.

V_i captures a set of controls, including age, gender, education and years of residence in the village. To deal with potential unobservable factors that might confound the social network effects, it also includes the residual of a control function. Similar to the two-stage least squares approach used in instrumental-variables regression this approach uses an instrumental variable, but instead of replacing the endogenous variable with the prediction of the first-stage, it adds the residual of the first-stage.[7]

[6] Note that our approach ressembles the model of Manski (1993), which inspired a large literature that aims to identify 'endogenous peer effects'. Our approach, however, differs in at least two important ways. First, we do not aim to capture how one's behavior is directly influenced by the behavior of peers. As we look at the influence of friends/relatives who experimented with new crops or improved seeds *in the past*, we avoid the 'reflection problem' that – as shown by Manski (1993) – complicates the identification of peer effects. Second, we use local *aggregate* effects instead of local *average* effects (on this difference see also Liu et al., 2014). We assume that networks provide access to information, and that the amount of information increases with the *size* of one's network that experimented with new crops or improved seeds, rather than the *proportion* of one's network that did so.

[7] Compared to the IV approach, it has the advantage that the coefficient of the residuals can be used as a heteroskedastic-robust Hausman test of endogeneity (Wooldridge, 2015).

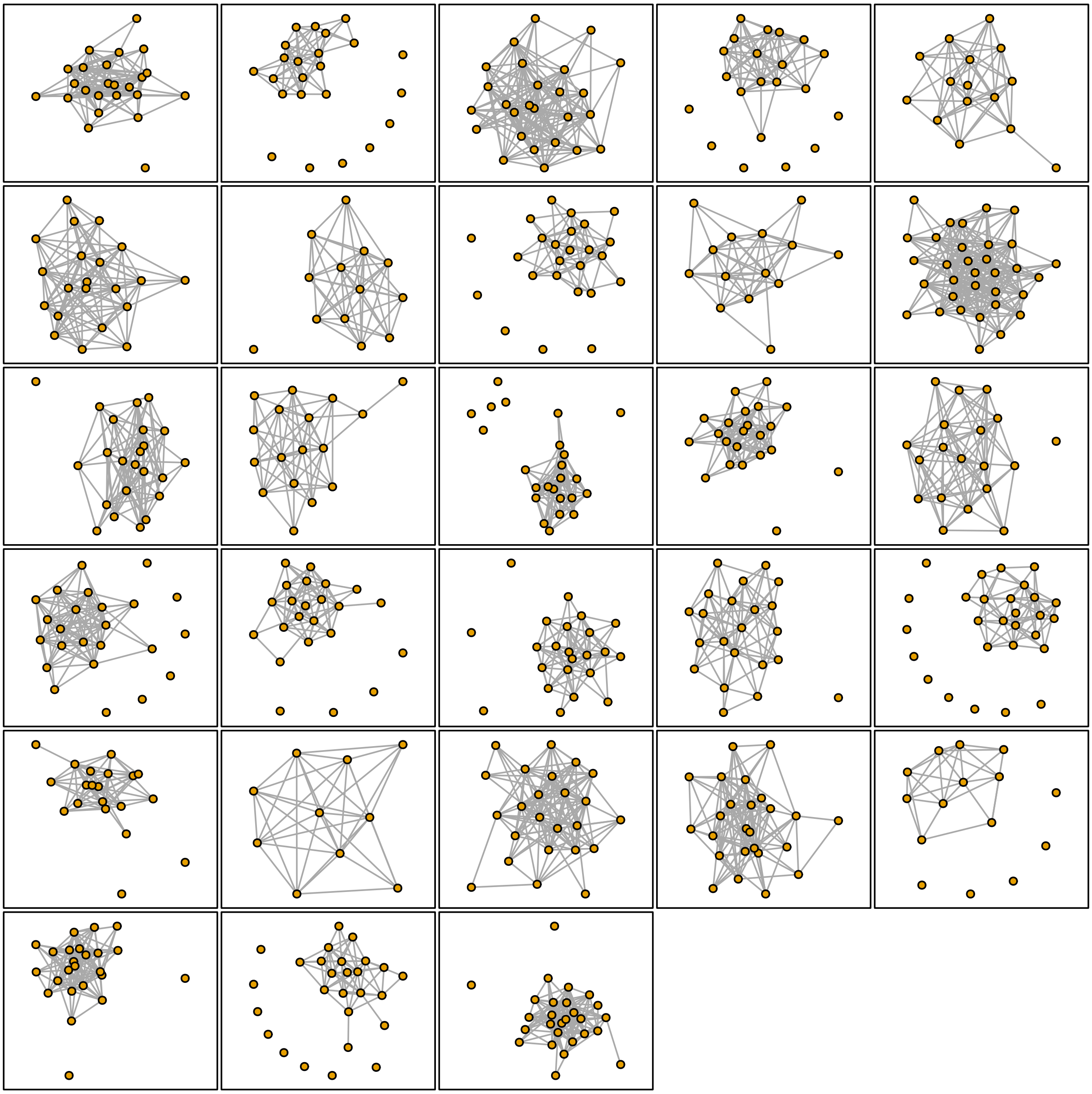

Fig. 1. Networks of friends/relatives (AND-ties), by village.

Table 3
Average network size by adoption of new crops and improved seeds.

Tie content	New crops			Improved seeds		
	No	Yes	p-value	No	Yes	p-value
Friends/relatives	9.105	9.521	0.339	8.847	9.451	0.270
Friends/relatives – information	4.895	5.594	0.010	6.494	7.399	0.036
Friends/relatives – support	2.280	2.996	0.007	2.529	2.704	0.602
Friends/relatives – information – no support	3.645	3.833	0.471	4.612	5.244	0.121
Friends/relatives – information – support	1.250	1.761	0.002	1.882	2.155	0.309
Friends/relatives – no information – support	0.960	1.162	0.127	0.565	0.480	0.466

Notes. N = 433. AND-ties are used for the definition of ties with friends/relatives. 'Friends/relatives – information': number of friends or relatives who invested before; 'Friends/relatives – support': number of friends or relatives who provide support; 'Friends/relatives – information – no support': number of friends or relatives who invested before and provide no support; 'Friends/relatives – information – support': number of friends or relatives who invested before and provide support; 'Friends/relatives – no information – support: number of friends or relatives who did not invest before and provide support. Two-sided p-values reported of a t-test.

