THE UNIVERSITY *of* EDINBURGH
Global Academy of
Agriculture and Food Systems

An econometric evaluation of the influence of social networks on technology adoption amongst Kenyan smallholder dairy farmers.

B160473

May 2023

The University of Edinburgh

Global Academy of Agriculture and Food Systems

Agricultural Economics (BSc Hons)

Undergraduate Dissertation

Wordcount: 10,990

Contents

List of Figures

List of Tables

Statement of personal contribution to the dissertation

The dataset used in this dissertation was collected for the purposes of Rosanna Morrison's PhD thesis by a team of 5 enumerators. Morrison and the author were both present at study sites throughout the data collection process, and jointly coordinated farmer surveying. The survey was developed by Morrison, and piloted/tested by Morrison, the author, and the enumerators. Preliminary cleaning of field data was carried out by the author and Morrison. All data cleaning, variable creation, and analysis relating to this dissertation were the sole work of the author, as was the composing of all the text and material in this document.

The data cleaning, analysis, and visualisation conducted for the purpose of this dissertation was carried out using the programming language R (Version 4.2.2) (R Core Team, 2022) and the RStudio software (Posit Team, 2022). R packages were used extensively. A full list of packages used is included in Appendix 2.

I confirm that all this work is my own except where indicated, and that:

1. I have read and understood the University's regulations in relation to academic misconduct (https://www.ed.ac.uk/academic-services/policiesregulations/regulations/assessment);
2. I have clearly referenced/listed all sources as appropriate;
3. I have referenced and appropriately indicated all quoted text (from books, web, etc), making appropriate use of quotation marks;
4. I have given the sources of all pictures, data, etc., that are not my own;

5. I have not made any use of the course work assessment material of any other student(s) either past or present, or colluded with others;
6. I have not submitted for assessment work previously submitted for this or any other course, degree or qualification, with the exception of materials from my Dissertation Plans and Literature reviews submitted in Professional Skills 4 and this course.
7. I have not incorporated any work from or used the help of any external professional agencies, including essay mills, other than extracts from attributed sources and proof-reading agencies whose services comply with University Regulations;
8. I have acknowledged in appropriate places any help that I have received from others (e.g. fellow students, teachers in schools, external sources);
9. I have complied with any other requirements specified in the course and programme handbooks;
10. I understand that the University of Edinburgh and TurnitinUK may make an electronic copy of my submitted work for assessment, similarity reporting and archiving purposes;
11. I understand that any false claim for any of the above will mean that the relevant piece of work will be penalised in accordance with the University regulations.

Abstract

This study evaluates factors influencing Kenyan smallholder dairy farmers' decision to adopt productivity-enhancing technologies, with a particular focus on identifying the influence of social networks. Dairy farming generates 4% of Kenyan GDP and contributes extensively to the income and food security of 1.8 million smallholders in the country, yet limited uptake of improved breed cattle, improved forages, and vaccination means that dairy productivity is low. This continues to constrain dairy development in the country, impeding nutritional and economic gains, and perpetuates the high greenhouse-gas intensity of Kenyan dairy systems.

Snowball sampling was used to collect survey data from 255 smallholders across four sites in West Kenya regarding demographic and household characteristics, dairy farming practices, and other external factors, as well as information about the members of farmers' social networks. Using this data, logistic regression models were constructed to identify the influence of the *adoption decisions* of farmers' network members (endogenous effects) and the *characteristics* of these network members (exogenous effects) on the likelihood of technology adoption. The influence of farmers' own characteristics and external factors is also investigated.

Farmers' probability of adopting dairy technologies was found to increase significantly with the number of adopters in their network. This constitutes clear evidence of endogenous effects, i.e. the behaviour of social network members influencing farmers' adoption decisions. The characteristics of farmers' network members (e.g., their age, educational attainment), however, did not have a significant influence. Technology-specific barriers to adoption are also identified.

This study is the first to quantify social network effects in any dairy or Kenyan agricultural system, thus contributing to the literature on how social networks shape technology adoption amongst farmers in developing countries. Findings are of policy relevance as they indicate that social networks could be harnessed for low-cost agricultural extension, and that interventions which facilitate interaction between farmers may spur the dissemination of agricultural technologies through the formation of new network connections. Future research should focus on understanding how to capitalise on these network effects and evaluate different interventions' impact on social network formation.

This work also provides insights relevant to extension systems in West Kenya, proposing context- and technology-specific recommendations towards dairy development in the area.

1. Introduction

Dairy farming is a key source of income and nutrition in Kenya. The country's dairy sector has an annual output of 5-6 billion litres, one of the largest in East Africa, and generates 4% of Kenyan GDP (Nguni and Wanjohi, 2019; Okello *et al.*, 2021). Nonetheless, milk supply in the country falls short of demand, leaving Kenya in a state of milk deficit which is likely to be exacerbated by population growth and increasing per capita demand (Government of Kenya, 2010a; Njeru, 2022).

The majority of Kenya's milk is produced by 1.8 million smallholder farmers, for whom the sale of milk constitutes an important source of household earnings (Bingi and Tondel, 2015; IFAD, 2020). Dairy farming also contributes to farmers' own food security through the provision of milk for household consumption and the production of manure to fertilise plots used for crop cultivation (Moll, Staal and Ibrahim, 2007; Makini *et al.*, 2019).

The productivity of these smallholders is low, averaging at 5-8 litres daily per cow – far below the potential 30 litres per cow per day (Okello *et al.*, 2021). It has long been recognised that the use of vaccination, improved breeds, and improved forages is key to raising smallholder milk production, with knock-on benefits on food security, economic development, and poverty reduction in rural Kenya (Government of Kenya, 2010a; Bonilla *et al.*, 2018). Such interventions can also mitigate the sector's carbon emissions by reducing the methane-intensity of milk produced (Opio *et al.*, 2017). However, these technologies remain underutilised, barring the achievement of nutritional and economic gains, and perpetuating Kenyan dairy's high greenhouse-gas intensity (Bingi and Tondel, 2015; Bonilla *et al.*, 2018).

To date, studies evaluating persistently low dairy technology adoption have centred around the influence of farm and farmer characteristics, and external factors such as market conditions, group membership, and access to extension.

Mounting evidence from across Sub-Saharan Africa and other developing countries indicates that social networks – the individuals and entities farmers interact and exchange knowledge with – are a significant determinant of technology adoption[1]. However, social networks and their influence on adoption have scarcely been studied in the context of Kenyan dairy systems, and a quantitative evaluation of their impact is yet to be undertaken.

With high inflation constraining government and development organisations' budgets (Clarke, 2021; World Bank, 2022) at a time when climate change is further threatening the livelihoods and food security of smallholders (Tadesse and Dereje, 2018; Toreni *et al.*, 2022; IPCC, 2022), maximising the effectiveness of scarce extension resources is paramount. A better understanding of social networks' influence on technology adoption will afford crucial insights towards optimising the distribution of these extension resources and harnessing social networks to broaden technology adoption.

[1] See, for example, Bandiera and Rasul (2006), Matuschke and Qaim (2009), Mekonnen, Gerber and Matz (2018), and Varshney *et al.* (2022).

1.1. Aims and objectives

This study's primary aim is to evaluate the influence of social networks on Kenyan smallholder dairy farmers' decision to adopt agricultural technologies. Drawing on primary data collected from farmers in Western Kenya – gathering information about both farmers and the members of their network – logistic regression analysis is used to identify the influence of both the behaviour and the characteristics of the members of farmers' networks, referred to as "endogenous" and "exogenous" effects, respectively (Manski, 1993). This is the first study to delineate such network effects in any dairy or Kenyan agricultural context. Three productivity-enhancing technologies are considered, namely improved forages, improved breeds, and vaccination.

In addition to network effects, this study also aims to evaluate how farmers' own characteristics and household traits affect the adoption of these technologies. The influence of external factors including group membership, market conditions, and the provision of information and training is also investigated.

Findings are drawn on to suggest future research and make context- and technology-specific policy recommendations towards the development of smallholder dairy systems in Kenya.

2. Literature Review

This literature review comprises two sections.

The first evaluates literature regarding the determinants of technology adoption amongst Kenyan dairy farmers. These resources were identified through keyword searches on Clarivate Web of Science[2] followed by title and abstract scanning using Covidence (Veritas Health Innovation, 2023). Studies selected were those pertaining specifically to smallholder dairy systems in West Kenya and the technologies treated in this study.

The second section treats social networks' influence on technology uptake in agricultural contexts. An overview of its theoretical underpinnings and key terminology is given, followed by a review of the empirical literature. Because of the limited literature on social networks effects in Kenyan or dairy systems, the studies discussed treat agricultural contexts more generally, and were selected based on their salience in the sphere of social network research. Whilst keyword searches on Web of Science were utilised, most papers in this section were identified via snowballing from key papers and recommendations from other researchers.

2.1. Determinants of technology adoption amongst West-Kenyan dairy farmers

A wealth of research has explored the determinants of dairy technology adoption amongst Kenyan smallholders. Many studies discussed hereunder were conducted in

[2]

close proximity to the study site of this work (Figure 1), such that their findings bear particular relevance.

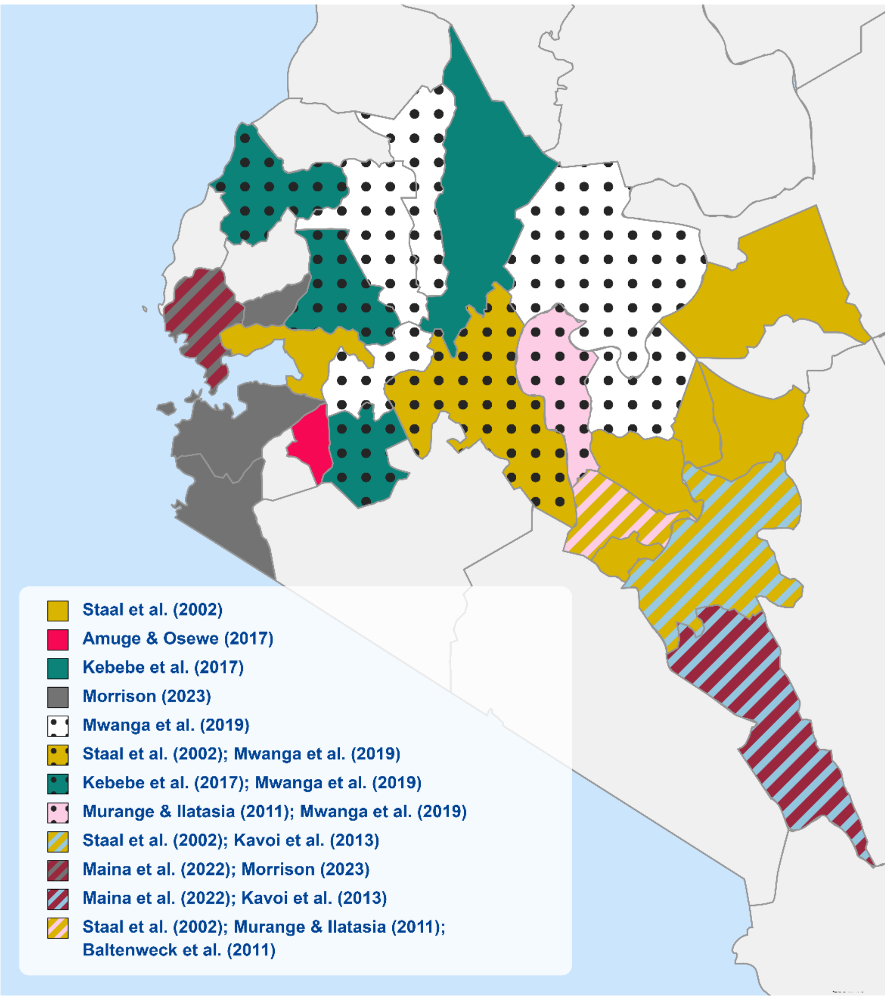


Figure 1: Map of West Kenya showing the counties where studies treated in the literature review were conducted. Note that this study uses the same data as Morrison (2023). Studies not shown above pertain to the country as a whole or the region more generally. The studies by Kebebe et al. *(2017) and Mwanga* et al. *(2019) treat dairy farmers in other countries in East Africa, however only results pertaining to Kenya are discussed hereunder. This figure was created by the author using MapChart (2023).*

In these studies, two broad classes of determinants of technology adoption are treated: farm and farmer characteristics[3], and external factors. These are discussed in turn hereunder.

[3] These are the characteristics of the farmers themselves, which are distinct from the characteristics of network members considered in measuring exogenous effects.

2.1.1. Farm and farmer characteristics

In Kebebe *et al.* (2017), socioeconomic characteristics of adopters and non-adopters of dairy technologies – including improved breeds and improved forages – are compared using Chi-squared tests. Strong complementarities were observed between the use of improved breeds and improved forages, though few differences between adopters and non-adopters were detected. Farmers using improved breed cattle had larger herds and were more reliant on dairying for their income, whereas those adopting improved forages had completed more years of formal education.

The positive influence of herd size on technology uptake is corroborated by Okello *et al.* (2021), who evaluated the determinants of vaccine and improved feed[4] adoption using generalised linear models. The size of land holdings was negatively associated with vaccination use. However, the inclusion of milk production as an explanatory variable – which is obviously linked to the use of dairy technologies – raises significant concerns regarding simultaneity bias, meaning that estimates may be inconsistent (Lynch and Brown, 2011). These findings must therefore be treated with caution.

Maina *et al.* (2022) also used regression techniques to model the adoption of *Brachiaria*, an improved forage. Contrary to the above finding regarding vaccination, *Brachiaria* use was found to be higher amongst those with larger holdings. Farmer age and herd size were also positively correlated with *Brachiaria* adoption[5], and a positive

[4] This refers to hay and silage, and not improved forages.
[5] The causal link between age and adoption was, however, unclear since experience growing fodder was associated with lower adoption.

association between the use of improved breeds and improved forage was again observed.

Amuge and Osewe (2017) similarly evaluated factors linked to the adoption of improved feeding technologies using generalised linear models. Age and, to a greater extent, educational attainment were significantly higher amongst adopters. Whilst the number of household members was positively related to adoption, the supply of labour had no influence. Here again though, certain explanatory variables raise concerns of simultaneity, which may have biased results.

Murage and Ilatsia (2011) similarly observed educational attainment to have a positive effect on uptake of improved breeding technologies. Their use was also positively correlated with herd size, in line with Kebebe *et al.* and Okello *et al.*. However, in Mwanga *et al.*'s (2019) study – whose sample size was almost 50 times larger – no link was found between use of artificial insemination and either farmer education or herd size, though again a strong correlation between forage and improved breeding technology use was noted.

Staal *et al.* (2002) used GIS data integrated with household survey responses to model the uptake of improved breeds and improved feeding technologies. Education was again found to be significantly linked to adoption of both, with improved breeds' uptake increasing with farmer experience. A higher supply of female labour also increased the likelihood of using improved breeds, in line with Jumba *et al.'s* (2020) observation that many dairy-related tasks are regarded as female endeavours. Higher numbers of economic dependents were linked to lower adoption, and a positive association between farm size and improved breed uptake was observed.

The study by Baltenweck, Yamano and Staal (2011) is unique in that a panel dataset is used. Whilst results reiterate synergies between improved breeds and improved forages, findings conflict with Maina *et al.*'s in that forage use was associated with smaller, as opposed to larger, holdings[6]. Education was again linked with uptake of both technologies, whilst farmer age was found to have the opposite effect. Female-headed households showed greater uptake over the study period. Instances of disadoption of both technologies were observed, emphasising the value of an intertemporal approach.

Overall, the picture these studies portray is far from consistent; solely the number of cattle owned and farmers' educational attainment are persistently and strongly linked to adoption.

2.1.2. External factors

2.1.2.1. Credit and marketing

Since sufficient capital is necessary to invest in a new technology, access to credit is expected to aid uptake (Ruzzante, Labarta and Bilton, 2021). This is corroborated by Murage and Ilatsia (2011), who recommend increasing credit access as a key policy intervention to raise adoption. In Maina *et al.* (2022), improved forage adopters had

[6] More than constituting a contradiction, this discrepancy highlights that forage varieties are best-suited to different ecological niches which are not equally common on larger and smaller farms. As noted by Paul *et al.* (2020), *Brachiaria*, studied by Maina *et al.*, is particularly well suited to growing under trees (such as bananas), which are more likely to be found on larger farmers, whereas Napier, treated by Baltenweck *et al.*, is better adapted to more marginal areas which smaller farms are likely to have a larger proportion of.

higher access to credit, whereas no variation in credit access between adopters and non-adopters was observed by Kebebe *et al.* (2017).

Okello *et al.* (2021), though, found a negative association between credit access and use of deworming and curative treatments. However, the authors interpreted this as evidence that those who can access credit can afford preventative health technologies and were therefore less likely to use deworming/curative treatments.

In many of the studies, however, access to credit is not treated directly because farmer groups and cooperatives generally offer loans to their members (Okello *et al.*, 2021), making it difficult to isolate the effect of credit access from that of group membership, discussed below.

The prices farmers face when selling milk and the transaction costs incurred in doing so also alter the benefits of technology adoption. Okello *et al.* (2021) found higher milk prices to be linked to uptake of vaccines, whilst Staal *et al.* (2002) acknowledged the influence of milk prices in determining the use of improved feeds. Kavoi, Hoag and Pritchett's (2013) econometric analysis also demonstrated that demand for improved forages and animal health technologies increases with milk prices.

In the literature, transaction costs of milk sales are generally proxied for by farmers' distance from market, which was recognised as a driver of forage adoption by Mwangi *et al.* (2005). Similarly, Kavoi, Hoag and Pritchett (2013) found walking distance from the nearest tarmac road – linked to market distance – to depress technology use. Baltenweck, Yamano and Staal (2011) corroborated this, observing proximity to marketing centres to be associated with higher adoption of all the technologies examined. The study by Staal *et al.* (2002) – which offers a particularly rigorous analysis in this regard given the rich GIS data drawn upon – also found dairy technology uptake to increase with proximity to markets. In Mwanga *et al.*'s (2019) and Kebebe *et al.*'s (2017) studies however, neither market prices nor distance significantly influenced adoption.

2.1.2.2. Information and extension

Despite farmer-to-farmer extension[7] increasingly replacing traditional extension across Africa (Simpson *et al.*, 2015), access to extensionists is still widely regarded as a determinant of technology adoption (Ruzzante, Labarta and Bilton, 2021). The work of Mwanga *et al.* (2019) and Maina *et al.* (2022) regarding improved forages agrees with this, though no such effect is found by Staal *et al.* (2002).

Notably, because of the curtailment of government extension during the liberalisation of Kenyan dairy markets in the 1990s, dairy cooperatives took on a central role in the promotion and provision of agricultural technologies, as detailed by Owango *et al.* (1998), Baltenweck, Yamano and Staal (2011), and Bingi and Tondel (2015). Membership in cooperatives is thus frequently used to proxy for farmers' access to extension. Okello *et al.* (2021) indeed found the use of artificial insemination to be significantly higher amongst cooperative members, whilst Amuge and Osewe (2017) found this also to be the case for feeding technologies. Provision of extension by

[7] A method of extension whereby select individuals known as 'lead-farmers' are trained and allowed to experiment with a technology, being subsequently expected to share it with other farmers (Ochieng, Silvert and Diaz, 2022). Its use has proliferated greatly across Sub-Saharan Africa (Simpson *et al.*, 2015) and it has been employed in West-Kenyan dairy systems (Kiptot and Franzel, 2015).

cooperatives was also cited by Murage and Ilatsia (2011) in explaining significant differences in artificial insemination adoption rates across study sites.

A rigorous review of Kenya's dairy development policy is however beyond the scope of this literature review, for which the work of Bingi and Tondel (2015) is referred to.

2.2. Social networks' influence on technology adoption

Studies dating to the 1940s have acknowledged the impact of social networks on farmers' decision to adopt agricultural technologies[8]. However, it was only during the 1990s that the theoretical underpinnings of studying social networks' influence were consolidated. The work of Manski (1993) greatly spurred the development of this field by delineating two ways in which social networks may influence an individual's decision, namely:

1. Endogenous effects[9], whereby the decision of network members (e.g., whether they adopt a technology) influences the individual's decision, and
2. Exogenous/contextual effects, whereby characteristics of network members (e.g., their age or socioeconomic status) influence the individuals' decision.

These terms will be referred to repeatedly throughout this dissertation. A sound understanding of them is therefore paramount[10].

---

[8] Ryan and Gross (1943) and Lionberger (1951) for example.
[9] This is not to be confused with "endogenous" or "endogeneity" used in a statistical sense e.g., as used in Avery (2005).
[10] The reader is referred to Manski, 1993, p. 533 and Bramoullé, Djebbari and Fortin, 2009, p. 41 if further clarification is required.

For the presence of either of these effects to be confirmed, it must be ascertained that the behaviour/decision of an individual and that of their network are not linked simply because they are both similar – what Manski refers to as “correlated effects”. An example of this is when a farmer and their network members all use tractors simply because they all farm large, flat land rather than because of any social network influence. To deal with such correlated effects and identify endogenous and exogenous effects, certain conditions in the data must be met, as identified by Bramoullé, Djebbari and Fortin (2009), a detailed discussion of which is beyond this review’s scope.