As an instrument, we use the *predicted* size of the individual friendship network obtained in the following way. In a first step, we predict individual friendship/relatives links at the village level, using a dyadic regression. The dyadic regression captures the exogenous influence of 'similarity' on individual characteristics (age, education and gender) and the minimum of the 'duration of residence' between two nodes living in the same village. These are important exogenous determinants of network formation. We know from the sociological literature, for example, that homophily is an important force for the formation of social ties (see, e.g. McPherson, Smith-Lovin, & Cook (2001), for a survey). As the formation of friendship takes time, we expect a friendship tie between two nodes to be more likely formed the more time they have had to interact with each other, which is captured by the minimum of the duration of residence in the village of both nodes. In a second step, we aggregate for each individual the predicted links at the village level. This does not only take care of the village size, but also extends similarity and minimum residence from the dyadic level to the village level.

The residual of the control function, estimated in the first stage using this instrument, captures the endogenous part of the observed network size, i.e. the variation in network size that is not due to similarity with others in the village and the duration of residence in the village. Including this residual in the second stage regression then deals with potential endogeneity. The dyadic regressions and the estimates of the first-stage control function can be found in Appendix C.

Note that this approach is conditional on a set of controls. First, as both predicted and observed network size increase with the size of the village, the effect of village size is not captured by the residual of the control function. If household decision-making varies with village size, it is important to control for village size in the second stage, which we will do by using fixed effects (see below). Second, the same reasoning applies to the individual characteristics used in the dyadic regressions that could directly influence household decision-making (age, education and years of residence). Even though we only use dyadic measures to predit the links, which together with the aggregation at the village level make that predicted network size depends on the intra-village distribution of individual characteristics, we cannot exclude the possibility that the predicted network size correlates with the individual characteristics. If they do, the residual of the control function will not capture them, and it is important that we add them as controls in the second stage (see the description of the controls above).