Distinguishing endogenous from exogenous effects is of great policy interest because if social networks influence individuals’ decisions via endogenous effects, increased adoption of a given technology among an individual’s network members will also increase that individual’s likelihood of adopting the same technology, thus propagating technologies through networks (Matuschke and Qaim, 2009). If it was solely exogenous effects driving networks’ influence, an individual’s decision to use a technology will not be affected by the adoption decision of the members of their network.

However, differentiating endogenous and exogenous effects poses econometric challenges arising from the difficulty in distinguishing the network’s influence on the individual from the individual’s influence on their network, referred to as the “reflection problem” (Manski, 1993). Two remedies to this problem identified by Manski (2000) and Brock and Durlauf (2001) have been utilised in the literature, these being:

1. treating individuals' behaviour as temporally lagged from that of their network – i.e., the individual chooses how to behave (whether to adopt a technology) after having observed the behaviour of their network, rather than deciding simultaneously – as in Varshney *et al.* (2022) and Matuschke and Qaim (2009), and
2. assuming that individual behaviour varies non-linearly with that of their network, as in Mekonnen, Gerber and Matz (2018) and Bandiera and Rasul (2006).

In addition to addressing these econometric issues, researchers must address the question of how 'social networks' are to be empirically defined. Three approaches to this have been adopted.

The first is to define social networks based on geographical proximity or membership in some group (such as ethnic group or caste). The limitations of this approach are obvious – a farmer's peers are unlikely to coincide completely and exclusively with the individuals in the same group/location – and have been repeatedly demonstrated[11]. However, this allows for 'typical' household surveys, not designed to examine social networks, to be repurposed for the evaluation of networks' influence. Krishnan and Patnam (2014) used such an approach, defining farmers' social networks as those living within 1km, thus allowing them to utilise rich household survey data to evaluate network effects amongst Ethiopian smallholders.

A second approach is known as 'random matching within sample'. This consists of first undertaking a census in the site studied, then matching survey participants with other

[11] See Udry and Conley (2005), and Mekonnen, Gerber and Matz (2018).

individuals/households in the census area at random (Mekonnen, Gerber and Matz, 2018). Participants' networks are defined as those amongst the randomly matched households with whom participants have some relationship/interaction[12].

The third approach is to allow study participants to actively identify their network. This is done by first selecting and surveying an initial sample of participants, who are asked to name individuals who are part of their network – referred to as a 'name generator' question[13] (Kowald and Axhausen, 2012). Individuals named are then surveyed, and these in turn provide a new set of names who are subsequently surveyed, et cetera, known as a snowball sampling approach (Figure 2). Matuschke and Qaim (2009), for example, use this method.

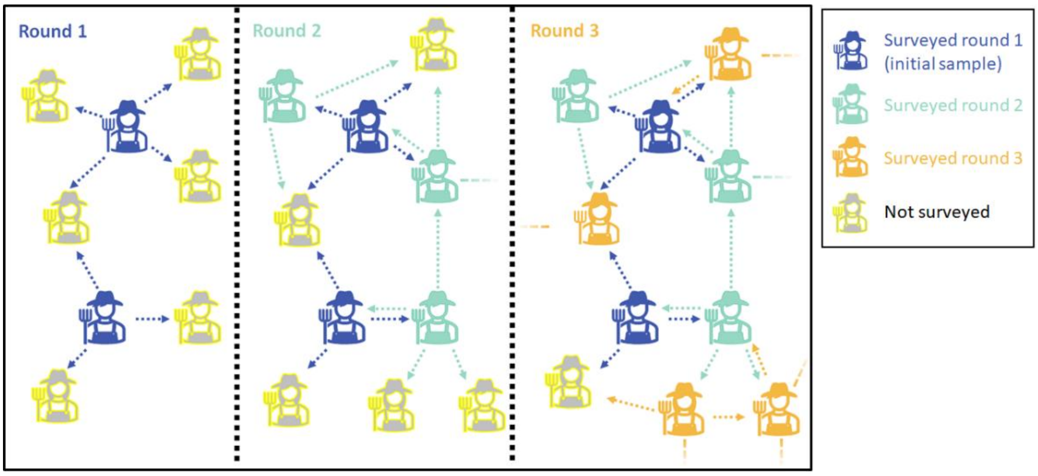


Figure 2: Illustrative figure showing 3 rounds of snowball sampling. The figure starts from an initial sample of 2 farmers, who name network members in a 'name generator' question. Named network members are surveyed in subsequent rounds, each providing the names of the members of their own network. Author's illustration created using Microsoft Powerpoint©.

[12] The veracity of this is sometimes confirmed by asking participants to name characteristics of the matched individual they claim to know.

[13] A cap is usually placed on the number of individuals that can be named for practical reasons (Santos and Barrett, 2008).

2.2.1. Empirical evidence

As recently as 2013, the literature on social network effects in agricultural settings was characterised as "distinctly underdeveloped" (Maertens and Barrett, 2013). Whilst studies on the topic treating agricultural systems across Africa have since proliferated (Takahashi, Muraoka and Otsuka, 2020), the literature on social networks pertaining to Kenyan dairy systems remains limited to the work of Kiptot and Franzel (2015, 2019) and Morrison (2023)[14], despite the sector's significant contribution to Kenyan nutrition, GDP and livelihoods.

Morrison and Kiptot and Franzel focused on the role of lead-farmers within farmer-to-farmer extension systems[15] and characteristics of these individuals which maximise technology diffusion. Beaman and Dillon (2018), Fisher *et al.* (2018), and Nöldeke, Winter and Grote (2020) addressed similar questions in other agricultural contexts in Sub-Saharan Africa. However, in focusing on the characteristics of lead-farmers associated with heightened technology dissemination, the social network effects underpinning this dissemination amongst farmers are not interrogated. In other words, these studies seek to establish *what* works best to spur technology dissemination without evaluating *how* social networks influence technology uptake. To do so, endogenous and exogenous effects ought to be identified. Yet, these have not been studied in the context of any dairy or Kenyan systems to date, let alone Kenyan dairy systems specifically.

---

[14] Mwema and Crewett (2019) and Giroux *et al.* (2023) also evaluate the influence of social networks on technology adoption in Kenya agricultural systems to some degree, but they do not pertain to the dairy sector, nor do they isolate endogenous and exogenous effects.

[15] See footnote 7.

The few studies which have identified social network effects in agricultural contexts indicate that endogenous effects – the behaviour of social network members influencing individuals' decisions – tend to be significant, though scarcely are exogenous effects significant. This is the case for the study by Mekonnen, Gerber and Matz (2018), which treated the influence of networks on adoption of improved planting techniques amongst Ethiopian smallholders. Bandiera and Rasul's work (2006) on the adoption of sunflower planting in Mozambique also found these to be significant. In Krishnan and Patnam (2014), strong evidence of endogenous effects amongst smallholders in Ethiopia was observed, though as mentioned, this study defined social networks based on geographical location, detracting from its accuracy.

Reference is also made to Matuschke and Qaim (2009), Maertens (2017), and Varshney *et al.* (2022), who adopted a similar methodological approach to that used here. All three identify network effects in Indian agricultural systems, consistently observing endogenous effects to be present, though solely in the latter study are exogenous effects significant.

Understanding social network effects in the context of Kenyan dairy systems is particularly pertinent. Firstly, many studies make reference to social networks' importance without directly evaluating their influence, highlighting a key gap in the literature. This includes the studies by Staal *et al.* (2002), Amuge and Osewe (2017), Kiptot and Franzel (2019), Okello *et al.* (2021), and Maina *et al.* (2022), whilst Mwanga *et al.* (2019) observed spatial clustering of farmers' preferred breeding technologies, which was interpreted as evidence of "the influence of neighbours" (Figure 3).

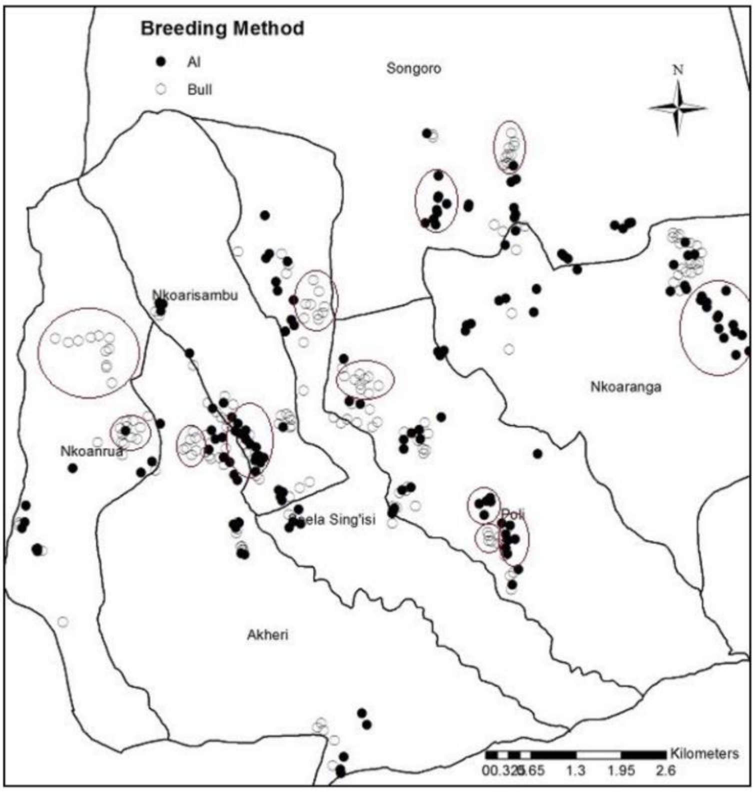


Figure 3: Evidence of spatial clustering in farmers' preferred breeding methods, with particularly salient clusters circled. Figure taken from Mwanga et al. *(2019). This was interpreted as evidence of "the influence of neighbours".*

Secondly, climate change is increasing the need for technology dissemination at a time when inflation is constraining extension budgets (Clarke, 2021; IPCC, 2022). An analysis of social network effects will provide insights towards more effective targeting of scarce extension resources, as well as contributing to policymakers' understanding of how social networks can be harnessed to disseminate technologies at a low cost.

3. Methods

3.1. Study site

The data used in this study was collected during February and March 2022 for research conducted by Morrison (2023). The author of this work formed part of the team conducting fieldwork. Data was collected across four locations in Western Kenya: Oyugis Township in Homa Bay county (hereafter Oyugis), Rongo Township in Migori county (hereafter Rongo), and parts of Vihiga and Siaya counties (Figure 4b). These sites were selected in coordination with practitioners from the *International Livestock Research Institute* (ILRI) involved in dairy-related projects in the region (Odongo, 2016; Victor, 2018; USAID, 2022). For reasons relating to Morrison's study, two sites had active dairy cooperatives (Oyugis, Rongo), whereas village-based advisors known to ILRI were present in the surveyed areas of Vihiga and Siaya.

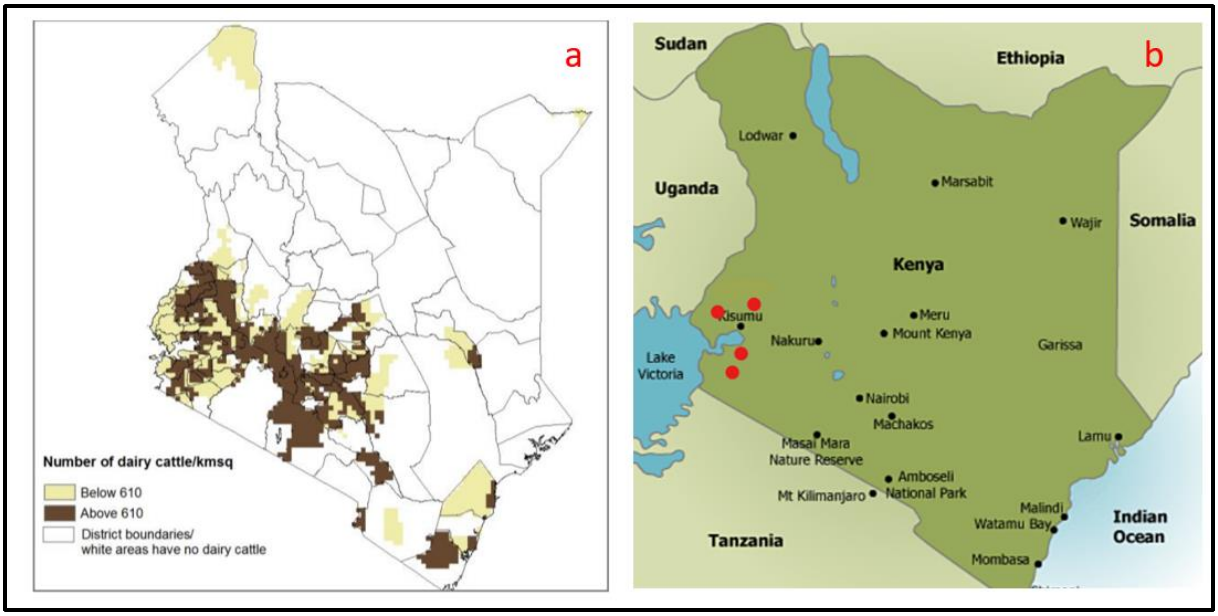


Figure 4: The stocking density of dairy cattle in Kenya (Panel a), and a map indicating the locations of study sites (Panel b). The former was taken from Ochungo et al. (2016), whereas the latter is from Morrison (2023).

Despite not being a "traditional dairy production area" (Odongo, 2016), Figure 4a shows relatively high densities of dairy cattle around study sites. Milk production is dominated by smallholders who rely on mixed crop-dairy systems (Odhiambo *et al.*, 2019). Most cattle are reared intensively (zero-grazing), though extensive grazing is sometimes used (Ochungo *et al.*, 2016; Onono and Ochieng, 2018). Notwithstanding the region's high dairy potential[16], productivity is generally low such that production currently lags behind the demand for milk in all four counties. Increasing smallholder productivity is a key target of local governments across these sites (Onono and Ochieng, 2018; Argwings-Kodbek, 2019; Odhiambo *et al.*, 2019; Ombima, 2021).

3.2. Data collection

In each site, a sample of 10 farmers representative of the areas' farming population in terms of age, gender, and farm size was selected from cooperative membership lists or village-based advisor contacts. These farmers participated in a structured survey administered by trained enumerators[17] assessing farmer and household characteristics, milk production and sales, use of dairy technologies, and sources of information about dairying. The survey was piloted with the same enumerators and ILRI staff ahead of data collection to ensure appropriateness and unambiguity of survey questions.

[16] As per Lukuyu *et al.* (2012), but also as attested by the wealth of research on dairy farming discussed in *Section 2.1.*.

[17] These were conducted in English or Swahili, with responses logged in English on electronic tablets by the enumerators.

To gather information about social networks, the 'name generator' and snowball sampling approach described in *Section 2.2.* was used[18], whereby participants were asked to name up to 4 individuals who they "regularly talk to about farming". Individuals named by participants were subsequently approached to participate in the study, though were not told by whom they were mentioned. Snowball sampling was carried out until the time allocated for each site[19] was expended.

A total of 258 valid responses were collected across the four sites, though 3 participants did not have any cows at the time of survey and thus were dropped from the sample[20].

3.2.1. Limitations and biases in data collection

3.2.1.1. Households as unitary entities

When it was not possible to survey the individual referred to, surveys were administered to another member of the same household. There were also instances of multiple individuals from the same household being referred to, in which case only one survey response was collected from that household. In light of this, it was assumed that household members shared a single network.

---

[18] See also Figure 2.
[19] 2-3 working days.
[20] The dataset is made available with this dissertation for examination purposes.

3.2.1.2. Incomplete networks

Restricting the number of network members to a maximum of four inclines participants to mention those with whom they have stronger links, yet may nevertheless result in network members being omitted (Santos and Barrett, 2008; Matuschke and Qaim, 2009). However, this is not particularly concerning here given that half of participants mentioned less than 4 individuals.

Due to time constraints, inability to reach certain farmers, and farmers declining to participate, it was not possible to survey every individual named by each participant. For only a third of participants was the entirety of their network surveyed, though for three-quarters of participants at least half of the network members they named were surveyed (Figure 5).

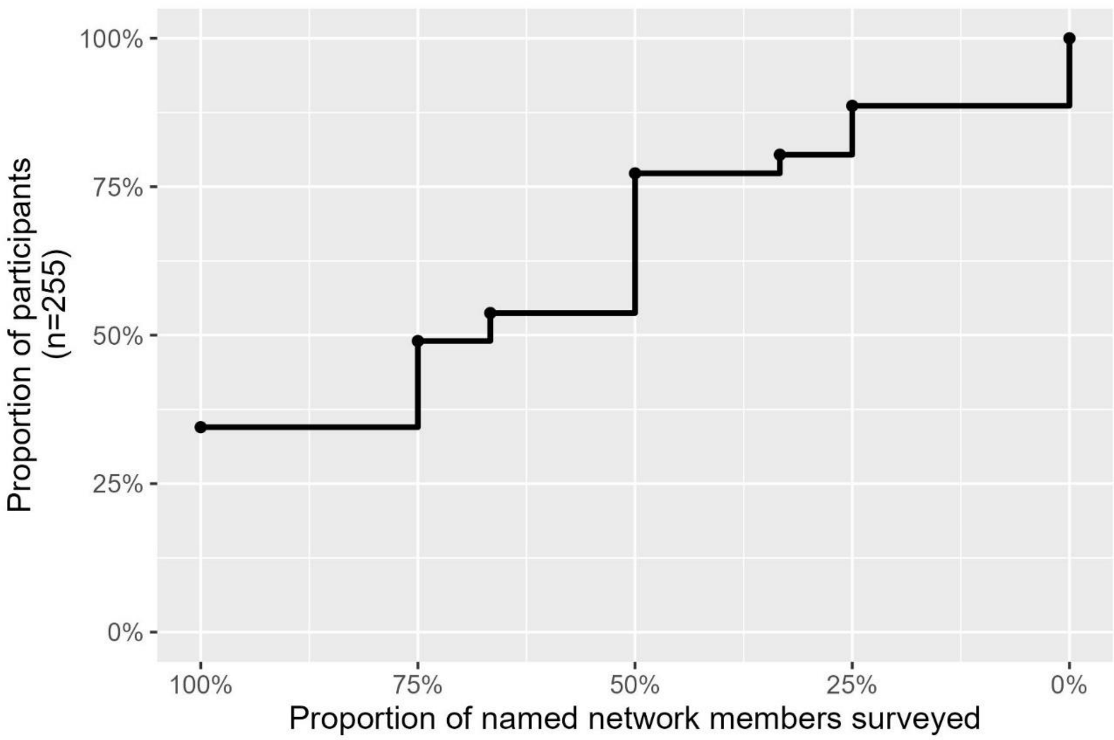


Figure 5: Cumulative frequency graph showing how the proportion of named network members that were surveyed varies in the sample.

3.2.1.3. Selection bias

Snowball sampling inherently gives rise to selection bias since participants determine who is subsequently surveyed. Better connected individuals are also more likely to be included in the sample (Kowald and Axhausen, 2012). To mitigate this, the initial sample was selected to be representative of the areas' farming population in terms of age, gender, and farm size.

Risk of selection bias also resulted from farmers' geographical location. Those in more remote locations were less likely to be surveyed due to time limitations, whereas the opposite was the case for named contacts in closer proximity to other participants (Figure 6), likely skewing the sample towards individuals in closer proximity to markets and road infrastructure.