Parameter μ captures fixed effects. We will include them in two different ways. First, we will use *village* fixed effects to control for observable and unobservable characteristics that are shared by all *farmers living in the same village*. This is important as farmers living in the same village are exposed to similar village characteristics which not only influence the formation of ego-networks but also the profitability of the investment. For example, larger villages may not only make it easier to form larger networks. They may also increase the profitability of investments, if they have better market access, better infrastructure, better agroecological conditions, etc. Second, we can use *network* fixed effects to control for observable and unobservable characteristics that are shared by *farmers in the same network*. In addition to dealing with village characteristics, they deal with the important issue of so-called 'correlated effects' (Manski, 1993). The estimates of the effect of the number of friends/relatives who adopted a new crop or improved seeds before, could be biased by correlations of socio-economic characteristics among friends/relatives. Observable and unobservable characteristics of people in the same network might be similar (e.g. due to homophily), giving rise to similar adoption decisions among them. This would lead to a spurious effect. Controlling for observable and unobservable characteristics that are shared by people connected via the same network removes this bias.

$$Y_i - \overline{Y} = \left(C_i - \overline{C}\right).\beta_1 + \left(V_i - \overline{V}\right).\beta_2 + (\mu - \overline{\mu}) + (\epsilon_i - \overline{\epsilon}) \qquad (2)$$

To apply network fixed effects we use the within transformation between ego and ego's direct connections, as shown by Eq. 2. Specifically, we average Eq. 1 over all the friends/relatives of ego and subtract this from Eq. 1 for ego. As the term $(\mu - \overline{\mu})$ will be equal to zero – as μ captures the observable and unobservable characteristics shared by the farmers in ego's network – the within-transformation removes an important source of endogeneity.

In addition to these *local* network fixed effects, there is also a *global* network fixed effects approach, which uses the average of the part of the village network to which ego is directly or indirectly connected with (Bramoullé, Djebbari, & Fortin, 2009; Calvo-Armengol, Patacchini, & Zenou, 2009). In practice, as most individuals in the villages in our sample are directly or indirectly connected with each other – except for a small number of isolates (see Fig. 1) – this approach comes very close to the use of village fixed effects.

Note that our specification is a linear probability model. The advantages of this approach compared to a logit or probit model are the easier interpretation of the estimated effects and the combination with fixed effects. There are two limitations with the use of a linear probability model. First, predicted probabilities might fall outside the interval $[0, 1]$ if adoption rates are very low or very high. However, this does not apply to our case. Second, it assumes that the marginal effects do not depend on the initial values of the covariates. Reassuringly, the estimates of a logit model give qualitatively similar results (see Table D.1 in Appendix D).

4.2. Results

Table 4 presents the results. All models use the same explanatory variables, as defined in the hypotheses section. The table presents three sets of three models. The second and third sets add village fixed effects and local network effects, respectively. Within each set, we vary the use of controls and the use of a control function.

Starting with the adoption of new crops (panel A), we observe that the residuals of the control function are not statistically significant in any of the models. Following Wooldridge (2015), this coefficient can be used as a heteroskedastic-robust Hausman test of endogeneity. The non-significance of this coefficient indicates that the estimated network effects are unlikely to have been affected by endogeneity. As a result, we will use the models without control function as they are more efficient.

We observe that the coefficient of 'Friends/relatives – support' is statistically significant in all models. Each additional friend/relative with whom support is exchanged increases a farmer's propensity to adopt a new crop with 1.6–2.8%. The coefficient of 'Friends/relatives – information" is also statistically significant when we apply fixed effects (Models 5 and 8). Each additional friend/relative who adopted new crops before increases a farmer's likelihood to adopt new crops with 1.5–2.3%.

Looking at the use of improved seeds (panel B), none of the support networks are statistically significant. The coefficient of 'Friends/relatives – information', however, is statistically significant in some of the models. Where village network fixed effects are used, we observe that each additional friend/relative who used improved seeds before increases the propensity to use improved seeds by 4.8%. Note that here we use Model 6 as the coefficient of the residuals of the control function is statistically significant.

The coefficients of the control variables are reported in Table B.1 in Appendix B. They show that the propensity to adopt new crops or improved seeds is higher among men, and increases with education. The use of improved seeds also increases with age and decreases with the years of residence in the village.

So far, we ignored the potential interaction between the information and support sharing of a farmer's social ties. The same friend/relative can share both information and support, and

Table 4
Regressions: the effects of information and support.

A. New crops									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Friends/relatives – support	0.020**	0.018**	0.018**	0.019**	0.016**	0.018***	0.028***	0.023**	0.024***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.006)	(0.009)	(0.008)	(0.008)
Friends/relatives – information	0.016**	0.010	0.005	0.021**	0.015*	0.041	0.032***	0.023**	0.029
	(0.008)	(0.008)	(0.016)	(0.008)	(0.008)	(0.025)	(0.009)	(0.009)	(0.028)
Residuals (control function)			0.004			−0.019			−0.004
			(0.011)			(0.017)			(0.020)
Observations	440	440	440	440	440	440	425	425	425

B. Improved seeds									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Friends/relatives – support	−0.003	−0.003	−0.002	−0.003	−0.004	−0.003	−0.004	−0.005	−0.006
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
Friends/relatives – information	0.012**	0.008	0.016*	0.015**	0.008	0.048**	0.013**	0.011*	0.002
	(0.005)	(0.005)	(0.009)	(0.006)	(0.006)	(0.019)	(0.006)	(0.006)	(0.010)
Residuals (control function)			−0.009			−0.034**			0.009
			(0.007)			(0.014)			(0.009)
Observations	440	440	440	440	440	440	425	425	425
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control function	No	No	Yes	No	No	Yes	No	No	Yes
Fixed effects	No	No	No	Village	Village	Village	Local	Local	Local

Notes. OLS regressions. Dependent variable equal to one if new crops or improved seeds were adopted in the two years after the baseline, zero otherwise. 'Friends/relatives – support': number of friends or relatives who provide support; 'Friends/relatives – information': number of friends or relatives who invested before. AND-ties are used for the definition of ties with friends/relatives. Controls were used for age, gender, education, and years of residence in the village. For the coefficients of the controls see Table B.1 in Appendix B. Standard errors (in parentheses) are clustered at the village level. ***, **, * indicate two-sided significance levels at 1, 5, and 10 %, respectively.

whether they do might matter for their effect on a farmer's propensity to adopt a new crop or improved seeds. To look at the interaction between both network functions, we replace the network measures by $C_i^{I(1)S(0)}$, $C_i^{I(1)S(1)}$ and $C_i^{I(0)S(1)}$, as defined before. Table 5 presents the results.

Starting with the adoption of new crops (panel A), we observe that the coefficient of 'Friends/relatives – information – support' is statistically significant in all models. Each additional friend/relative who adopted new crops before and with whom support is exchanged increases a farmer's propensity to adopt a new crop with 4–7%. The coefficient of 'Friends/relatives – information – no support' is smaller and significant in only a few models. The difference in size of the effect suggests that the effect of information is stronger if the social ties also provide support. A Wald test rejects the null hypothesis that both coefficients are equal to each other in Model 2 (chi2 = 4.54, p-value = 0.042). The difference in effects is somewhat smaller in Model 5 (chi2 = 2.32, p-value = 0.140) and Model 8 (chi2 = 3.49, p-value = 0.073). The coefficient of 'Friends/relatives – no information – support' is not statistically significant in any of the models. This indicates that the effect of support among friends/relatives is conditional on these friends/relatives having experimented with new crops before.