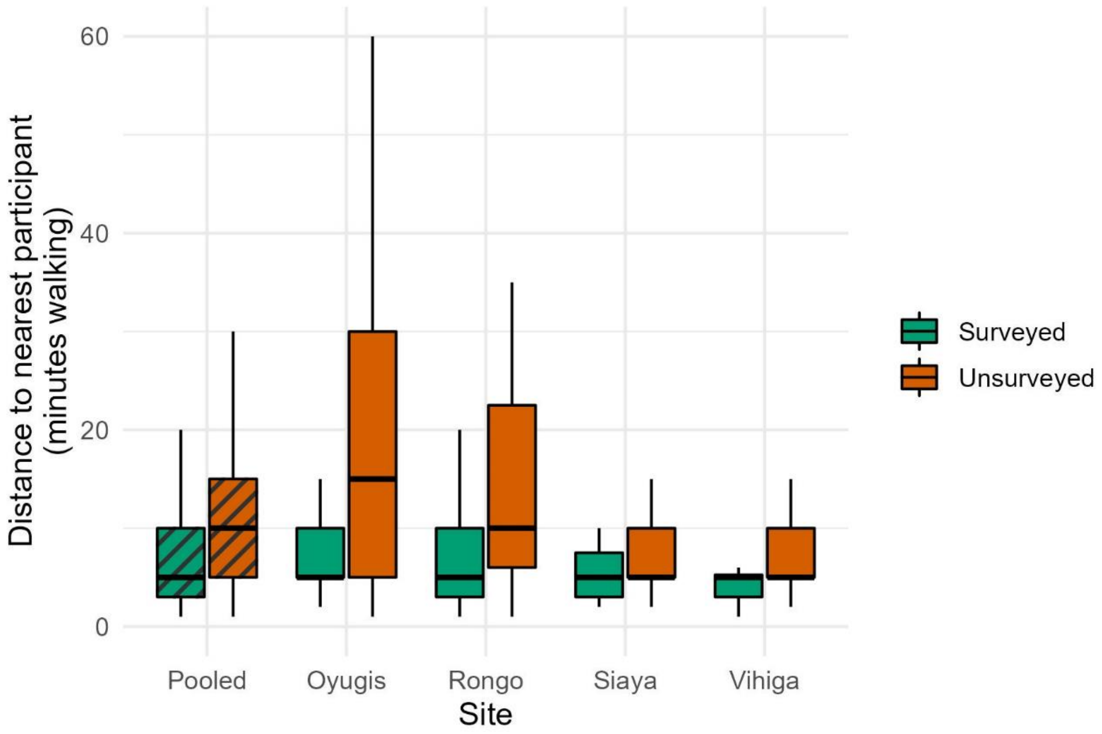


Figure 6: Boxplots showing the distance of surveyed and unsurveyed named network members from the nearest participant who named them. The distribution is shown for the whole sample ("Pooled", differentiated by crosshatching) and disaggregated by study site. Outliers are not shown. Unsurveyed network members were consistently further away from the nearest participant than network members who were surveyed.

3.3. Data analysis and model specification

Following preliminary cleaning[21], further cleaning and variable creation was undertaken using R, the full code for which is available here[22]. A description of the dataset was then carried out presenting summary statistics, figures, and tables as appropriate to convey features of relevance, for which the full code is provided[23].

Following this, an econometric model was constructed to identify factors' influence on technology adoption. Logistic regression[24] analysis was performed[25] owing to the dependent variable being a binary variable indicating technology adoption/non-adoption.

The conceptual framework employed is as follows.

Farmer q adopts a given technology T if the expected benefits from its adoption ε_{qT} exceed a given threshold π.

$$Y_{qT} = 1 \; if \; \varepsilon_{qT} > \pi \;\Rightarrow V_q \cdot b + e_q > \pi \qquad (1.1)$$

$$Y_{qT} = 0 \; if \; \varepsilon_{qT} < \pi \;\Rightarrow V_q \cdot b + e_q < \pi \qquad (1.2)$$

where Y_{qT} is farmer q's adoption decision regarding technology T, where 1 indicates adoption, V_q is a vector of explanatory variables, b is a set of parameters to

[21] This was conducted by the author of this work and Rosanna Morrison during and immediately after data collection (Feb-Apr22), consisting primarily of amendment of input errors and removal of anomalous entries. The full code for this, however, is not shown owing to it having treated sensitive/personal data; the data made available is such that these processes have already been executed.
[22] Alternatively, copy this link: https://github.com/x-cassar/UG-Dissertation-Social-networks.git.
[23] The full code for all figures and tables presented in this dissertation is available here: https://github.com/x-cassar/UG-Dissertation-Social-networks.git. Note that to run the code for figures and tables, as well as regressions, the "Data Cleaning.Rmd" file must first be run using the dataset disclosed with this dissertation; this will create another CSV file which is used as an input to the other RMD scripts.
[24] This is a specific type of generalised linear models which deals with binary classification problems.
[25] Similarly to Staal *et al.* (2002) and Murage and Ilatsia (2011).

be estimated, and e_q is an error term. Three classes of explanatory variables (V_q) are considered:

- X_q, a vector of farm and farmer characteristics,
- I_q, a vector of external factors, and
- S_q, a vector of variables capturing the influence of social networks.

$$\varepsilon_{qT} = f(X_q, I_q, S_q) \tag{2}$$

The influence social network effects can be decomposed further,

$$S_q = f(\, a_{n(q)T},\, X_{n(q)}) \tag{3}$$

where $a_{n(q)T}$ captures the adoption decision of q's network members – $n(q)$ – and $X_{n(q)}$ is a vector of variables capturing the characteristics of the members of q's network, which respectively serve to capture the endogenous and exogenous effects of social networks. To overcome the issue of statistical identification associated with the reflection problem[26], endogenous effects are modelled non-linearly and thus a squared term is also introduced[27], such that

$$S_q = f(\, a_{n(q)T},\, {a_{n(q)T}}^2, X_{n(q)}) \tag{4}$$

The regression model estimated is thus

$$Y_{qT} = C + \lambda \cdot X_q + \rho \cdot I_q + \beta_1 \cdot a_{n(q)T} + \beta_2 \cdot {a_{n(q)T}}^2 + \gamma \cdot X_{n(q)} + \delta_s + e_q \tag{5}$$

where C is a constant, e_q is an error term, δ_s captures site fixed-effects, and $\lambda, \rho, \beta_1, \beta_2$and γ are parameters to be estimated. The focus of this study is the

[26] See *Section 2.2.*.
[27] Similarly to Bandiera and Rasul (2006) and Mekonnen, Gerber and Matz (2018).

identification of parameters β_1, β_2 or γ, the former two capturing endogenous effects and the latter exogenous effects. If either is found to be different from 0, this indicates that social networks directly influence farmers' technology adoption decision.

3.3.1. Dependent variables

Three technologies are considered in this study.

The first is improved breeds of cattle. Breeds such as Holstein-Friesian and Ayrshire can produce considerably more milk than local varieties (e.g., Zebu) (Murage and Ilatsia, 2011; Onono and Ochieng, 2018), however their uptake is low (Odongo, 2016). Farmers who owned any cattle which were pure improved breeds or crosses were treated as utilising this technology.

The second technology is improved forages. Napier grass[28] is the most common of these, but *Brachiaria*, *Calliandra calothyrsus*, and *Desmodium intortum* are also widely used (Paul *et al.*, 2020; Maina *et al.*, 2022). These can greatly increase milk production compared to feeding local grasses, and are generally used in combination with improved cattle breeds (*Section 2.1.1.*). Broader adoption can alleviate feed shortages presently stunting dairy development in West Kenya (Onono and Ochieng, 2018; Paul et al., 2020). Farmers are treated as adopting this technology if they regularly used any improved forage.

Vaccination is the third technology. Vaccination against East Coast Fever in particular – the disease causing the most cattle deaths in East/South Africa – can greatly reduce

---

[28] *Pennisetum purpureum*.

mortalities, particularly amongst calves (Opio *et al.*, 2017; Jumba *et al.*, 2020). Farmers reporting having ever vaccinated dairy livestock are treated as adopters.

A logistic regression model was constructed for each of these, with a binary variable indicating adoption/non-adoption serving as the dependent variable.

3.3.2. Explanatory variables

3.3.2.1. Social networks' influence

In this study, a participant's social network is defined as those individuals named by that participant when asked who they regularly speak to about farming. However, only those individuals named who were also surveyed could be considered as part of their network given that the technology use and characteristics of unsurveyed network members are unknown.

As in Mekonnen, Gerber and Matz (2018), endogenous effects are captured by including the number of adopters in participants' social network as a variable in the regression. The square of this was also included to overcome the "reflection problem" (*Section 2.2.*). If the parameter associated with either of these variables is statistically significant, this is taken as confirmation of the presence of endogenous effects. In light of studies conducted to date[29], it is expected that the parameter associated with the number of adopters will be positive whilst that associated with the squared term will be negative.

[29] Namely Bandiera and Rasul (2006) and Mekonnen, Gerber and Matz (2018).

To capture exogenous effects, that is the influence of network members' characteristics on farmers' likelihood of adoption, five variables measuring characteristics of participants' social network members are included in the regression, the rationale and expected effect for which are detailed in Table 1 below. The selection of these variables was based on the work of Matuschke and Qaim (2009) and Mekonnen, Gerber and Matz (2018). Any parameters associated with these variables being significant indicates that the characteristics of social network members do bear significant influence on farmers' adoption decision, i.e. that exogenous effects are present.

Table 1

Rationale for inclusion and expected effect of variables included in the regressions to capture the influence of network member characteristics, i.e., exogenous effects.
Their inclusion is in line with Matuschke and Qaim (2009) and Mekonnen, Gerber and Matz (2018).
+ = predicted positive effect, - = predicted negative effect.

Variable	Predicted Effect	Rationale
Network member mean age	+	Having network members with more experience in dairy farming may allow farmers to draw on peers' knowledge to better exploit dairy technologies, increasing their incentive for adoption. This is measured as the mean age of the individuals named as part of a farmer's network.
Network mean educational attainment	+	Farmers surrounded by individuals with higher levels of education can draw on their knowledge to gain a better understanding of aspects of dairy farming, including technologies. To measure this, no education, primary, and above primary education are coded as 1,2, and 3 respectively and the mean of these for network members is taken.
Network mean number of economic dependents	-	If a farmer's network members have larger numbers of economic dependents, they have less time to impart their knowledge or lend labour, such that they may lesser incline the farmer to adopt techologies relative to network members with fewer dependents (Udry and Conley, 2005). This is measured as the mean number of economic dependents of the individuals named as part of a farmer's network

Network mean farm size	+	Farm size can proxy for household wealth, linked to better access to information, which can be drawn on by other farmers to further their understanding of technologies. This is calculated by converting the three farm size categories, 0-0.5ac, 0.6-2.5ac and >2.5ac, to 1,2 and 3 respectively, taking the mean of these for farmers' named network members.
Network mean number of cows owned	+	Network members who own more cattle may have a better understanding of dairy farming, which farmers can draw on to better understand the impacts of dairy technologies. This is measured by taking the mean number of cows owned amongst the members of a farmer's network.

These variables were consistent across the regressions.

The data used meets the conditions necessary for the identification of social network effects in the potential presence of correlated effects, as identified by Bramoullé, Djebbari and Fortin (2009), confirming that endogenous and exogenous effects can be measured accurately[30].

3.3.2.2. Farm and farmer characteristics

To account for and evaluate the influence of farm and farmer characteristics, a series of variables were introduced, selected based on previous studies[31]. These are presented in Table 2, along with the rationale for inclusion and their expected effect.

Where survey respondents were not the main decision-maker on dairy, the age, education, and number of economic dependents of the respondent were used nonetheless.

[30] This can be verified by evaluating the cited paper and the full dataset disclosed with this dissertation.
[31] See *Section 2.1.*.

Table 2
Rationale for inclusion and expected effect of farm- and farmer-level variables included in the regressions.
+ = predicted positive effect, - = predicted negative effect.

Variable	Predicted Effect	Rationale
Age	+	Whilst young farmers are less risk-averse and more willing to experiment with technologies (Kebebe *et al.*, 2017), older farmers are generally more experienced[32] and thus better able to exploit technologies, increasing their incentive to adopt (Murage and Ilatsia, 2011; Okello *et al.*, 2021). This variable is coded as participant age in years.
Education	+	Educated farmers are better able to understand technologies (Murage and Ilatsia, 2011) and less risk averse (Ruzzante, Labarta and Bilton, 2021). Variable is coded as a categorical variable with three levels: no formal education, primary education, and above primary education.
Decision maker gender (male=1)	-	In Kenya, female household members are generally responsible for many dairy-related activities (Staal *et al.*, 2002; Kebebe *et al.*, 2017; Jumba *et al.*, 2020). Where decision makers are female, technology adoption is therefore expected to be higher due to more importance being attributed to dairying. However, female-headed households tend to be poorer, which may impede uptake (Sheahan and Barrett, 2017).
Economic dependents	-	A higher number of economic dependents generally implies lower labour (per Staal *et al.*, 2002) and capital availability for dairy farming, which is expected to reduce the likelihood of technology adoption (Staal *et al.*, 2002). This is coded as the number of economic dependents reported.
Farm size	+	Farm size generally reflects the wealth of the household, and is thus expected to be linked with better technology access (Ruzzante, Labarta and Bilton, 2021). This is despite dairy farming possibly being less intensive when space is less constraining, and larger farmers generally being more oriented towards crop production, which reduce incentives to adopt technologies (Kebebe *et al.*, 2017; Mushonga *et al.*, 2017). This is coded as a categorical variable with three levels: 0-0.5ac, 0.6-2.5ac, and above 2.5ac.
Cows owned	+	Number of cows owned may proxy for household wealth, linked to increased technology access, and may incentivise adoption due to returns to scale (Wambugu, Kirimi and Opiyo, 2011). This is measured by the number of cattle owned who have given birth at least once.

[32] Whilst data on farming experience was available, this was not included due to its tendency to be covariate with age, as per Ruzzante, Labarta and Bilton (2021).

Because improved breeds may bear calves more frequently than local breeds (Staal *et al.*, 2002), the number of cows owned may be dependent on improved breed cattle ownership. Similarly, given that vaccines reduce calf mortality[33], the number of cows owned may also depend on uptake of this technology. Therefore, to avoid simultaneity bias – which may occasion inaccurate estimates (Lynch and Brown, 2011) – the variable for number of cows owned was not included in regressions on improved breed and vaccine uptake.

A binary variable indicating whether farmers used improved breed cattle was also included in the regression on improved forage use given frequently-observed synergies between these two technologies.

3.3.2.3. External factors

Similarly to above, variables are included to capture the influence of external factors – presented in Table 3 – and were selected based on previous empirical research. Site-level dummy variables were also included to control for differences between sites.

These variables were consistent across regressions.

[33] Vaccination against ECF "reduc[es] calf mortality from over 20% to around 2%" (Perry, 2016).

Table 3

Rationale for inclusion and expected effect of external factor variables included in the regressions. Their inclusion is in line with other studies from the region.
+ = predicted positive effect, - = predicted negative effect.

Variable	Predicted Effect	Rationale
Group membership	+	Group membership is here primarily used to proxy for credit access (*Section 2.1.2.*). This is a binary variable equal to 1 when the respondent formed part of a farmer group, social group, or finance group.
Named network members	+	The number of individuals named by participants indicates how well-connected, active in farming communities, and willing to learn from other farmers participants are (Mekonnen, Gerber and Matz, 2018). This is measured as the number of names provided in the name generator question (max=4), irrespective of whether those individuals were surveyed or not. Importantly, this also controls for participants naming different numbers of network members; without the inclusion of this variable the estimated effect of the number of adopters in network would be imbued with any influence related to the number of network members named.
Milk selling price	+	When milk selling prices are higher, benefits of increased milk output enabled by technology adoption are greater as farmers can sell milk for higher earnings (*Section 2.1.2.*). This is the milk selling price reported by each participant. Where multiple prices were reported, the highest was used[34].
Market distance	-	Costs associated with transporting milk, associated with farmers' distance to market, may dampen the benefits of technology adoption (*Section 2.1.2.*). Market distance was measured in km[35].
Receipt of information and training	+	Receipt of information and training increases awareness and knowledge of technologies, allowing farmers to understand their benefits and better exploit them. This is coded as 5 binary yes/no variables indicating whether the respondent "ever received information or training regarding dairy livestock farming" from 5 sources: • media (including TV, radio, newspapers and books) • lead-farmers (including volunteer farmer trains and farmer field schools) • cooperatives • government extension (including government projects), and • non-government extension (encompassing non-government extensionists, NGO projects, and private veterinarians). These were kept distinct so as to account for any variation between sources' impact which may arise from their structural differences.

[34] For some instances where no price was reported, the selling price was assumed to be the mean selling price amongst network members.
[35] For some instances missing data for this variable, their market distance was taken to be the average market distance of named network members living within 15 minutes walking distance.

3.3.3. Validity checks and robustness

Instances missing data for any of the variables were excluded from the dataset on which regressions were run, and appropriate tests were carried out to ensure that the assumptions of logistic regressions were not contravened; both these are discussed further in *Section 4.2.*.

To confirm the robustness of estimates, regressions were also run on a sample including solely participants for whom at least 50% of named network members were surveyed[36] and again on a sample including just those participants who were the main decision-maker on dairy farming in the household. These are discussed hereunder.

[36] This was the highest threshold that could be set whilst maintaining tolerable levels of multicollinearity.

4. Results

4.1. Descriptive statistics

4.1.1. Technology use

As shown in Table 4, improved forage was the most broadly used of the technologies[37], followed by vaccination and improved breed cattle. Vihiga showed the highest rate of technology use, with uptake being markedly lower in Siaya.

Table 4

Uptake of dairy technologies amongst survey participants, disaggregated by study site and in the whole sample (Pooled). 'Average rate of technology' use is the average of the rate of use of the three technologies.

Site	n	Improved breed use rate (%)	Improved forage use rate (%)	Vaccine use rate (%)	Average rate of technology use (%)
Oyugis	66	73.8	78.8	67.7	73.4
Rongo	57	60.7	86.0	61.4	69.4
Siaya	70	18.8	42.9	47.1	36.3
Vihiga	62	66.1	88.5	88.3	81.0
Pooled	255	54.0	72.8	65.5	64.1

Figure 7 below shows that a third of the total sample (37%) utilised all three technologies, significantly more than the 12% who used none. Apart from use of all three technologies, use of vaccination and improved forage, and solely improved forage were the most frequent combinations observed. Notably, improved cattle were rarely used in isolation.

[37] For information regarding specific forage varieties, see *Supplementary Figure 1*. Reference is here also made to footnote *6*, which touches on how the suitability of forage varieties varies with farm size. A similar pattern to that noted in the footnote is here observed, whereby Brachiaria ($p<0.001$) (and Desmodium [$p<0.05$]) is used significantly less by those with farms of 0-0.5ac than those with larger farms, whereas Napier was least used on farms greater than 2.5ac (though this difference was not statistically significant), in line with the distribution implied by Paul *et al.* (2020).

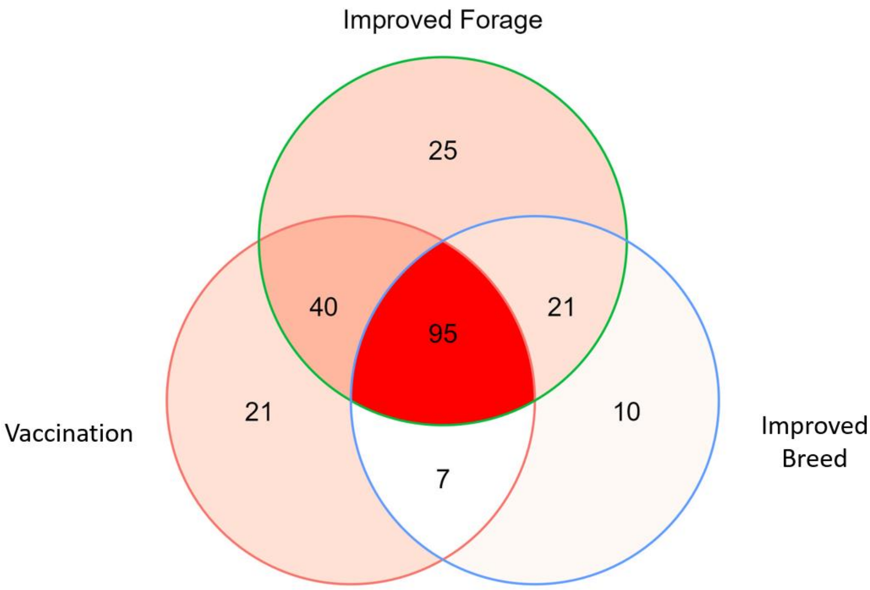


Figure 7: Venn diagram showing how the use of different technologies overlaps. Instances with missing information regarding the use of any of the three technologies (n=6) were dropped, and those not using any of the technologies (n=30) are necessarily not shown. The total number of instances shown is thus 219.

The main benefits of improved breeds participants mentioned include increased milk production, faster-growing calves, prevention of inbreeding, and high reproductive frequency. Some also noted that they constitute “a form of security [and] can be used as collateral”.

Increased milk production was also the main benefit of improved forages mentioned, with improved milk quality and animal health also cited. Conversely, the high price of improved forages and a lack of access to seeds were frequent cited as impeding uptake, with a lack of knowledge and space, and not owning improved breed cattle also mentioned as reasons for non-adoption.

In the case of vaccination, improved animal health and reduced disease incidence and mortality were the benefits noted, with some also highlighting improved milk yields[38], similarly to Jumba *et al.*'s findings (2020). A few farmers specified protection from East Coast Fever.

Figure 8 shows that farmers utilising technologies were more likely to be aware of benefits technologies confer, despite some adopters being unable to mention any advantages of technologies they used. Notably, amongst those forage adopters unaware of its benefits, only a fifth owned improved breed cattle (as opposed to 54% in the broader sample)[39].

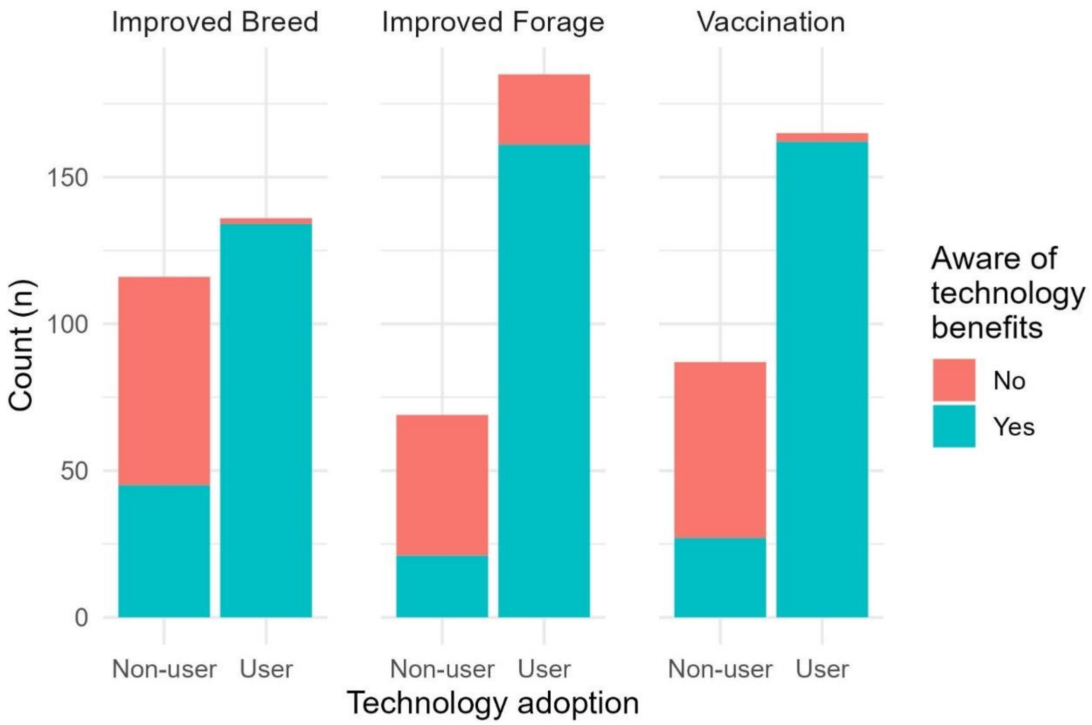


Figure 8: Three panels of bar charts showing the number of adopters and non-adopters of each technology. The colour indicates whether participants were aware of any benefits stemming from the use of that technology.

[38] This may be linked to reduced calf mortality from East Coast Fever vaccination, since the presence of live calves stimulates cows to produce milk for longer (Jumba *et al.*, 2020).
[39]Non-decision-making participants were not overrepresented in this cohort, indicating that this statistics is not driven by participants unaware of their household's dairy practices.

4.1.2. Farmer and farm characteristics

Summary statistics of the farmer and farm characteristics are shown in Table 5 below.

Table 5

The mean of farm and farmer characteristics, with the standard deviation shown in brackets where appropriate. Values are rounded to 1 decimal place.

	Pooled	Oyugis	Rongo	Siaya	Vihiga
Participant gender (% male)	51.6	62.1	48.2	51.4	43.5
Decisionmaker gender (% male)	63.5	69.7	59.6	70	53.2
Age (years)	53.4 (14.3)	55.7 (11.5)	54.4 (16.5)	49.3 (14.5)	54.8 (13.6)
Dairy farming experience (years)	16.3 (11.1)	15.2 (8.6)	19.1 (13.0)	12.4 (9.7)	19.2 (11.5)
Economic Dependents (#)	5.9 (3.4)	6.1 (4.2)	5.8 (3.4)	5.3 (2.5)	6.6 (3.5)
Mobile phone access (1=yes)	98.0	100	100	95.7	96.8
Education: None (%)	5.9	0.0	10.5	5.7	8.1
Education: Primary (%)	49.4	30.3	47.4	68.6	50
Education: Above primary (%)	44.7	69.7	42.1	25.7	41.9
Farm size: 0-0.5ac	28.2	19.7	12.3	38.6	40.3
Farm size: 0.6-2.5ac	49.4	53	49.1	47.1	48.4
Farm size: >2.5ac	22.4	27.3	38.6	14.3	11.3
Cows owned (#)	1.8 (1.5)	2.5 (2.5)	1.7 (0.9)	1.5 (0.8)	1.3 (0.6)
Milk output per cow (L/day)	3.0 (2.4)	3.6 (3.0)	3.7 (2.4)	1.8 (1.4)	2.9 (2.1)
Proportion of milk produced sold (%)	20.9 (20.1)	23.7 (20.8)	26.5 (20.9)	13.6 (17.6)	21.0 (19.4)
Percentage of income from dairy (%)	44.8 (37.5)	52.1 (38.2)	59.7 (36.9)	22.5 (33.4)	48.5 (30.8)

Of the 255 valid survey respondents, 48% were women. However, the main decision-maker on dairy farming was male in almost two-thirds of households. The average participant was 53 years old, having 16 years of dairy farming experience and a mean of 6 economic dependents; little variation in these characteristics was observed across sites. Access to mobile-phones was practically ubiquitous (98%). Only 6% of participants had not received formal education, with roughly equal proportions having completed primary and above primary education.

Holdings of 0.6-2.5 acres were the most frequent across sites, with farms being slightly larger in Oyugis and Rongo. On average, survey participants owned between 1 and 2 cows, with only 6 participants – all from Oyugis – owning more than 4 heads[40]. The average daily milk output per cow was 3L on average[41], though in Siaya this was considerably lower.

Roughly half of households' milk output was sold on average, though this too was lower in Siaya (22%), not least because only a third of households in this site sold any milk whilst over 70% sold milk in the other three sites. On average, dairy farming generated a fifth of household income, falling to 13% in Siaya.

4.1.3. External factors

Only 39 participants reported not being part of any group, with 62% and 51% respectively forming part of finance and social[42] groups; 49% of participants were part of cooperatives[43]. Female participants more frequently formed part of groups (90%) than males (79%).

[40] These instances were not excluded from the regression dataset because an evaluation of their influence on regression estimates indicated that their impact was not particularly high, such that their inclusion did not skew any estimates.
[41] This is considerably lower than that observed by Tegemeo Institute of Agricultural Policy and Development and Kenyan Dairy Board (2021).
[42] Predominantly self-help and welfare groups.
[43] These were not necessarily dairy cooperatives. In Oyugis and Rongo, around a quarter of participants formed part of the dairy cooperatives from which initial participants were selected.

Most participants named the maximum of 4 individuals as part of their network, of which an average of 63% were surveyed (Figure 5). No significant differences in the number of individuals named by participant gender were observed, though in Siaya the propensity to name 4 network members was lower (Figure 9). Furthermore, those who were part of a group mentioned 0.5 more network members on average.

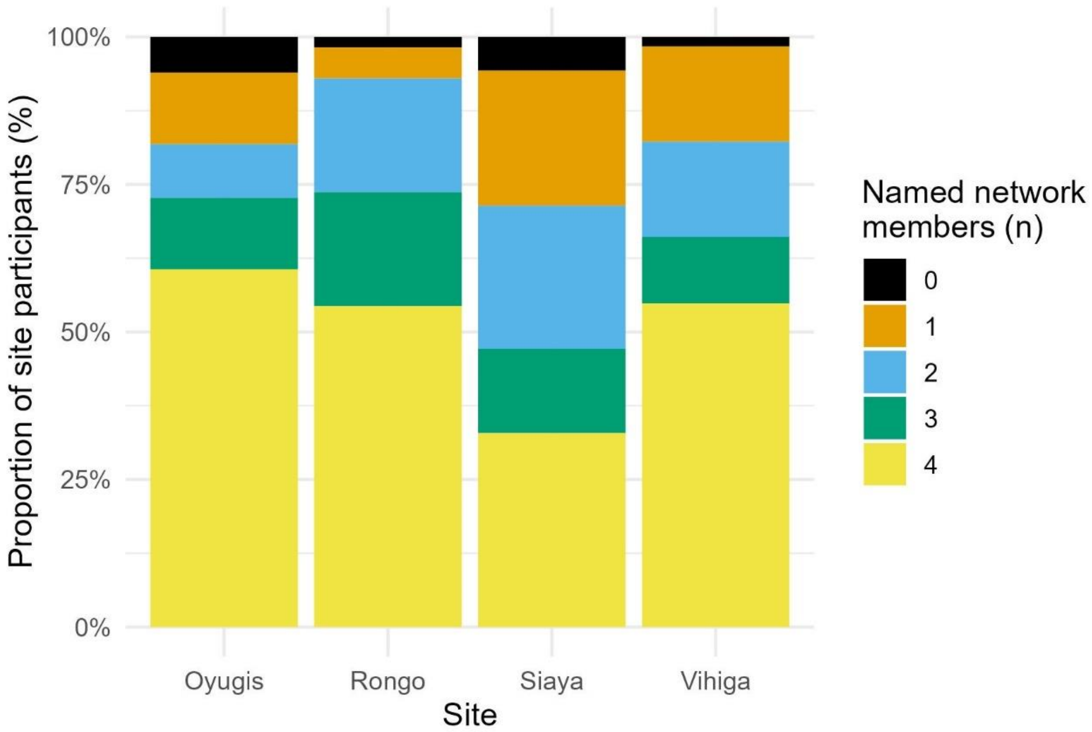


Figure 9: Stacked bar chart showing how many network members were named by participants, disaggregated by study site.

The prices farmers received for selling milk on markets averaged at 52 KES/L[44] and were relatively consistent across sites. Prices paid by cooperatives were around 20% lower (Figure 10), likely owing to check-off credit systems cooperatives operate.

[44] This is about 50% higher than that observed by Tegemeo Institute of Agricultural Policy and Development and Kenyan Dairy Board (2021), likely owing to milk shortages across the study areas (Mwenda, 2022).

Participants' distance from the nearest market centre averaged 5km, though this was lower in Oyugis (3.2km).

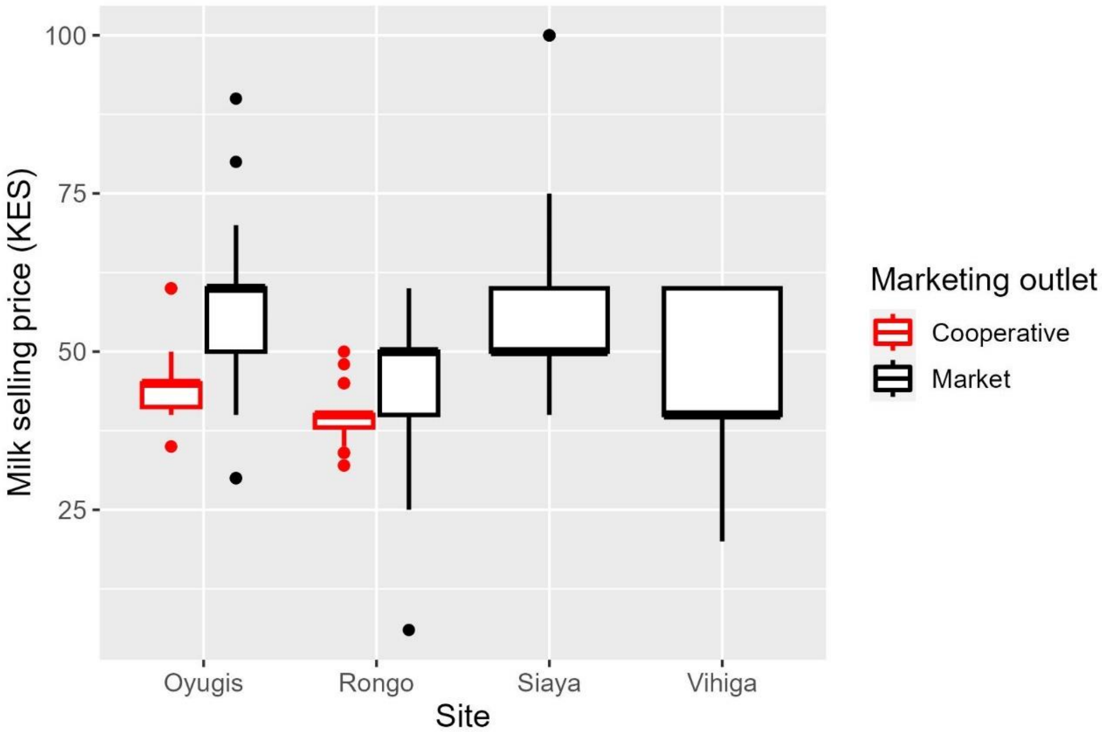


Figure 10: Box plots showing the distribution of cooperative and market milk selling prices across study sites. No dairy cooperatives operated in the surveyed areas of Siaya and Vihiga, hence no cooperative price is shown for these.

A third of survey participants reported having received information or training from an extensionist or dairy development project, split roughly equally between government and non-government extension/projects (Figure 11). Media were the most frequently mentioned as a source that farmers had received information from in the past, with 17% of participants having received information/training from lead-farmers[45]. In the majority of cases, farmers had received information from only one of the five sources shown in Figure 11. When asked who they would seek information on dairy farming

[45] See footnote 7.

from, government extensionists/projects was the most frequently selected of the five of sources shown, followed by dairy cooperatives and non-government extensionists[46]. 139 participants said they would go to other farmers or neighbours for information on dairying, considerably more than any of the sources shown in Figure 11.

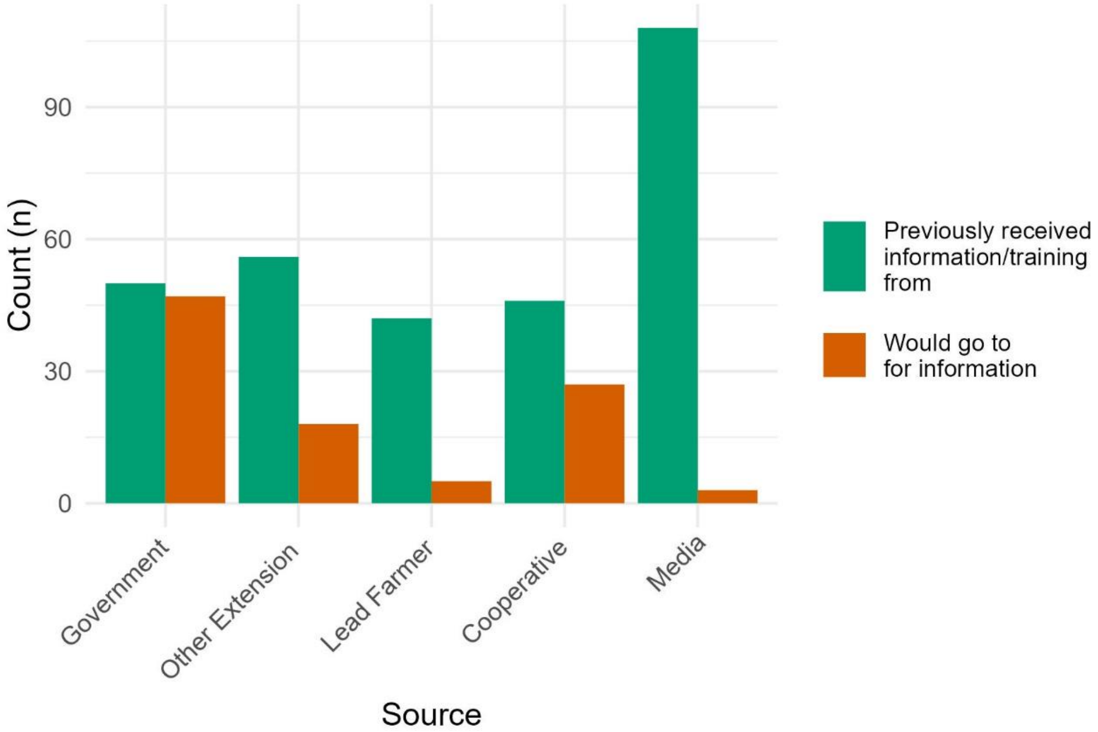


Figure 11: Bar chart showing the number of participants who had previously received information/training from different sources (green) and how many would go to these sources for information on dairy farming (orange). Participants could select multiple sources which they would go to for information, and equally could have received information/training from multiple sources. The categories "Government" and "Other Extension" encompass government extensionists and government projects, and non-government, NGO projects, and private vets respectively, whilst "Lead Farmer" encompasses farmer field schools and volunteer farmer trainers.

4.1.4. Social networks

The average participant had just over 1 adopter of each technology present in their network (Table 6), though this was lower in Siaya. Farmers who adopted a given

[46] Encompassing also NGO projects.

technology had between 0.8 (for vaccination) and 1.2 (for improved cattle) more farmers using it in their network than non-adopters.

Table 6
Two-panelled table showing the percentage of participants with at least 1 technology adopter in their network, and the average number of technology adopters in farmers' networks, respectively, disaggregated by technology and study site.

Proportion of participants with at least adopter in network (%)	Site	Improved breed	Improved forage	Vaccination
	Oyugis	69.7%	69.7%	66.7%
	Rongo	84.2%	94.7%	89.5%
	Siaya	22.9%	42.9%	52.9%
	Vihiga	74.2%	83.9%	85.5%
	Pooled	61.2%	71.4%	72.5%
Average number of technology adopters in network (#)		**Improved breed**	**Improved forage**	**Vaccination**
	Oyugis	1.50	1.56	1.23
	Rongo	1.47	2.00	1.47
	Siaya	0.24	0.56	0.70
	Vihiga	1.24	1.53	1.50
	Pooled	1.09	1.38	1.20

The panels of Figure 12 below map the relationship between characteristics of survey participants and those of the members of their network. The almost horizontal trendlines shows that no patterns are noticeable indicating that the mean age, number of economic dependents, and number of cows owned amongst network members varied little with changes in those of participants.

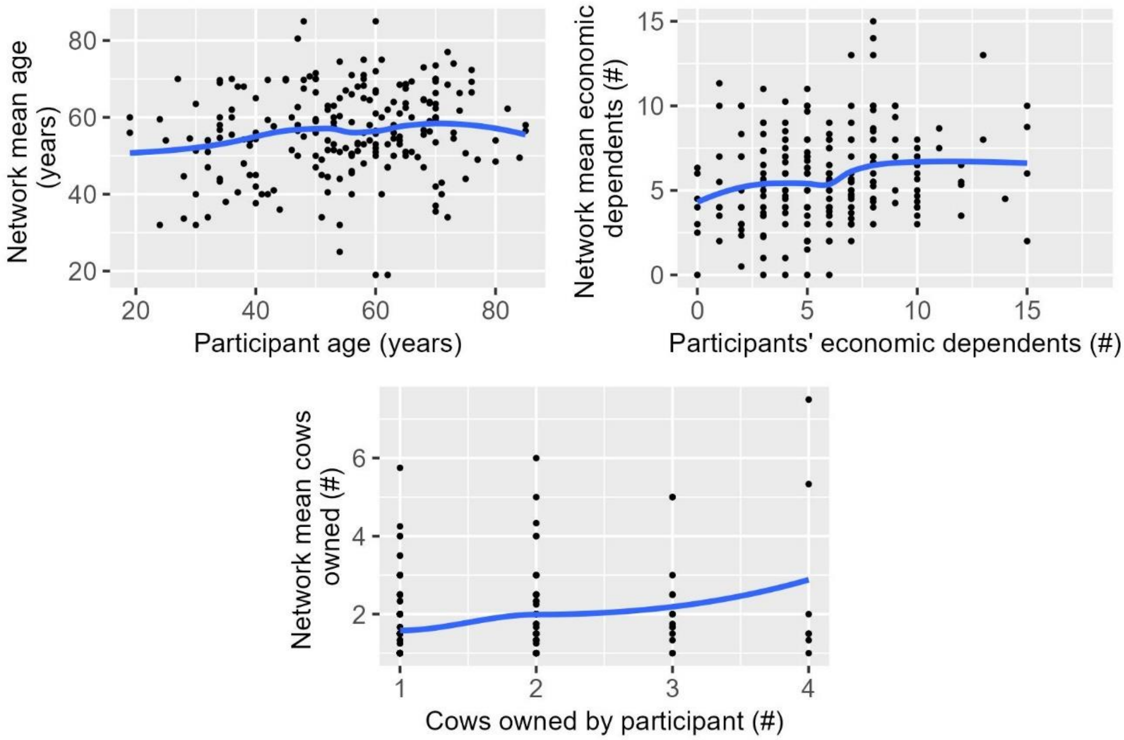


Figure 12: Scatterplots showing the relationship between participant age, number of economic dependents, and cows owned, and the mean of those characteristics amongst their network members. Trendlines are shown in blue and were plotted using locally estimated scatterplot smoothing. Points with extremely high values for number of economic dependents (>15) and those owning more than 4 cows are not shown and ignored in drawing trendlines due to their high influence on its form. The upward tending line in the graph for number of cows owned is due to 2 instances pulling the trendline upwards; when these two instances are excluded, the fit is closer to horizontal.

Homophily[47] in terms of educational attainment and farm size was however apparent, with participants naming network members in the same education and farm size category most frequently (Table 7A,B). Participants from households with male decision-makers were significantly more likely to name individuals from households with male decision-makers, though no such gender bias was observed when the decision-maker was female (Table 7C).