Looking at the use of improved seeds (panel B), the network effects are substantially weaker. The coefficient of 'Friends/relatives – information – no support' is statistically significant in some of the models with fixed effects. The coefficient of 'Friends/relatives – information – support' is significant in Model 6. The significant coefficient of the residuals of the control function indicates some endogeneity, which requires us to use this model. Interestingly, the size of both coefficients is very similar. This implies that the effect of information does not depend on the provision of support. The coefficient of 'Friends/relatives – no information – support' is again not statistically significant in any of the models.

4.3. Robustness tests

In this section, we present some robustness tests. One might argue that some of the identified effects could be spurious because of influential observations or measurement error. We look at both possibilities in this section.

4.3.1. Influential observations

Ego-network size tends to be unequally distributed among fellow villagers. In each village, only a few farmers have a large number of connections, while most of them have only a few connections. This implies that the results might be driven by some influential observations, which could affect the robustness of the estimates. Fig. A.1 in Appendix A presents the distributions of the size of the ego-networks used in the analyses, which confirms that the distributions are right-skewed. To test whether the results are driven by the most connected individuals, we 'winsorize' the network sizes of the 1–2% farmers with the largest ego-network. Tables E.1 and E.2 in Appendix E present the new results. We observe that most of the results remain robust.

4.3.2. Measurement error

The results might also be affected by errors in the measurement of the network sizes. An important source of measurement error could be incomplete sampling of the village networks. When calculating network sizes we have only included the social ties that we captured with the survey (converting missings to zero). However, using elicited ties among a sample of individuals to estimate network degree only works if sufficiently large samples are used. As demonstrated by Advani and Malde (2018) and Chandrasekhar and Lewis (2011), sampling rates of below 70% might generate considerable bias in the estimated effects of network measures in regression analysis. Fig. A.2 in Appendix A presents the distribution of the sample proportions across the 28 villages used in our study. In all villages we sampled at least 50% of the households, and the average proportion sampled of the 28 villages is 72.27%.

As a robustness test, we run the same regressions using only the villages in which we sampled at least 70% of the households. As a result, we only keep 14 of the villages and the average proportion sampled increases to 83.52%. Tables E.1 and E.2 in Appendix E present the results. We observe that most of the effects are robust.

Table 5
Regressions: the effects of information and support, and their interaction.

A. New crops

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Friends/relatives – information – no support	0.013	0.008	−0.001	0.020**	0.014*	0.039	0.031***	0.022**	0.024
	(0.008)	(0.008)	(0.014)	(0.008)	(0.008)	(0.024)	(0.009)	(0.009)	(0.026)
Friends/relatives – information – support	0.050***	0.042**	0.035*	0.054***	0.040**	0.063**	0.072***	0.057***	0.059*
	(0.015)	(0.016)	(0.020)	(0.018)	(0.018)	(0.029)	(0.022)	(0.020)	(0.033)
Friends/relatives – no information – support	0.001	0.000	−0.005	0.004	0.006	0.015	0.015	0.012	0.012
	(0.022)	(0.022)	(0.019)	(0.025)	(0.025)	(0.022)	(0.031)	(0.029)	(0.027)
Residuals (control function)			0.008			−0.018			−0.001
			(0.010)			(0.016)			(0.019)
Observations	440	440	440	440	440	440	425	425	425

B. Improved seeds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Friends/relatives – information – no support	0.010*	0.007	0.014	0.014**	0.009	0.056**	0.017***	0.015**	0.031
	(0.005)	(0.005)	(0.011)	(0.006)	(0.006)	(0.022)	(0.006)	(0.006)	(0.032)
Friends/relatives – information – support	0.014	0.008	0.015	0.014	0.002	0.045**	0.012	0.009	0.024
	(0.008)	(0.008)	(0.010)	(0.009)	(0.009)	(0.020)	(0.011)	(0.011)	(0.032)
Friends/relatives – no information – support	−0.021	−0.016	−0.011	−0.010	0.004	0.023	−0.009	−0.007	−0.000
	(0.018)	(0.016)	(0.021)	(0.022)	(0.021)	(0.024)	(0.027)	(0.027)	(0.028)
Residuals (control function)			−0.008			−0.040**			−0.014
			(0.008)			(0.017)			(0.026)
Observations	440	440	440	440	440	440	425	425	425
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control function	No	No	Yes	No	No	Yes	No	No	Yes
Fixed effects	No	No	No	Village	Village	Village	Local	Local	Local