[47] Defined as "the tendency for people to seek out or be attracted to those who are similar to themselves".

Table 7

Table comparing the educational attainment, farm size, and decision-maker gender of participants with those of network members named, shown in panels A, B and C respectively.

A	Participant Education	Network Education		
		None	Primary	Above primary
	None	19.2%	46.2%	34.6%
	Primary	8.8%	64.5%	26.7%
	Above primary	5.5%	24.5%	70.0%
B	Participant Farm Size	Network Farm Size		
		0-0.5ac	0.6-2.5ac	>2.5ac
	0-0.5ac	36.4%	44.5%	19.1%
	0.6-2.5ac	22.9%	53.7%	23.4%
	>2.5ac	9.2%	33.6%	57.1%
C	Decisionmaker gender in participant's household	Network decisionmaker gender		
		Female	Male	
	Female	50.9%	49.1%	
	Male	24.1%	75.9%	

4.2. Logistic regressions

Survey responses missing data on farm/farmer characteristics or external factors (n=16) were dropped from the sample prior to conducting regression. Instances for which no data about their network was available – either because no network members were named (n=10)[48], or because none of the named network members were surveyed (n=29)[49] – were also removed. The dataset regressions were run on thus consisted of 200 instances.

[48] It seems unlikely that some participants do not talk to *any* other individuals about farming. It may be that in these cases, as noted in footnote 9 of Fafchamps and Gubert (2007), participants may have refused to mention any network members because they perceived the question as asking them to "rank individuals they regarded as equivalently close to them". It could not however be verified whether this was the case.

[49] See Section 3.2.1.2..

In Table 8, summary statistics of the regression variables are presented for this dataset. The rate of technology use is slightly elevated compared to the full sample (approx. +5%). The number of network members named and the number of adopters in participants' networks is also higher, as is the rate of receipt of information/training from lead-farmers and cooperatives. Other variables are almost identical.

Table 8

Summary statistics of regression variables for the data used for the logistic regressions. Instances with missing data, and those who mentioned no network members or for whom none of the named network members were surveyed were dropped. The final sample size was 200. Values are rounded to 3 significant figures.

Variable	Mean	S.D.	Min.	Max.
Dependent variables				
Improved breed use (yes=1)	0.596	0.492	0.00	1.00
Improved forage use (yes=1)	0.769	0.423	0.00	1.00
Vaccination use (yes=1)	0.693	0.462	0.00	1.00
Farmer and farm characteristic variables				
Age (years)	54.6	14.2	19.0	85.0
Education: None	0.060	0.238	0.00	1.00
Education: Primary	0.460	0.5	0.00	1.00
Education: Above primary	0.480	0.501	0.00	1.00
Decisionmaker gender (1=male)	0.625	0.485	0.00	1.00
Economic Dependents (#)	5.87	3.47	0.00	25.0
Farm size: 0-0.5ac	0.235	0.425	0.00	1.00
Farm size: 0.6-2.5ac	0.515	0.501	0.00	1.00
Farm size: >2.5ac	0.25	0.434	0.00	1.00
Cows owned (#)	1.80	1.61	1.00	15.0
External factor variables				
Group membership (yes=1)	0.865	0.343	0.00	1.00
Named network members (#)	3.12	1.12	1.00	4.00
Milk selling price (KES)	51.7	9.65	30.0	100
Market distance (km)	4.97	4.02	0.03	20.0
Info. received: Government	0.420	0.495	0.00	1.00
Info. received: Other extension	0.170	0.377	0.00	1.00
Info. received: Lead farmer	0.220	0.415	0.00	1.00
Info. received: Coop	0.220	0.415	0.00	1.00
Info. received: Media	0.255	0.437	0.00	1.00
Oyugis	0.260	0.44	0.00	1.00
Rongo	0.265	0.442	0.00	1.00
Vihiga	0.245	0.431	0.00	1.00
Siaya	0.230	0.422	0.00	1.00
Social network variables				
Improv. breed users (#)	1.32	1.14	0.00	4.00
Improv. forage users (#)	1.68	1.09	0.00	4.00
Vaccine users (#)	1.42	0.974	0.00	4.00
Network mean age (years)	55.6	11.1	19.0	77.0
Network mean educational attainment †	2.40	0.525	1.00	3.00
Network mean economic dependents (#)	5.71	2.77	0.00	15.0
Network mean farm size^	2.06	0.615	1.00	3.00
Network mean cows owned (#)	1.81	1.06	1.00	7.50

† ^ See Section 3.3.2.1. for measurement of these variables.

Extremely influential points (i.e. those with highly elevated Cook's Distance values) were excluded from regressions. Robustness checks including multicollinearity diagnosis – the results of which are shown in Supplementary Table 1– were also carried out[50]. Logistic regression results are presented in Table 9. The values shown are inflated by 100 to aid readability, such that a value of 1 indicates a 1% increase in adoption probability for a unit increase in that variable.

[50] These processes were carried out using the "car" (Fox *et al.*, 2022) package in R and R base functions. The entire code for these tests is available here, https://github.com/x-cassar/UG-Dissertation-Social-networks.git, documented in "Dissertation Regressions.rmd".

Table 9

Average marginal effects of logistic regressions run on the sample excluding instances with missing data (see above).

Standard errors are shown in brackets. Estimates and standard errors are multiplied by 100 to aid readability, such that a value of 1 indicates a 1% increase in probability for a unit increase in the variable. Variables relating to social network effects are boxed for emphasis. Statistically significant effects are marked in red for emphasis.

Dependent variable: 1 if participant adopts technology, 0 otherwise.

Regressions on full sample						
Variable	Improved breed		Improved forage		Vaccination	
Age (years)	0.31	(0.20)	0.19	(0.20)	0.39°	(0.21)
Relative to education: Above primary						
Education: None	-19.67	(12.70)	-36.38*	(14.80)	-19.45	(14.43)
Education: Primary	5.00	(6.70)	-12.30°	(6.47)	-11.95	(7.41)
Decisionmaker gender (1=male)	0.02	(6.12)	-2.55	(5.76)	9.85	(6.40)
Economic Dependents (#)	-1.99*	(0.81)	0.01	(0.91)	-1.00	(0.95)
Relative to farm size: 0.6-2.5ac						
Farm size: 0-0.5ac	-1.06	(7.02)	-8.38	(6.71)	-7.03	(7.50)
Farm size: >2.5ac	13.53°	(6.93)	-7.36	(7.87)	-4.28	(7.45)
Cows owned (#)			3.05	(3.70)		
Improved breed cattle (1=yes)			6.73	(6.62)		
Group membership (yes=1)	-2.03	(8.75)	5.27	(8.39)	23.78*	(9.97)
Named network members (#)	-2.68	(2.93)	-2.99	(3.23)	-3.41	(3.24)
Selling price (KES)	0.18	(0.30)	0.14	(0.31)	0.32	(0.36)
Market Distance (km)	1.47	(0.90)	0.14	(0.78)	-0.94	(0.81)
Info. Received: Government	14.52*	(6.94)	9.23	(6.95)	13.06°	(6.87)
Info. Received: Other extension	18.87*	(7.47)	8.90	(7.05)	4.23	(7.43)
Info. Received: Lead farmer	5.33	(7.60)	9.18	(7.28)	-7.41	(8.56)
Info. Received: Coop	-2.50	(8.17)	12.54°	(7.22)	0.46	(7.79)
Info. Received: Media	0.54	(6.57)	-0.14	(6.93)	14.47*	(6.49)
Relative to site: Oyguis						
Site: Rongo	-18.57°	(9.74)	25.19*	(10.76)	-0.97	(11.61)
Site: Siaya	-32.56*	(13.51)	10.31	(11.87)	-13.76	(12.52)
Site: Vihiga	-4.07	(10.18)	30.96**	(9.48)	31.09***	(9.22)
Improv. Breed users (#)	20.24*	(7.94)				
Square of improv. Breed users	-1.63	(2.56)				
Improv. Forage users (#)			15.95*	(7.37)		
Square of improv. Forage users			-2.62	(1.94)		
Vaccine users (#)					22.37*	(8.87)
Square of vaccine users					-6.15*	(2.46)
Network mean age (years)	-0.20	(0.26)	-0.33	(0.26)	-0.29	(0.29)
Network mean educational attainment†	10.59°	(6.25)	-3.55	(6.24)	-4.37	(6.81)
Network mean economic dependents(#)	-1.36	(1.07)	-1.12	(1.15)	-2.55*	(1.14)
Network mean farm size^	-8.12	(5.00)	2.24	(5.30)	4.05	(5.84)
Network mean cows owned (#)	2.87	(3.78)	4.19	(3.67)	4.92	(3.53)
N	198		197		198	
Log Likelihood	-7483.8		-7249.0		-8623.3	
McFadden P.R2	0.44		0.32		0.29	
AUC	0.91		0.86		0.85	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ° $p < 0.1$.

† ^ See Section 3.3.2.1. for measurement of these variables.

All three regressions are highly significant ($p<0.005$), and the high AUC values[51] indicate that the model fits the data well.

Improved breed cattle. The receipt of information and training from government and non-government extension (+15%,+19% respectively), and the number of adopters in the farmer's network (+20% per additional adopter) all increase farmers' probability of using improved breed cattle. Conversely, the number of economic dependents had a negative influence on the likelihood of improved breed use (-2% for each additional dependent). Farmers in Siaya were 33% less likely to use this technology than farmers in Oyugis.

Improved forage. The probability of farmers who lacked formal education adopting improved forages was 36% lower than those with above primary education, whilst the likelihood of adoption was higher in Rongo (+25%) and Vihiga (+31%) relative to Oyugis. Each additional adopter of improved forage increased the likelihood of adoption by 16% on average.

Vaccination. Being a member of a group and having received information from media sources respectively raised the probability of vaccination adoption by 24% and 14%. Participants in Vihiga also showed a higher propensity to adopt relative to Oyugis (+31%). On average, for each vaccine user in the farmers' network, the adoption probability increased by 22%, though a unit increase in the square of the number of adopters in network reduced the adoption probability by 6%. The mean number of

[51] Area under receiver operating characteristic curve. This measure, widely used in the field of machine learning, indicates the accuracy with which the model predicts uptake (Janssens and Martens, 2020). A similar metric is used by Staal *et al.* (2002) in assessing the goodness of fit of the models they construct.

economic dependents amongst network members was found to significantly affect the likelihood of adoption, decreasing the adoption probability by 3% per unit increase.

To ensure the robustness of estimated effects, regressions were also run on a dataset excluding those participants for whom less than 50% of the named network members were surveyed (hereafter 50%+ regressions) and another excluding participants who were not decision-makers on dairy farming, as noted above. The summary statistics for each of these datapools are available in Supplementary Table 2.

The results of these regressions were similar to those shown above, however the Pseudo-R^2 values of the 50%+ regressions, the results of which are shown in Table 10, were significantly higher than those of the full regressions. Owing to these regressions' higher explanatory power, their results are interpreted hereunder, as done by Matuschke and Qaim (2009).

Table 10
Average marginal effect of the logistic regressions run on instances for which 50% or more of the named network members were surveyed, with the standard error shown in brackets. Estimates and standard errors are multiplied by 100 to aid readability, such that a value of 1 indicates a 1% increase in probability of adoption for a unit increase in the variable. For emphasis, social network effects are boxed and statisically significant effects marked in red. Dependent variable: 1 if participant adopts technology, 0 otherwise. aGSIF[52] values are available in Supplementary Table 3.

Variable	Improved breed		Improved forage		Vaccination	
Age (years)	0.30	(0.20)	0.26	(0.20)	0.49*	(0.22)
Relative to education: Above primary						
Education: None	-18.02	(13.41)	-35.05**	(12.83)	-13.42	(14.74)
Education: Primary	0.55	(7.44)	-12.49*	(5.98)	-10.76	(8.01)
Decisionmaker gender (1=male)	-1.19	(7.07)	-3.26	(5.83)	6.15	(7.01)
Economic dependents (#)	-2.01*	(0.83)	-1.07	(1.00)	-0.87	(1.03)
Relative to farm size: 0.6-2.5ac						
Farm size: 0-0.5ac	-4.70	(8.13)	-13.21*	(6.37)	-9.07	(8.37)
Farm size: >2.5ac	10.91	(7.01)	-15.90*	(7.03)	-5.16	(7.74)
Cows owned (#)			6.92°	(4.05)		
Improved breed cattle (1=yes)			-0.48	(6.34)		
Group membership (yes=1)	-5.80	(8.87)	3.69	(7.84)	27.25**	(10.46)
Named network members (#)	-3.52	(3.05)	-6.69*	(3.14)	-4.22	(3.35)
Selling price (KES)	0.29	(0.31)	0.39	(0.30)	0.34	(0.38)
Market distance (km)	-0.13	(0.98)	-0.40	(0.78)	-1.10	(0.88)
Info. received: Government	12.09°	(7.03)	20.37***	(5.45)	10.91	(7.43)
Info. received: Other extension	17.88*	(7.72)	18.66**	(5.76)	-0.72	(8.38)
Info. received: Lead farmer	2.08	(7.76)	5.65	(9.25)	-5.98	(9.29)
Info. received: Coop	-2.95	(8.31)	13.40°	(7.53)	-1.14	(8.19)
Info. received: Media	0.46	(6.62)	-0.35	(7.21)	13.20°	(6.97)
Relative to site: Oyugis						
Site: Rongo	-9.61	(11.04)	42.84***	(8.70)	-1.68	(12.63)
Site: Siaya	-23.56	(14.62)	11.16	(10.78)	-17.29	(13.15)
Site: Vihiga	1.34	(11.76)	42.72***	(7.74)	32.09***	(9.75)
Improv. breed users (#)	20.74*	(9.14)				
Square of improv. breed users	-1.23	(2.87)				
Improv. forage users (#)			17.78*	(7.50)		
Square of improv. forage users			-2.80	(1.94)		
Vaccine users (#)					24.07*	(9.66)
Square of vaccine users					-6.53*	(2.65)
Network mean age (years)	-0.17	(0.28)	-0.49°	(0.29)	-0.42	(0.30)
Network mean educational attainment†	10.44	(6.63)	-2.34	(6.13)	-5.33	(7.26)
Network mean economic dependents(#)	-0.51	(1.16)	-1.14	(1.15)	-3.03*	(1.25)
Network mean farm size^	-7.66	(5.60)	4.59	(5.02)	8.21	(6.26)
Network mean cows owned (#)	0.83	(4.02)	6.37	(3.89)	5.38	(3.72)
N	172		170		172	
Log Likelihood	-6145.8		-4953.9		-7326.7	
McFadden P.R2	0.47		0.47		0.32	
AUC	0.91		0.92		0.86	

Instances with 50%+ of named network members surveyed only

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ° $p < 0.1$.
† ^ See Section 3.3.2.1. for measurement of these variables.

[52] Adjusted generalised standard error inflation factor (Fox and Monette, 1992).

The results of this regression are generally unchanged from the full regression, though some differences are of note.

In the regression on improved breed uptake, the effect of participants being from Siaya (as opposed to Oyugis) is still large, but no longer statistically significant. The effect of receiving training/information from government sources is smaller and not significant.

For improved forage uptake estimates, the effect of having received no education and primary education are both statistically significant (as opposed to just the former), though their magnitude is unchanged. Having a farm larger than 2.5ac or smaller than 0.5ac both had a statistically significant reduction on the likelihood of forage adoption, a result not observed in the full regression. The number of network members named was also negatively linked to the likelihood of adoption, this being statistically significant. The effect of having received government and non-government extension are larger than in the main regression and statistically significant. The effect of participants being from Rongo or Vihiga was slightly more pronounced, though still statistically significant.

Unlike in the full regression on vaccination, the effect of age on vaccine adoption was statistically significant in the 50%+ regression, with an additional year of age increasing the adoption probability by 0.5% on average. The effect of group membership is slightly more pronounced, whilst the effect of information receipt from media is slightly lower and no longer statistically significant[53]. The effect of being in Vihiga, and the influence of variables associated with the number of adopters in network and the

[53] Its p-value rises from 0.026 to 0.058.

mean number of economic dependents amongst network members are slightly higher, remaining statistically significant.

The R^2 values for regressions excluding non-decision-makers – the results of which are available in Supplementary Table 4 – were lower than for other regressions.

5. Discussion

This section will interpret the above results within the context of wider research. Results pertaining to social network effects will be treated first, followed by a discussion of findings related to each of the technologies, then other results of significance; for each of these, research and policy recommendations are made at the end of subsections or interspersed throughout. This work's limitations and future research are then discussed, before concluding.

5.1. Social networks' influence

Two main findings regarding social networks' influence can be drawn from this study's results.

Firstly, farmer's likelihood of adopting a given technology increases with the number of adopters of that technology in their network. For all three technologies, the presence of an additional adopter increased farmers' probability of adoption by 21% on average. This shows that in this context, the behaviour of social network members influences farmers' adoption decision, constituting strong evidence of endogenous effects, in line with the literature to date. However, diminishing marginal effects were observed – owing to the negative effects of the square of the number of adopters[54] – meaning

[54] Only in the regression for vaccine uptake was the effect of the squared term statistically significant, unlike in Bandiera and Rasul (2006) and Mekonnen, Gerber and Matz (2018) in which the squared term was persistently significant. This is likely owing to the fact that a maximum of 4 adopters could be present in farmers' networks in this study, whereas up to 6 and 10 adopters respectively were present in Mekonnen, Gerber and Matz's and Bandiera and Rasul's studies, such that the variability in the squared term was here relatively limited, constraining the models' ability to capture this effect accurately.

that the impact of an additional adopter being present is smaller when more adopters are present in a farmer's network.

Secondly, in line with Matuschke and Qaim's findings (2009), the characteristics of network members were found not to significantly influence adoption. The sole exception to this was the effect of network members' number of economic dependents in the regression on vaccine uptake, the marginal effect of which was very small (-3%); no convincing causal pathway could be identified to explain this result. Different formulations and combinations of variables were tested, yet characteristics of social network members (except the number of economic dependents in the regression on vaccine uptake) were persistently found not to affect adoption, giving confidence that exogenous effects (i.e. the influence of network member characteristics) are not significant in this context.

Matuschke and Qaim caution that taking the mean of network member characteristics – the approach generally used to capture network effects[55] – may potentially mask influential traits of certain individuals in farmers' networks. If, for example, having a farmer over 80 years old in a farmer's network significantly increases that farmer's likelihood of adopting a technology, this effect would not be detected. Regressions were thus also run taking the minimum and maximum values of network characteristics (instead of the mean), yielding equivalent results, giving further confidence in the veracity of this finding.

[55]This is used by Bramoullé, Djebbari and Fortin (2009), Matuschke and Qaim (2009), Mekonnen, Gerber and Matz (2018), and Varshney *et al.* (2022).

5.1.1. Policy implications regarding network effects

Firstly, the presence and large impact of endogenous effects shows that social networks could be harnessed by extensionists and policymakers as a low-cost method of agricultural extension in this context. More research is however required to determine how the influence of social networks can be better capitalised on. Kelley *et al.*'s work (2023) highlighting the importance of visual cues in spurring technology dissemination may be a valuable entry point for future studies.

Secondly, endogenous effects being present supports Kiptot and Franzel (2019) and Morrison's (2023) suggestion that interventions which bring farmers into contact with other farmers may increase the uptake of agricultural technologies[56]. These are likely to result in the formation of new network connections, meaning that *ceteris paribus* each adopter exerts a positive influence on more farmers, thus spurring the spread of technologies. Furthermore, exogenous effects not being significant implies that network connections with adopters will raise farmers' adoption probability irrespective of the characteristics of those network members, facilitating the implementation of such interventions. However, it was not within the scope of this study to identify how different interventions affect the formation of social network connections in this context. Future research should thus evaluate this question[57], with the use of panel data likely to offer particularly valuable insights (Udry and Conley, 2005).

Thirdly, accounting for the influence of network effects within extension targeting strategies may serve to heighten the impact of extension systems in Kenya. A

[56] A similar recommendation is also made by Matuschke and Qaim (2009) and Varshney *et al.* (2022), as well as Giroux *et al.* (2023).
[57] Giroux *et al.*'s (2023) work somewhat addresses this question in the context of Kenyan maize systems.

redistribution of extension resources towards harder-to-reach areas with lower uptake rates may be cost-effective and should be considered by policymakers given that networks themselves propagate technologies.

Fourthly, since farmers' decisions can be shaped by others' experience with technologies, this study supports the model underpinning farmer-to-farmer extension[58]. This is also corroborated by the fact that over half of participants said they would seek out information on dairying from other farmers or neighbours. However, contact with lead-farmers did not have a significant impact on technology uptake, and few participants said they would go to lead-farmers for information[59] (Figure 11). This could be driven by poor lead-farmers, in which case strategies for lead-farmer selection and training used in this context may need to be revised. Alternatively, this result could be indicative of social network effects being more effective than lead-farmers at increasing technology uptake, in which case research resources would be better spent identifying and understanding network effects rather than concentrating on lead-farmer identification[60].

With caution, these results could also be applied to other agricultural systems in West Kenya and smallholder dairy systems elsewhere.

[58] See footnote 7 for definition.
[59] Only 5% of those who had received information or training from lead-farmers in the past said they would go to them for information about dairying in the future.
[60] Studies which focus on lead-farmers include Kiptot and Franzel (2015), Beaman and Dillon (2018), Fisher *et al.* (2018), and Nöldeke, Winter and Grote (2020).

5.2. Adoption of dairy technologies

5.2.1. Improved breed cattle

In line with Staal *et al.* (2002), having a larger number of economic dependents was here associated with a lower likelihood of using improved breed cattle, though the marginal effect of an additional adopter was small (-2%). Given the labour-intensity of improved breed cows (Argwings-Kodbek, 2019), it is unsurprising that adoption is lowest amongst those with other caring responsibilities and thus less time for farming (Staal *et al.*, 2002).

The receipt of information from non-government extension was also, as expected, positively associated with improved breed uptake. This suggests that knowledge gaps regarding improved breed husbandry are present and can be effectively addressed via extension. However, awareness of the benefits of improved cattle amongst non-adopters was higher than for other technologies, implying that factors other than knowledge constraints may primarily be impeding uptake.

Whilst the effect of farm size was not statistically significant in regression results, Figure 13 below clearly indicates that adoption rates do increase as holdings expand, as in Staal *et al.* (2002) and Baltenweck, Yamano and Staal (2011). This trend likely relates to those with larger farms generally being wealthier, as purported by Wambugu, Kirimi and Opiyo (2011), suggesting that financial costs of improved breed cattle may constitute a major barrier to uptake in this context. Anecdotal evidence of this is also offered by farmers citing “high resale value” and that “they can be used as collateral” amongst improved breeds’ benefits.

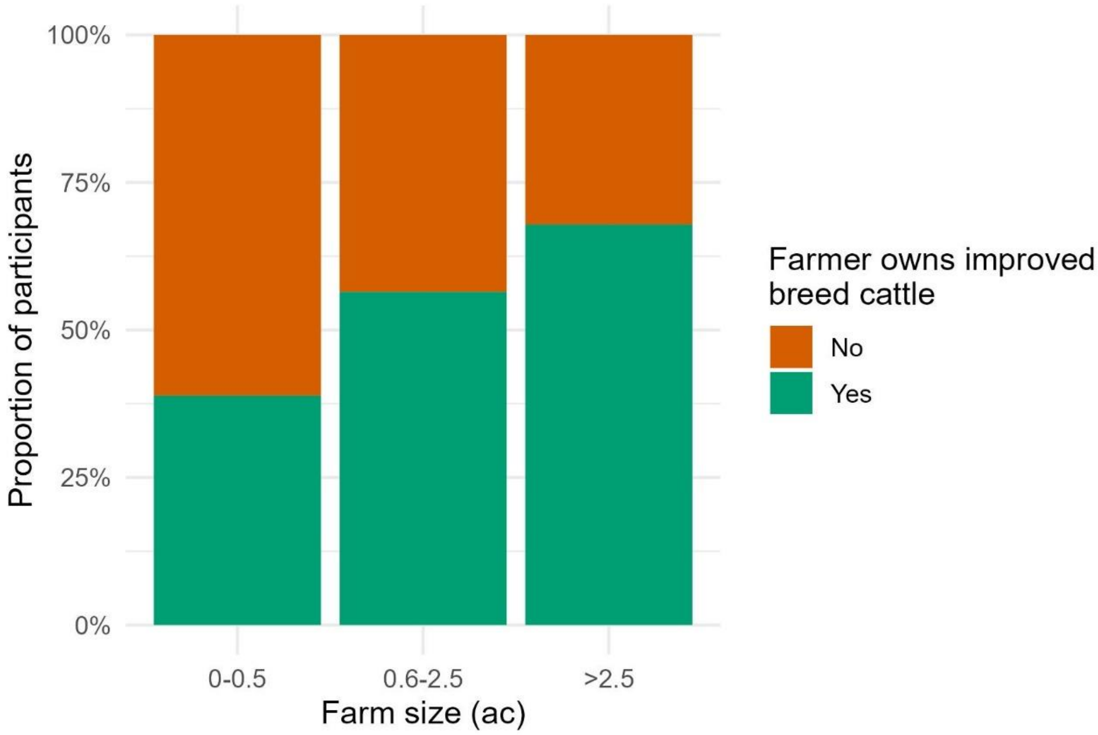


Figure 13: Stacked bar chart showing the rate of improved breed cattle ownership by farm size. Pairwise t-tests indicated that adoption rates were significantly different between farms of 0-0.5ac and 0.6-2.5ac (-17.6%, p<0.01) and between farms under 0.5ac and those over 2.5ac (-29.0%, p<0.01); the difference in adoption rate between 0.6-2.5ac farms and those larger than 2.5ac was not statistically significant (-11.4%, p=0.32).

Improved breed cattle was the technology least used in isolation (Figure 7). This is likely due to the benefits flowing from other technologies being higher when a farmer owns improved cattle, i.e. increases in milk production from feeding improved forage are larger, and improved breeds are more susceptible to disease meaning that the potential costs of vaccine non-adoption are higher (Perry, 2016)[61].

Considering the above, three policy conclusions regarding improved breed cattle may be drawn. Firstly, financial barriers may be excluding poorer farmers from accessing improved breeds, aligning with Owango *et al.* (1998) and Bingi and Tondel's (2015)

[61] The fact that the propensity of improved cattle owners to adopt other technologies did not vary with farm size suggests that this finding is not driven by the category of farmers with the largest farm sizes not being constrained by financial/capital limitations.

argument that the privatisation of breeding services has adversely affected improved breed uptake in the area. Addressing this barrier is key to raising smallholder productivity. Secondly, if improved breed cattle do indeed serve as a depository of value to be borrowed against, increasing uptake will improve dairy productivity but could also spur rural economic development by broadening farmers' access to credit. This provides a greater motivation for policymakers to put the dissemination of improved breed cattle at the heart of dairy development strategies. Thirdly, improved breed cattle amplifying the benefits of other dairy technologies emphasises the importance of promoting dairy technologies as a package (Sheahan and Barrett, 2017).

5.2.2. Improved forages

In the regression for improved forage uptake, the influence of educational attainment was more pronounced than for other technologies, with the effect of having received either no education or primary education (relative to above primary education) being significantly negative. This could be due to less educated farmers being more cash-constrained[62], decreasing their likelihood of dedicating scarce farmland to non-food crops given that it is harder for them to access food markets[63] (Kihiu and Amuakwa-Mensah, 2021). The effect of owning a farm under 0.5 acres (as opposed to 0.6-2.5ac) having a statistically significant negative effect gives credence to this interpretation, as

[62] According to Geda *et al.* (2001), "the most important determinant of poverty status is the level of education". Kihiu and Amuakwa-Mensah (2021) find educational attainment to be linked to dietary diversity, which is associated with market access.
[63] In accordance with this, the rate of improved forage use was approx. 15% lower in households without access to electricity or internet.

does the fact that a sixth of forage non-adopters surveyed explicitly cited a lack of space as a reason not to use this technology.

The negative estimate for the effect of having holdings larger than 2.5ac may appear to contract this. However, this result likely relates to Kebebe *et al.*'s observation (2017) that farmers with larger holdings use less intensive models of dairy farming and allow livestock to graze more, such that they are less reliant on feeding forages. Larger farms may also have a comparative advantage at growing crops due to scale economies, which they may be reluctant to sacrifice by growing fodder (Paul *et al.*, 2020).

Findings thus indicate that in Western Kenya, improved forages' space requirements are important to consider in the development of future varieties because the high opportunity-cost of planting forages in terms of land may be limiting uptake, as noted by Paul *et al.* (2020). The identification and promotion of forage planting techniques suitable to the region which make use of marginal land or minimise the area required[64] will bolster the use of this technology. As subdivision of farms persists amidst rural population growth, causing farm sizes to diminish, this challenge will become increasingly pertinent (Lukuyu *et al.*, 2013).

The positive correlation between improved forage use and improved breed ownership frequently observed in the literature (*Section 2.1.1.*) was not statistically significant in the regression. However, few adopters of improved breed cattle did not use improved forages (*Figure 7*), and a number of farmers who did not use improved forages mentioned not owning improved breeds as a reason for non-adoption, clearly

[64] Such as intercropping and agroforestry (Njarui *et al.*, 2017; Paul *et al.*, 2020).

indicating strong synergies between these technologies. The low rate of crossbreed use amongst forage adopters who were unaware of forages' benefits (pg.46) also suggests that the benefits of forages are most apparent in combination with improved breed cows. This reiterates the importance of promoting technologies as a package where appropriate, as adoption in isolation may mean that farmers fail to realise technologies' benefits.

Contact with government and non-government extension significantly increased the likelihood of forage uptake. However, this effect may be inflated since many farmers mentioned extensionists as a source of improved forage seed, possibly referring to free seed hand-outs, as noted by Mwangi and Wambugu (2003). This result should therefore be treated with caution[65].

5.2.3. Vaccination

In the regression for vaccination, apart from the network effects discussed above, only the average marginal effect of farmer age and group membership are found to be significant, with both having a positive effect on adoption probability.

Older farmers with longer experience in dairy farming may be more likely to have experienced cattle/calf losses due to East Coast Fever (ECF) themselves, such that they attribute greater value to the protection vaccination offers. Noteworthily, age's effect was not significant in the regression excluding participants who were not decision-

[65] Cooperatives were also frequently mentioned as a source of improved forage seed, and similarly the receipt of information/training from cooperatives has a strong positive estimated effect in the regression on improved forage (+13% [p<0.1]), corroborating that seed provision may be inflating these estimates.

makers, casting doubts on whether age is a meaningful determinant of adoption. However, since the only study on vaccine adoption determinants in Kenyan dairy systems is that by Okello *et al.*, whose results are likely biased due to simultaneity, it is difficult to corroborate or deny the significance of farmer age. Jumba *et al.*'s (2020) call for further research on the relationship between farmer age and vaccine perceptions is thus reiterated.

In evaluating the significance of group membership, it is important to note that a key barrier to vaccine adoption repeatedly cited in the literature[66] is the fact that ECF vaccines are currently manufactured and sold in batches of 40 doses. This means that for vaccination costs to be minimised, 40 cattle must be mobilised and vaccinated simultaneously since vaccines must be administered within 4 hours. Jumba *et al.* (2020) observed that farmer groups are central to facilitating cattle mobilisation for vaccination; this is likely also the case here, thus explaining why group membership is so significantly linked to uptake. Whilst this re-emphasises addressing ECF packaging as "a research priority"(Perry, 2016)[67], it also highlights that disseminating technologies via farmer groups may be an effective strategy when technologies display scale economies.

Vaccination was the only technology for which having received information via media (TV, radio, newspapers) was associated with higher technology adoption[68]. This may be

---

[66] See Perry (2016), Jumba (2019), Patel *et al.* (2019), and Jumba *et al.* (2020).

[67] According to Perry (2016), ILRI is undertaking research to address this. A report published by ILRI (2018) suggests that packages of 10 doses were able to be developed, though it is unclear whether these are yet available for purchase by smallholders in Kenya. Patel *et al.* (2019) also detailed a process by which the number of doses per batch could be reduced.

[68] This was not statistically significant in the 50%+ regression (P-value=0.058), though it was significant across all other regressions (see Table 9, Supplementary Table 4).

reflective of knowledge regarding vaccination being more about information – such as the benefits of vaccines and where to acquire them – rather than practices to be learnt. In line with the work of Areal *et al.* (2020), this result suggests that mass media could constitute an effective vehicle for the promotion and dissemination of dairy technologies, particularly given the *quasi*-ubiquitous access to mobile phones in Kenya[69] and the fact that many participants reported having received information from media sources in the past (Figure 11). More research, however, is required for media's extension potential to be better understood and harnessed. Evaluating the impact of existing platforms such as iCow (2023) and MFarm which provide smallholders with information on farming and markets via SMS may be particularly insightful.

5.3. Differences between study sites

Amongst the most pronounced findings is the variation in technology adoption rates between sites.

Most stark is the discrepancy between participants in Siaya and those in other study sites, whereby technology uptake as well as dairy production and milk sales were markedly lower in Siaya[70]. The fact that Siaya had the lowest rate of information/training receipt from government and non-government extension and lead-farmers certainly contributed to the relatively low adoption. Participants in Siaya naming fewer individuals as part of their network (Figure 9) also likely impeded uptake

[69] 99.2% of survey participants had access to a mobile phone.
[70] To account for the possibility of structural differences in dairy farming between Siaya and other sites, regressions were rerun excluding instances from Siaya. The results of this are shown in *Supplementary Table 4*, and are fairly consistent with the results of the main regression.

since *ceteris paribus* each adopter would be in contact with fewer farmers on average, slowing the spread of technologies (Morrison, 2023).

The converse is true of Vihiga, where adoption rates were highest (Table 4) despite no active dairy cooperatives being present[71]. Indeed, in the regressions for improved forages and vaccination, being from Vihiga was associated with a significant increase in the likelihood of adoption relative to Oyugis. Contact with lead-farmers and non-government extension was highest for this site, serving to increase adoption. Whilst not apparent in Figure 9, it was evident during fieldwork (and corroborated by Morrison [2023]) that farmers in Vihiga showed more collegiality, being more open and interconnected with one another: contrarily to Siaya, these stronger, denser networks likely spurred the spread of technologies, contributing to the elevated adoption rates.

These observations serve to highlight the role of both social networks[72] and agricultural extension in shaping adoption, and reaffirm that interventions which promote interaction between farmers and facilitate the formation of new network connections can increase technology dissemination.

Despite higher technology adoption rates in Vihiga, milk output and sales lagged behind those in cooperative sites (Rongo and Oyugis). Therefore, whilst Vihiga presents a promising case of dairy development being possible without the oft-cumbersome establishment of dairy cooperatives (Bonilla *et al.*, 2018), the lack of

[71] The absence of dairy cooperatives was expected to lower uptake given their role in dairy extension (see *Section 2.1.2.*).
[72] The reader is strongly encouraged to consult Morrison (2023) for further discussion on social networks' contribution to inter-site differences in adoption rates.

organised marketing avenues may be undercutting farmers' incentive to fully exploit productivity gains enabled by technologies. This is particularly regrettable given the area's milk shortages (Ombima, 2021), and emphasises the importance of pairing technology dissemination with the facilitation of milk marketing.

5.4. Biased distribution of extension

As shown in Table 11 below, amongst those participants who had not previously received information/training from government or non-government extensionists, farmers who mentioned one of these as a source of information they would go to showed significantly higher rates of technology adoption. This is suggestive of the bias noted by Ruzzante, Labarta and Bilton (2021), whereby farmers more inclined to adopt technologies due to some unobserved trait are also more likely to have contact with extensionists. Estimates for these variables must therefore be treated with caution since they could in part be capturing the influence of this unobserved trait associated with adoption.

Table 11

Table showing the frequency of technology use amongst those who would (Yes) and would not (No) go to a government or non-government extensionist for information on dairy farming amongst those who have not received information/training from either in the past.

Would you go to an extensionist for information?	No (n=129)	Yes (n=23)
Rate of improved breed use	34.1%	82.6%
Rate of improved forage use	61.2%	87.0%
Rate of vaccination use	53.5%	82.6%

5.5. Negative effect of the number of network members named

The effect of the number of network members named by participants, contrary to expectations, was consistently negative, this even being statistically significant in the regression on improved forages. This result, which suggests that better connected individuals are less likely to adopt technologies, thus appears to contradict the above recommendation to increase interaction between farmers to spur technology dissemination via networks.

However, great caution must be exerted in interpreting this result. Firstly, the purpose of the name generator question was not to quantify the number of individuals in participants' networks, but rather to serve as a conduit to gather information about participants' network members. In fact, the number of individuals that could be named was capped at four. It is therefore dubious how appropriate this variable is to accurately capture the relationship between farmers' connectedness and their likelihood of adoption. Secondly, this regression's sample is biased towards better-connected farmers because of:

- the use of snowball sampling for data collection, which as discussed in *Section 3.2.1.3.* inherently gives rise to bias towards better-connected individuals,
- the exclusion of those who named 0 network members – i.e., the poorest connected – from the regression dataset, and
- the exclusion of those for whom none of the named network members were surveyed, who were disproportionately likely to be those who named fewer network members (*Figure 14*),

such that this result cannot be readily generalised to the broader farming population in the area.

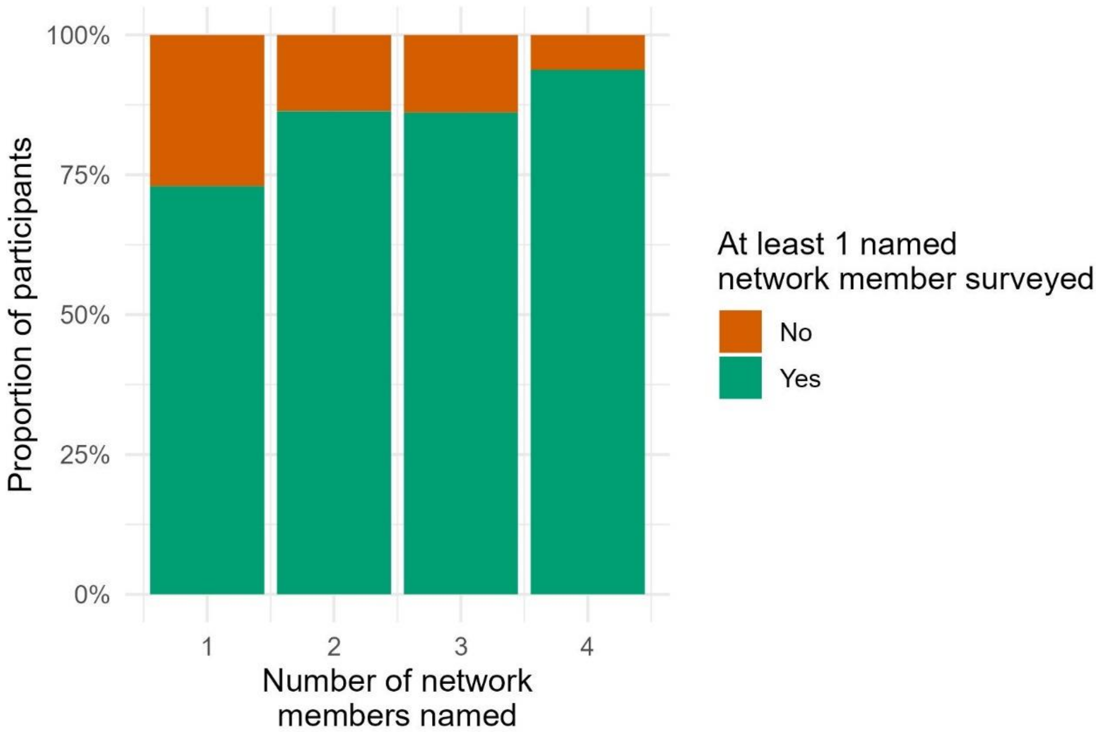


Figure 14: Stacked bar chart showing the proportion of participants for whom at least 1 named network member was surveyed. The likelihood of at least 1 network member being surveyed increased with the number of network members named.

Also, the effect of this variable was not significant in any of the other regressions for improved forage uptake[73], suggesting this result is spurious. Further still, the work of Morrison (2023) – which uses the same data though undertakes a detailed analysis of social network structures – repeatedly and clearly observes technology adoption to be

[73] I.e., the regression run on the sample excluding decision makers (shown in Table 9), the regression from which non-decision-makers were excluded, and the regression from which participants from Siaya were excluded (as described in footnote 70). Results for the latter two are shown in Supplementary Table 4.

positively associated with how well-connected farmers are. We are therefore confident that this result does not undermine this study's recommendations.

5.6. Limitations and future work

Given that this work utilises an original dataset collected for research by Morrison (2023), the approach utilised had to be moulded around the data available. Significantly, this was cross-sectional data, meaning that it was not possible to evaluate changes in technology adoption over time, as in Baltenweck, Yamano and Staal (2011), nor how networks changed over time, as recommended by Udry and Conley (2005).

The nature of the data available also limited the approach used to evaluate social networks' influence to a relatively simplified one, whereby the sole outcome considered was the adoption or non-adoption of technologies. How social networks influence farmers' awareness and knowledge of technologies was not evaluated because these were not rigorously addressed in surveys.

For certain variables, the variation in the data was limited owing to study sites being similar and relatively close, such that these factors' effect may not have been modelled accurately. This was likely the case for market distance and milk prices, the effects of which took the expected sign[74] but were not statistically significant. Study sites being limited to West Kenya also means that the external validity of results and recommendations is uncertain.

[74] These also match those observed in other studies, including Owango *et al.* (1998), Staal *et al.* (2002), and Kavoi, Hoag and Pritchett (2013).

Furthermore, analyses using more complex econometric models which account for any overlap between technologies, or double-/triple-hurdle approaches (as in Mwema and Crewett [2019]) were not undertaken due to time limitations[75]. These are left for future work, as is a more detailed treatment of gendered differences in network effects as undertaken by Beaman and Dillon (2018) and Mekonnen, Gerber and Matz (2018).