Notes. OLS regressions. Dependent variable equal to one if new crops or improved seeds were adopted in the two years after the baseline, zero otherwise. 'Friends/relatives – information – no support': number of friends or relatives who invested before and provide no support; 'Friends/relatives – information – support': number of friends or relatives who invested before and provide support; 'Friends/relatives – no information – support: number of friends or relatives who did not invest before and provide support. AND-ties are used for the definition of ties with friends/relatives. Controls were used for age, gender, education, and years of residence in the village. For the coefficients of the controls see Table B.1 in Appendix B. Standard errors (in parentheses) are clustered at the village level. ***, **, * indicate two-sided significance levels at 1, 5, and 10 %, respectively.

5. Discussion and conclusion

In rural societies, the uptake of investment opportunities, such as new agricultural crops or improved seeds of existing crops, is influenced by access to information and support in the form of finance and insurance, which are commonly provided by friends or relatives. Previous empirical studies (reviewed in the introduction) on how networks facilitate the adoption of more profitable technologies in the sector agriculture have mainly focused on social learning through the sharing of information. The same friend or relative, however, can share both information and support at the same time. Therefore, it is important to isolate both functions as well as to study their interaction, which has not been done before.

Using data on social networks and the adoption of new agricultural crops and improved seeds of a sample of farmers from 28 Ugandan villages, we analysed how the propensity to adopt new crops or improved seeds is influenced by a farmer's number of friends/relatives with whom they share support and/or information about crops or improved seeds. Our results support that farmers are more likely to experiment with new crops or improved seeds the more friends/relatives they have who did so before. Moreover, this effect on the adoption of new crops is stronger if the friends/relatives also exchange support (in the form of a gift or a loan). Interestingly, we do not find an effect of support from farmers who did not adopt new crops before. In other words, the effect of support among friends/relatives is conditional on these friends/relatives having experimented with new crops before.

This could be due to several mechanisms. First, it might be that only farmers who experimented before with new crops are able or inclined to provide enough support for it to have a positive influence on adoption behavior. Farmers who experimented before tend to be wealthier (see the descriptives in Table 1), or might have a better understanding of the need for support when experimenting with new crops, as they have done so before. Second, it could be that information that influences adoption behaviour only comes from farmers who 'successfully' experimented with new crops. The stronger information effect where it is combined with support, could then be the result of the positive influence of successful experimentation on the ability to provide support. Third, the positive interaction could be due to agricultural extension services that share both information and free inputs. Extension programs in the area use model farmers who would receive free inputs and demonstrate to other farmers who to use new crops or improved seeds on their farm. However, the farmers emulating the model farmer would not automatically qualify for the receipt of input gifts, and it is unlikely they would receive them from the model farmer. As a result, while it is little plausible that extension services explain the positive interaction between both network functions, they could be behind the past adoption decisions of relatives and friends, and the resulting information they share.

It is also interesting to note that we only identified an effect of support networks on the adoption of new crops. No effect on the adoption of improved seeds was identified. We believe that this is due to the higher costs and risks involved in the adoption of new crops, compared to improved seeds. Liquidity-constrained and risk averse farmers are more able and inclined to experiment with new crops, if they have a larger support network, as this increases their access to finance and informal insurance.

Together, our findings suggest that adoption decisions of new risky technologies are better understood when multiple social network functions are taken into consideration. While we focused on the role of support and information sharing, future lines of research could consider additional network functions. Social networks of trade relations are an interesting candidate, as reliable access to markets where agricultural produce is sold or the necessary inputs are bought might influence the profitability and risk of new technologies.

CRediT authorship contribution statement

Ben D'Exelle: Conceptualization, Methodology, Writing – original draft, Funding acquisition. **Arjan Verschoor:** Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2023.106241.

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