In addition to a lack of research on interventions' impact on social networks, the interaction of geographies, infrastructure, markets, and farmer groups in the formation of social networks in the context of Kenyan/dairy systems also remains understudied. More of such research is required for social networks to be better harnessed for technology dissemination.

Another major limitation is that while the presence of endogenous network effects is established, the mechanisms and pathways which drive this are not evaluated, examples of which include social learning, mimicry, scale economies and social insurance[76]. Anthropological/sociological research addressing this question in the context of West-Kenyan dairy systems is key to understanding how network effects can best be harnessed, but also important in suggesting improvements to econometric evaluations, particularly on the point as to whether non-adopters in farmers' networks may also be influencing farmer behaviour, which has not been considered in any such studies to date.

[75] Mixed effect models were however tested, with results being consistent with the regressions presented.
[76] See Bandiera and Rasul (2006, p.871-872).

5.7. Conclusion

This study was the first to investigate the influence of social networks in any dairy or Kenyan agricultural context. It showed that Kenyan smallholder dairy farmers' probability of using improved breed cattle, improved forages, and vaccination increases significantly with the number of adopters of that technology in their social network. This constitutes strong evidence of endogenous effects and shows that social networks can be harnessed to disseminate agricultural technologies amongst smallholders. As high inflation continues to constrain extension budgets, the identification of social networks as a low-cost vehicle for technology dissemination is a particularly welcome finding.

This research holds significant importance given that the three technologies evaluated were recognised by the FAO as crucial for improving smallholder productivity and mitigating the Kenyan dairy sector's methane emission (Opio *et al.*, 2017). The identification of network effects and technology-specific barriers to adoption thus guides research and policy efforts aimed at improving the livelihoods and wellbeing of Kenyan smallholders and achieving the Kenyan Government's emission-reduction targets set out in the National Climate Change Response Strategy (2010b).

References

Allison, P. (2012) ‘When Can You Safely Ignore Multicollinearity?’, *Statistical Horizons*, 10 September. Available at: https://statisticalhorizons.com/multicollinearity/ (Accessed: 14 April 2023).

Amuge, M.L. and Osewe, D.O. (2017) ‘Socio-economic Factors Influencing Adoption of Feed Based Dairy Technologies among Smallholder Farmers in Ekerenyo Sub-County, Kenya’, *Asian Journal of Agricultural Extension, Economics & Sociology*, pp. 1–8. Available at: https://doi.org/10.9734/AJAEES/2017/32357.

Areal, F.J. *et al.* (2020) ‘Does TV edutainment lead to farmers changing their agricultural practices aiming at increasing productivity?’, *Journal of Rural Studies*, 76, pp. 213–229. Available at: https://doi.org/10.1016/j.jrurstud.2020.03.001.

Arel-Bundock, V. *et al.* (2023) ‘marginaleffects: Predictions, Comparisons, Slopes, Marginal Means, and Hypothesis Tests’. Available at: https://cran.r-project.org/web/packages/marginaleffects/index.html (Accessed: 28 April 2023).

Argwings-Kodbek, G. (2019) ‘9. Siaya: Stagnation in a Low-Potential, Small Farm District’, in. Cornell University Press, pp. 191–213. Available at: https://doi.org/10.7591/9781501737442-013.

Arnold, J.B. *et al.* (2021) ‘ggthemes: Extra Themes, Scales and Geoms for “ggplot2”’. Available at: https://cran.r-project.org/web/packages/ggthemes/index.html (Accessed: 6 May 2023).

Avery, G. (2005) ‘Endogeneity in Logistic Regression Models’, *Emerging Infectious Diseases*, 11(3), pp. 503–505. Available at: https://doi.org/10.3201/eid1103.050462.

Baltenweck, I., Yamano, T. and Staal, S.J. (2011) 'Dynamic Changes in the Uptake of Dairy Technologies in the Kenya Highlands', in T. Yamano, K. Otsuka, and F. Place (eds) *Emerging Development of Agriculture in East Africa: Markets, Soil, and Innovations*. Dordrecht: Springer Netherlands, pp. 85–97. Available at: https://doi.org/10.1007/978-94-007-1201-0_6.

Bandiera, O. and Rasul, I. (2006) 'Social Networks and Technology Adoption in Northern Mozambique', *The Economic Journal*, 116(514), pp. 869–902. Available at: https://doi.org/10.1111/j.1468-0297.2006.01115.x.

Bates, D. *et al.* (2023) 'lme4: Linear Mixed-Effects Models using "Eigen" and S4'. Available at: https://cran.r-project.org/web/packages/lme4/index.html (Accessed: 6 May 2023).

Beaman, L. and Dillon, A. (2018) 'Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali', *Journal of Development Economics*, 133, pp. 147–161. Available at: https://doi.org/10.1016/j.jdeveco.2018.01.009.

Bingi, S. and Tondel, F. (2015) 'Recent developments in the dairy sector in Eastern Africa', *Briefing note of the European Centre for Development Policy Management*, (78), p. 19.

Bonilla, J. *et al.* (2018) *Impact evaluation of the Smallholder Dairy Commercialization Programme in Kenya*. 2018th edn. International Initiative for Impact Evaluation. Available at: https://doi.org/10.23846/tw4IE73.

Bramoullé, Y., Djebbari, H. and Fortin, B. (2009) 'Identification of peer effects through social networks', *Journal of Econometrics*, 150(1), pp. 41–55. Available at: https://doi.org/10.1016/j.jeconom.2008.12.021.

Brock, W.A. and Durlauf, S.N. (2001) ‘Chapter 54 - Interactions-Based Models’, in J.J. Heckman and E. Leamer (eds) *Handbook of Econometrics*. Elsevier, pp. 3297–3380. Available at: https://doi.org/10.1016/S1573-4412(01)05007-3.

Clarke, S. (2021) *Inflation rising in Africa, but central banks to be tolerant*, *Economist Intelligence Unit*. Available at: https://www.eiu.com/n/inflation-rising-in-africa-but-central-banks-to-be-tolerant/ (Accessed: 22 October 2022).

Fafchamps, M. and Gubert, F. (2007) ‘The formation of risk sharing networks’, *Journal of Development Economics*, 83(2), pp. 326–350. Available at: https://doi.org/10.1016/j.jdeveco.2006.05.005.

FC, M. and Davis, T.L. (2022) ‘ggpattern: “ggplot2” Pattern Geoms’. Available at: https://CRAN.R-project.org/package=ggpattern (Accessed: 19 April 2023).

Firke, S. *et al.* (2023) ‘janitor: Simple Tools for Examining and Cleaning Dirty Data’. Available at: https://CRAN.R-project.org/package=janitor (Accessed: 11 March 2023).

Fisher, M. *et al.* (2018) ‘Awareness and adoption of conservation agriculture in Malawi: what difference can farmer-to-farmer extension make?’, *International Journal of Agricultural Sustainability*, 16(3), pp. 310–325. Available at: https://doi.org/10.1080/14735903.2018.1472411.

Fox, J. *et al.* (2022) ‘car: Companion to Applied Regression’. Available at: https://CRAN.R-project.org/package=car (Accessed: 11 March 2023).

Fox, J. and Monette, G. (1992) ‘Generalized Collinearity Diagnostics’, *Journal of the American Statistical Association*, 87(417), pp. 178–183. Available at: https://doi.org/10.1080/01621459.1992.10475190.

Gao, C.-H., Yu, G. and Dusa, A. (2022) ‘ggVennDiagram: A “ggplot2” Implement of Venn Diagram’. Available at: https://CRAN.R-project.org/package=ggVennDiagram (Accessed: 11 March 2023).

Geda, A. *et al.* (2001) ‘Determinants of poverty in Kenya: A household level analysis.’, *ISS Working Paper Series/General Series*, (347), pp. 1–20. Available at: https://repub.eur.nl/pub/19095/wp347.pdf.

Giroux, S. *et al.* (2023) ‘Smallholder social networks: Advice seeking and adaptation in rural Kenya’, *Agricultural Systems*, 205, p. 103574. Available at: https://doi.org/10.1016/j.agsy.2022.103574.

Gohel, D. *et al.* (2023) ‘flextable: Functions for Tabular Reporting’. Available at: https://CRAN.R-project.org/package=flextable (Accessed: 11 March 2023).

Government of Kenya (2010a) ‘Kenya National Dairy Master Plan (Volume II)’. Ministry of Livestock Development. Available at: https://kilimo.go.ke/wp-content/uploads/2021/06/DMP-VOL-ll-STRATEGIES-AND-ACTION-PLANS.pdf (Accessed: 14 January 2023).

Government of Kenya (2010b) *National Climate Change Response Strategy*. Nairobi, Kenya: Government of Kenya. Available at: https://cdkn.org/sites/default/files/files/National-Climate-Change-Response-Strategy_April-2010.pdf.

Hugh-Jones, D. (2022) ‘huxtable: Easily Create and Style Tables for LaTeX, HTML and Other Formats’. Available at: https://CRAN.R-project.org/package=huxtable (Accessed: 3 April 2023).

iCow (2023) *iCow – iCow Kenya home*. Available at: https://icow.co.ke/ (Accessed: 25 April 2023).

IFAD (2020) *Smallholder Dairy Commercialization Programme, IFAD*. Available at: https://www.ifad.org/en/web/operations/-/project/1100001305 (Accessed: 24 February 2023).

ILRI (2018) *Corporate Report 2016-2017*. Nairobi, Kenya: International Livestock Research Institute. Available at: https://cgspace.cgiar.org/bitstream/handle/10568/92517/ilri_corporate_report_2017.pdf?sequence=8&isAllowed=y.

'IPCC Sixth Assessment Report - Regional fact sheet - Africa' (2022). Available at: https://www.ipcc.ch/report/ar6/wg1/downloads/factsheets/IPCC_AR6_WGI_Regional_Fact_Sheet_Africa.pdf (Accessed: 19 October 2022).

Janssens, A.C.J.W. and Martens, F.K. (2020) 'Reflection on modern methods: Revisiting the area under the ROC Curve', *International Journal of Epidemiology*, 49(4), pp. 1397–1403. Available at: https://doi.org/10.1093/ije/dyz274.

Jumba, H. (2019) *Gender perspectives in economic assessment of east coast fever vaccination on household welfare among smallholder dairy cattle farmers in Uasin Gishu County, Kenya*. Thesis. Egerton University. Available at: http://41.89.96.81:8080/xmlui/handle/123456789/2325 (Accessed: 18 April 2023).

Jumba, H. *et al.* (2020) 'Use of the infection and treatment method in the control of East Coast fever in Kenya: does gender matter for adoption and impact?', *Gender, Technology and Development*, 24(3), pp. 297–313. Available at: https://doi.org/10.1080/09718524.2020.1829359.

Kassambara, A. (2023) ‘ggpubr: “ggplot2” Based Publication Ready Plots’. Available at: https://CRAN.R-project.org/package=ggpubr (Accessed: 11 April 2023).

Kavoi, M. m., Hoag, D.L. and Pritchett, J. (2013) ‘Influence of Institutional and Socio-Economic Factors on the Supply Response of Smallholder Dairy Farms in the Marginal Zones of Kenya’, *Journal of International Development*, 25(3), pp. 393–411. Available at: https://doi.org/10.1002/jid.1741.

Kebebe, E.G. *et al.* (2017) ‘Characterisation of adopters and non-adopters of dairy technologies in Ethiopia and Kenya’, *Tropical Animal Health and Production*, 49(4), pp. 681–690. Available at: https://doi.org/10.1007/s11250-017-1241-8.

Kelley, E.M. *et al.* (2023) ‘Casting a Wider Net: Sharing Information Beyond Social Networks. [Manuscript submitted for publication].’ Available at: https://static1.squarespace.com/static/5b1c4743266c07336b65a08c/t/641b1603764dd1644ef05ce2/1679496710342/Casting_a_Wider_Net__Sharing_Information_Beyond_Social_Networks+%283%29.pdf.

Kihiu, E.N. and Amuakwa-Mensah, F. (2021) ‘Agricultural market access and dietary diversity in Kenya: Gender considerations towards improved household nutritional outcomes’, *Food Policy*, 100, p. 102004. Available at: https://doi.org/10.1016/j.foodpol.2020.102004.

Kiptot, E. and Franzel, S. (2015) ‘Farmer-to-farmer extension: opportunities for enhancing performance of volunteer farmer trainers in Kenya’, *Development in Practice*, 25(4), pp. 503–517. Available at: https://doi.org/10.1080/09614524.2015.1029438.

Kiptot, E. and Franzel, S. (2019) ‘Developing sustainable farmer-to-farmer extension: experiences from the volunteer farmer–trainer approach in Kenya’, *International*

Journal of Agricultural Sustainability, 17(6), pp. 401–412. Available at: https://doi.org/10.1080/14735903.2019.1679576.

Kowald, M. and Axhausen, K.W. (2012) ‘Focusing on Connected Personal Leisure Networks: Selected Results from a Snowball Sample’, *Environment and Planning A: Economy and Space*, 44(5), pp. 1085–1100. Available at: https://doi.org/10.1068/a43458.

Krishnan, P. and Patnam, M. (2014) ‘Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?’, *American Journal of Agricultural Economics*, 96(1), pp. 308–327. Available at: https://doi.org/10.1093/ajae/aat017.

Leeper, T.J. *et al.* (2021) ‘margins: Marginal Effects for Model Objects’. Available at: https://CRAN.R-project.org/package=margins (Accessed: 11 March 2023).

Lionberger, H.F. (1951) ‘Sources and use of farm and home information by low-income farmers in Missouri’. Available at: https://mospace.umsystem.edu/xmlui/handle/10355/57800 (Accessed: 29 March 2023).

Long, J.A. (2022) ‘jtools: Analysis and Presentation of Social Scientific Data’. Available at: https://CRAN.R-project.org/package=jtools (Accessed: 11 March 2023).

Lüdecke, D. *et al.* (2023) ‘performance: Assessment of Regression Models Performance’. Available at: https://CRAN.R-project.org/package=performance (Accessed: 11 March 2023).

Lukuyu, B. *et al.* (2012) ‘Disseminating Improved Practices: Are Volunteer Farmer Trainers Effective?’, *The Journal of Agricultural Education and Extension*, 18(5), pp. 525–540. Available at: https://doi.org/10.1080/1389224X.2012.707066.

Lukuyu, B.A. *et al.* (2013) ‘Integrated maize management options to improve forage yield and quality on smallholder farms in Kenya’, *Field Crops Research*, 153, pp. 70–78. Available at: https://doi.org/10.1016/j.fcr.2013.06.003.

Lynch, S.M. and Brown, J.S. (2011) ‘Chapter 8 - Stratification and Inequality Over the Life Course’, in R.H. Binstock and L.K. George (eds) *Handbook of Aging and the Social Sciences (Seventh Edition)*. San Diego: Academic Press (Handbooks of Aging), pp. 105–117. Available at: https://doi.org/10.1016/B978-0-12-380880-6.00008-3.

Maertens, A. (2017) ‘Who Cares What Others Think (or Do)? Social Learning and Social Pressures in Cotton Farming in India’, *American Journal of Agricultural Economics*, 99(4), pp. 988–1007. Available at: https://doi.org/10.1093/ajae/aaw098.

Maertens, A. and Barrett, C.B. (2013) ‘Measuring Social Networks’ Effects on Agricultural Technology Adoption’, *American Journal of Agricultural Economics*, 95(2), pp. 353–359. Available at: https://doi.org/10.1093/ajae/aas049.

Maina, K. *et al.* (2022) ‘Opportunity cost of adopting improved planted forage: Evidence from the adoption of Brachiaria grass among smallholder dairy farmers in Kenya’, *African Journal of Agricultural and Resource Economics*, 17(1), pp. 48–63. Available at: https://doi.org/10.53936/afjare.2022.17(1).3.

Makini, F. *et al.* (2019) *Innovation Opportunities in Dairy Livestock in Kenya*. Forum for Frica Agricultural Research in Africa.

Mangiafico, S. (2023) ‘rcompanion: Functions to Support Extension Education Program Evaluation’. Available at: https://CRAN.R-project.org/package=rcompanion (Accessed: 11 March 2023).

Manski, C.F. (1993) ‘Identification of Endogenous Social Effects: The Reflection Problem’, *The Review of Economic Studies*, 60(3), pp. 531–542. Available at: https://doi.org/10.2307/2298123.

Manski, C.F. (2000) ‘Economic Analysis of Social Interactions’, *Journal of Economic Perspectives*, 14(3), pp. 115–136. Available at: https://doi.org/10.1257/jep.14.3.115.

MapChart (2023) *Africa - Detailed | Create a custom map, MapChart*. Available at: https://mapchart.net/africa-detailed.html (Accessed: 2 April 2023).

Matuschke, I. and Qaim, M. (2009) ‘The impact of social networks on hybrid seed adoption in India’, *Agricultural Economics*, 40(5), pp. 493–505. Available at: https://doi.org/10.1111/j.1574-0862.2009.00393.x.

Mekonnen, D.A., Gerber, N. and Matz, J.A. (2018) ‘Gendered Social Networks, Agricultural Innovations, and Farm Productivity in Ethiopia’, *World Development*, 105, pp. 321–335. Available at: https://doi.org/10.1016/j.worlddev.2017.04.020.

Moll, H.A.J., Staal, S.J. and Ibrahim, M.N.M. (2007) ‘Smallholder dairy production and markets: A comparison of production systems in Zambia, Kenya and Sri Lanka’, *Agricultural Systems*, 94(2), pp. 593–603. Available at: https://doi.org/10.1016/j.agsy.2007.02.005.

Morrison, R. (2023) *Farmer networks and the adoption of agricultural innovations in East Africa - Unpublished PhD Thesis*. University of Edinburgh.

Murage, A.W. and Ilatsia, E.D. (2011a) ‘Factors that determine use of breeding services by smallholder dairy farmers in Central Kenya’, *Tropical Animal Health and Production*, 43(1), pp. 199–207. Available at: https://doi.org/10.1007/s11250-010-9674-3.

Murage, A.W. and Ilatsia, E.D. (2011b) 'Factors that determine use of breeding services by smallholder dairy farmers in Central Kenya', *Tropical Animal Health and Production*, 43(1), pp. 199–207. Available at: https://doi.org/10.1007/s11250-010-9674-3.

Mushonga, B. *et al.* (2017) 'Artificial Insemination in Nyagatare District: Level of Adoption and the Factors determining its Adoption', *Alexandria Journal of Veterinary Sciences*, 55(1), p. 1. Available at: https://doi.org/10.5455/ajvs.273226.

Mwanga, G. *et al.* (2019) 'Multi-country investigation of factors influencing breeding decisions by smallholder dairy farmers in sub-Saharan Africa', *Tropical Animal Health and Production*, 51(2), pp. 395–409. Available at: https://doi.org/10.1007/s11250-018-1703-7.

Mwangi, D.M. *et al.* (2005) 'Improved livelihoods from grasslands; the case of Napier grass in smallholder dairy farms in Kenya', in D.A. McGilloway (ed.) *Grassland: A Global Resource*. Wageningen: Wageningen Academic Publishers, pp. 347–350. Available at: https://www.webofscience.com/wos/woscc/full-record/WOS:000233301400027 (Accessed: 1 April 2023).

Mwangi, D.M. and Wambugu, C. (2003) 'Adoption of forage legumes: the case of Desmodium intortum and Calliandra calothyrsus in central Kenya', *Tropical Grasslands*, 37(4), pp. 227–238.

Mwema, C. and Crewett, W. (2019) 'Social Networks and Commercialisation of African Indigenous Vegetables in Kenya: A Cragg's Double Hurdle Approach', *Cogent Economics & Finance*. Edited by G. Aye, 7(1), p. 1642173. Available at: https://doi.org/10.1080/23322039.2019.1642173.

Mwenda, E. (2022) *Farmers reap big as milk prices hit record high, Business Daily*. Available at: https://www.businessdailyafrica.com/bd/markets/commodities/farmers-reap-big-as-milk-prices-hit-record-high-3816430 (Accessed: 24 April 2023).

Nahhas, R.W. (2023) *5.19 Collinearity | Introduction to Regression Methods for Public Health Using R*. Available at: https://bookdown.org/rwnahhas/RMPH/mlr-collinearity.html (Accessed: 1 April 2023).

Nguni, P. and Wanjohi, E. (2019) 'Increasing Small-Scale Dairy Farmers' Participation to Formal Milk Markets'. Kenya Markets Trust. Available at: https://www.kenyamarkets.org/increasing-small-scale-dairy-farmers-participation-to-formal-milk-markets/ (Accessed: 14 January 2023).

Njarui, D.M. *et al.* (2017) 'Determinants of forage adoption and production niches among smallholder farmers in Kenya', *African Journal of Range and Forage Science*, 34(3), pp. 157–166.

Njeru, T.N. (2022) 'Kenya's dairy sector is failing to meet domestic demand. How it can raise its game', *The Conversation*, 13 February. Available at: http://theconversation.com/kenyas-dairy-sector-is-failing-to-meet-domestic-demand-how-it-can-raise-its-game-176017 (Accessed: 8 January 2023).

Nöldeke, B., Winter, E. and Grote, U. (2020) 'Seed Selection Strategies for Information Diffusion in Social Networks: An Agent-Based Model Applied to Rural Zambia', *Journal of Artificial Societies and Social Simulation*, 23(4), p. 9.

Ochieng, W., Silvert, C.J. and Diaz, J. (2022) 'Exploring the Impacts of Lead Farmer Selection on Community Social Learning: The case of Farmer-to-Farmer Model: A Review of Literature', *Journal of International Agricultural and Extension Education*, 29(3), pp. 7–31. Available at: https://doi.org/10.4148/2831-5960.1022.

Ochungo, P. *et al.* (2016) ‘Mapping aflatoxin risk from milk consumption using biophysical and socio-economic data: A case study of Kenya’, *African Journal of Food,* 16. Available at: https://doi.org/10.18697/ajfand.75.ILRI08.

Odhiambo, C.O. *et al.* (2019) ‘Adaptation of Smallholder Dairy Farmers in South Western Kenya to the Effects of Climate Change’, *Atmospheric and Climate Sciences*, 9(3), pp. 456–478. Available at: https://doi.org/10.4236/acs.2019.93031.

Odongo, D. (2016) ‘Easing bottlenecks to uptake of dairy farming in western Kenya’, *ILRI Clippings*, 4 July. Available at: https://clippings.ilri.org/2016/07/04/easing-bottlenecks-to-uptake-of-dairy-farming-in-western-kenya/ (Accessed: 29 March 2023).

Okello, D. *et al.* (2021) ‘Determinants of utilization of agricultural technologies among smallholder dairy farmers in Kenya’, *Journal of Agriculture and Food Research*, 6, p. 100213. Available at: https://doi.org/10.1016/j.jafr.2021.100213.

Ombima, P. (2021) *Vihiga farmers get Sh3.7m cattle to boost milk production*, *The Star*. Available at: https://www.the-star.co.ke/news/2021-03-05-vihiga-farmers-get-sh37m-cattle-to-boost-milk-production/ (Accessed: 23 February 2023).

Onono, J.O. and Ochieng, A. (2018) ‘Review of challenges and opportunities for dairy cattle farming under mixed system of Homa Bay County, Western Kenya’, *Journal of Agricultural Extension and Rural Development*, 10(10), pp. 202–210. Available at: https://doi.org/10.5897/JAERD2018.0987.

Ooms, J. (2023) ‘writexl: Export Data Frames to Excel “xlsx” Format’. Available at: https://CRAN.R-project.org/package=writexl (Accessed: 11 March 2023).

Opio, C. *et al.* (2017) *Options for low-emission development in the Kenya dairy sector*. Rome: FAO. Available at: https://www.fao.org/3/i7669e/i7669e.pdf (Accessed: 20 April 2023).

Owango, M. *et al.* (1998) 'Dairy co-operatives and policy reform in Kenya: effects of livestock service and milk market liberalisation', *Food Policy*, 23(2), pp. 173–185. Available at: https://doi.org/10.1016/S0306-9192(98)00027-X.

Patel, E. *et al.* (2019) 'Infection and treatment method (ITM) vaccine against East Coast fever: reducing the number of doses per straw for use in smallholder dairy herds by thawing, diluting and refreezing already packaged vaccine', *BMC Veterinary Research*, 15(1), p. 46. Available at: https://doi.org/10.1186/s12917-019-1787-y.

Paul, B.K. *et al.* (2020) 'Improved feeding and forages at a crossroads: Farming systems approaches for sustainable livestock development in East Africa', *Outlook on Agriculture*, 49(1), pp. 13–20. Available at: https://doi.org/10.1177/0030727020906170.

Pedersen, T.L. and RStudio (2022) 'ggforce: Accelerating "ggplot2"'. Available at: https://CRAN.R-project.org/package=ggforce (Accessed: 11 March 2023).

Perry, B.D. (2016) 'The control of East Coast fever of cattle by live parasite vaccination: A science-to-impact narrative', *One Health*, 2, pp. 103–114. Available at: https://doi.org/10.1016/j.onehlt.2016.07.002.

Posit Team (2022) 'RStudio: Integrated Development Environment for R'. Boston, MA: Posit, PBC. Available at: http://www.posit.co/.

R Core Team (2022) 'R: A language and environment for statistical computing'. Vienna, Austria: R Foundation for Statistical Computing. Available at: https://www.R-project.org/.

Revelle, W. (2022) ‘psych: Procedures for Psychological, Psychometric, and Personality Research’. Available at: https://CRAN.R-project.org/package=psych (Accessed: 11 March 2023).

Robin, X. *et al.* (2021) ‘pROC: Display and Analyze ROC Curves’. Available at: https://CRAN.R-project.org/package=pROC (Accessed: 11 March 2023).

Ruzzante, S., Labarta, R. and Bilton, A. (2021) ‘Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature’, *World Development*, 146, p. 105599. Available at: https://doi.org/10.1016/j.worlddev.2021.105599.

Ryan, B. and Gross, N. (1943) ‘The diffusion of hybrid seed corn in two Iowa communities’, *Rural sociology*, 8(1), p. 15. Available at: https://www.proquest.com/openview/7de2b2276a089fe888071663de12b6a0/1?pq-origsite=gscholar&cbl=1817355 (Accessed: 29 March 2023).

Santos, P. and Barrett, C.B. (2008) ‘What Do We Learn About Social Networks When We Only Sample Individuals? Not Much’. Rochester, NY. Available at: https://doi.org/10.2139/ssrn.1141838.

Sheahan, M. and Barrett, C.B. (2017) ‘Ten striking facts about agricultural input use in Sub-Saharan Africa’, *Food Policy*, 67, pp. 12–25. Available at: https://doi.org/10.1016/j.foodpol.2016.09.010.

Signorell, A. *et al.* (2023) ‘DescTools: Tools for Descriptive Statistics’. Available at: https://cran.r-project.org/web/packages/DescTools/index.html (Accessed: 6 May 2023).

Simpson, B. *et al.* (2015) *Farmer to farmer extension: Issues in planning and implementation.* USAID. Available at: https://reliefweb.int/report/cameroon/farmer-farmer-extension-issues-planning-and-implementation.

Staal, S.J. *et al.* (2002) 'Location and uptake: integrated household and GIS analysis of technology adoption and land use, with application to smallholder dairy farms in Kenya', *Agricultural Economics*, 27(3), pp. 295–315. Available at: https://doi.org/10.1016/S0169-5150(02)00075-0.

Tadesse, G. and Dereje, M. (2018) 'Impact of Climate Change on Smallholder Dairy Production and Coping Mechanism in Sub-Saharan Africa - Review', *Agricultural Research & Technology: Open Access Journal*, 16(4), pp. 1–13. Available at: https://doi.org/10.19080/ARTOAJ.2018.16.556000.

Takahashi, K., Muraoka, R. and Otsuka, K. (2020) 'Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature', *Agricultural Economics*, 51(1), pp. 31–45. Available at: https://doi.org/10.1111/agec.12539.

Tegemeo Institute of Agricultural Policy and Development and Kenyan Dairy Board (2021) *Report on a study on cost of milk production in Kenya*. Egerton University, p. 67. Available at: https://www.kdb.go.ke/wp-content/uploads/2021/06/Cost-of-milk-production-report..pdf (Accessed: 10 April 2023).

Toreni, A. *et al.* (2022) *Drought in East Africa August 2022*. Luxembourg: Publications Office of the European Union, p. 28. Available at: https://edo.jrc.ec.europa.eu/documents/news/GDODroughtNews202208_East_Africa.pdf (Accessed: 19 October 2022).

Udry, C.R. and Conley, T.G. (2005) 'Social networks in Ghana', in *The Social Economics of Poverty*. Routledge, pp. 232–255.

USAID (2022) ‘Kenya Crops and Dairy Market Systems’. Available at: https://www.usaid.gov/sites/default/files/2022-05/KCDMS_Fact_Sheet_2022.pdf (Accessed: 11 March 2022).

Varshney, D. *et al.* (2022) ‘Social networks, heterogeneity, and adoption of technologies: Evidence from India’, *Food Policy,* 112, p. 102360. Available at: https://doi.org/10.1016/j.foodpol.2022.102360.

Veritas Health Innovation (2023) ‘Covidence systematic review software’. Melbourne, Australia. Available at: www.covidence.org.

Victor, M. (2018) *Kenya crops and dairy market systems development activity (KCDMSD)*. Available at: https://www.ilri.org/research/projects/kenya-crops-and-dairy-market-systems-development-activity-kcdmsd (Accessed: 11 March 2023).

Wambugu, S., Kirimi, L. and Opiyo, J. (2011) *Productivity trends and performance of dairy farming in Kenya*. Working Paper. Tegemeo Institute. Available at: http://41.89.96.81:8080/xmlui/handle/123456789/2323 (Accessed: 18 March 2023).

Waring, E. *et al.* (2022) ‘skimr: Compact and Flexible Summaries of Data’. Available at: https://CRAN.R-project.org/package=skimr (Accessed: 11 March 2023).

Wickham, H. *et al.* (2019) ‘Welcome to the Tidyverse’, *Journal of Open Source Software*, 4(43), p. 1686. Available at: https://doi.org/10.21105/joss.01686.

Wickham, H., Chang, W., *et al.* (2023) ‘ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics’. Available at: https://CRAN.R-project.org/package=ggplot2 (Accessed: 11 March 2023).

Wickham, H., Bryan, J., *et al.* (2023) ‘readxl: Read Excel Files’. Available at: https://CRAN.R-project.org/package=readxl (Accessed: 11 March 2023).

World Bank (2022) *Kenya's Economic Recovery Remains Strong, Although Slowed by Drought and Inflation [Press Release]*. Press Release. Available at: https://www.worldbank.org/en/news/press-release/2022/12/08/kenya-s-economic-recovery-remains-strong-although-slowed-by-drought-and-inflation (Accessed: 25 March 2023).

Xie, Y. *et al.* (2023) 'tinytex: Helper Functions to Install and Maintain TeX Live, and Compile LaTeX Documents'. Available at: https://cran.r-project.org/web/packages/tinytex/index.html (Accessed: 6 May 2023).

Zhu, H. *et al.* (2021) 'kableExtra: Construct Complex Table with "kable" and Pipe Syntax'. Available at: https://CRAN.R-project.org/package=kableExtra (Accessed: 11 March 2023).

Acknowledgements

I would like to thank my supervisors Andrew Barnes and Alan Duncan for their guidance and assistance whilst writing this dissertation and during my studies at Edinburgh.

I would especially like to thank Rosie Morrison for allowing and enabling me to partake in this research, for her trust, and her support over these months.

Thanks also to Jon Hillier and Susan Jarvis for repeatedly answering my questions about how to format this dissertation, and to Silvia Perez-Espona for her patience and support regarding matters pertaining to the ethical approval of this project. Thank you to the staff at the International Livestock Research Institute, including James Rao, for their support to collect this data. Thank you to Gordon Littlejohn for the technical support he offered throughout my degree.

A special thank you to the team of enumerators for their integral role in the collection of this data and, moreover, making me feel so welcome in their country; it is thanks to them that my time in Kenya was so rich and memorable, and that this study so meaningful to me.

Thank you to my family and friends, Nanna Mary, and Santa Liena.

Appendix 1 – Ethical Approval

THE UNIVERSITY *of* EDINBURGH
The Royal (Dick) School of Veterinary Studies

Human Ethical Review Committee (HERC)

Royal (Dick) School of Veterinary Studies

The University of Edinburgh

Roslin

EH25 9RG

Email HERC.vets@ed.ac.uk

30/11/2022

Dear ,

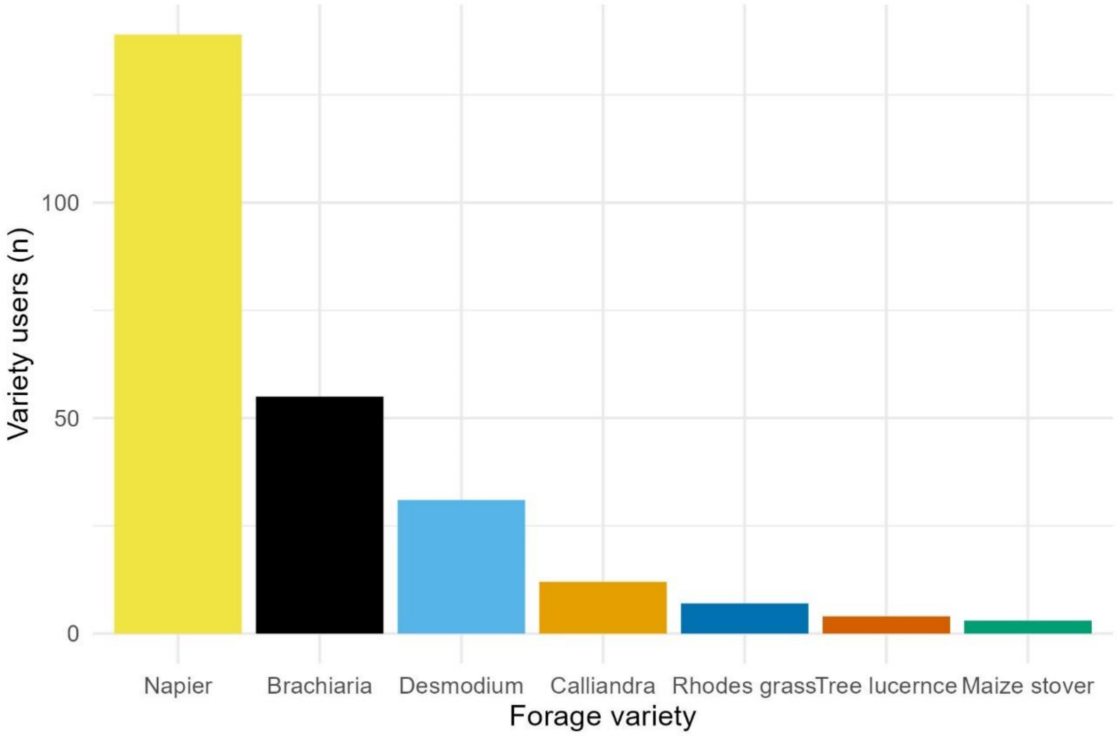
The research described in your application HERC_2022_168 entitled ''*An econometric estimation of the influence of extension and social networks on technology knowledge and uptake amongst Kenyan dairy farmers*'' now has HERC ethical approval.

You may proceed with this research only on the basis that it conforms to the description you provided and the assurances you made in your application. If you undertake research that deviates in any significant way from the application you submitted, that research does not have the HERC's approval. If, following the receipt of ethical approval, you find that you want or need to change your methods and/or materials in any significant way, you must submit a revised application.

Appendix 2 – R packages used

car	(Fox et al., 2022)
DescTools	(Signorell *et al.*, 2023)
flextable	(Gohel *et al.*, 2023)
ggforce	(Pedersen and RStudio, 2022)
ggpattern	(FC and Davis, 2022)
ggplot	(Wickham, Chang, et al., 2023)
ggpubr	(Kassambara, 2023)
ggthemes	(Arnold *et al.*, 2021)
ggVennDiagram	(Gao, Yu and Dusa, 2022)
huxtable	(Hugh-Jones, 2022)
janitor	(Firke et al., 2023)
jtools	(Long, 2022)
kableExtra	(Zhu et al., 2021)
lme4	(Bates *et al.*, 2023)
margins	(Leeper et al., 2021)
marginaleffects	(Arel-Bundock *et al.*, 2023)
performance	(Lüdecke et al., 2023)
pROC	(Robin et al., 2021)
psych	(Revelle, 2022)
rcompanion	(Mangiafico, 2023)
readxl	(Wickham, Bryan, et al., 2023)
skimr	(Waring et al., 2022)
tidyverse	(Wickham et al., 2019)
tinytex	(Xie *et al.*, 2023)
writexl	(Ooms, 2023)

Appendix 3 – Supplementary figures and tables



Supplementary Figure 1: Bar chart showing the number of participants using different varieties of improved forage.

Supplementary Table 1: Adjusted generalised standard error inflation factor (aGSIF) values for the regressions on the full dataset, the results of which are presented in Table 9. The value of all variables is below the threshold of 1.6, above which multicollinearity becomes a concern, bar for the case of case of terms involving an interaction (Nahhas, 2023). However, the high aGSIF between the terms involved in interactions can be ignored (Allison, 2012).

Variable	Improved Breed	Improved Forage	Vaccination
Age (years)	1.14	1.17	1.17
Education	1.28	1.34	1.25
Decisionmaker gender	1.17	1.16	1.19
Economic Dependents (#)	1.16	1.12	1.13
Farm size	1.22	1.24	1.14
Cows owned (#)		1.16	
Improved breed cattle (1=yes)		1.27	
Group membership (yes=1)	1.2	1.16	1.13
Named network members (#)	1.35	1.58	1.39
Selling price (KES)	1.24	1.25	1.24
Market Distance (km)	1.47	1.43	1.26
Info. received: Government	1.29	1.21	1.14
Info. received: Other extension	1.13	1.2	1.17
Info. received: Lead farmer	1.16	1.17	1.18
Info. received: Coop	1.32	1.21	1.26
Info. received: Media	1.34	1.42	1.30
Site	1.46	1.44	1.38
Improv. breed users (#)	2.99		
Square of improv. breed users	2.85		
Improv. forage users (#)		3.27	
Square of improv. forage users		3.01	
Vaccine users (#)			3.26
Square of vaccine users			3.19
Network mean age (years)	1.25	1.19	1.19
Network mean education attianment†	1.40	1.40	1.30
Network mean economic dependents (#)	1.30	1.28	1.24
Network mean farm size^	1.36	1.35	1.29
Network mean cows owned (#)	1.24	1.23	1.22

Supplementary Table 2: Summary statistics of the data used for the supplementary regressions to check robustness, the first excluding those participants for whom less than 50% of the named network members were surveyed, the second excluding participants who were not decisionmakers on dairy farming.

	50%+ network members surveyed				Decisionmakers			
Variable	**Mean**	**S.D.**	**Min.**	**Max.**	**Mean**	**S.D.**	**Min.**	**Max.**
Dependent variables								
Improved breed use (yes=1)	0.593	0.493	0.00	1.00	0.633	0.483	0.00	1.00
Improved forage use (yes=1)	0.751	0.433	0.00	1.00	0.782	0.414	0.00	1.00
Vaccination use (yes=1)	0.688	0.465	0.00	1.00	0.708	0.456	0.00	1.00
Farmer and farm characteristics								
Age (years)	55.1	14.2	19.0	85.0	56.3	13.2	19.0	85.0
Education: None	0.0632	0.244	0	1	0.0702	0.256	0	1
Education: Primary	0.471	0.501	0	1	0.444	0.498	0	1
Education: Above primary	0.466	0.5	0	1	0.485	0.501	0	1
Decisionmaker gender (1=male)	0.621	0.487	0.00	1.00	0.573	0.496	0.00	1.00
Economic Dependents (#)	5.85	3.55	0.00	25.0	5.89	3.54	0.00	25.0
Farm size: 0-0.5ac	0.247	0.433	0	1	0.246	0.432	0	1
Farm size: 0.6-2.5ac	0.489	0.501	0	1	0.497	0.501	0	1
Farm size: >2.5ac	0.264	0.442	0	1	0.257	0.438	0	1
Cows owned (#)	1.88	1.70	1.00	15.0	1.87	1.72	1.00	15.0
External factor variables								
Group membership (yes=1)	0.856	0.352	0.00	1.00	0.86	0.348	0.00	1.00
Named network members (#)	3.03	1.16	1.00	4.00	3.12	1.12	1.00	4.00
Milk selling price (KES)	51.7	9.83	30.0	100	51.8	9.79	30.0	100
Market Distance (km)	4.71	3.77	0.03	20.0	5.05	4.16	0.03	20.0
Info. received: Government	0.408	0.493	0.00	1.00	0.444	0.498	0.00	1.00
Info. received: Other extension	0.155	0.363	0.00	1.00	0.175	0.381	0.00	1.00
Info. received: Lead farmer	0.218	0.414	0.00	1.00	0.228	0.421	0.00	1.00
Info. received: Coop	0.224	0.418	0.00	1.00	0.222	0.417	0.00	1.00
Info. received: Media	0.247	0.433	0.00	1.00	0.263	0.442	0.00	1.00
Oyugis	0.264	0.442	0	1	0.275	0.448	0	1
Rongo	0.282	0.451	0	1	0.275	0.448	0	1
Vihiga	0.23	0.422	0	1	0.24	0.428	0	1
Siaya	0.224	0.418	0	1	0.211	0.409	0	1
Social network variables								
Improv. breed users (#)	1.43	1.17	0.00	4.00	1.41	1.13	0.00	4.00
Improv. forage users (#)	1.82	1.10	0.00	4.00	1.70	1.06	0.00	4.00
Vaccine users (#)	1.52	0.99	0.00	4.00	1.45	0.977	0.00	4.00
Network mean age (years)	55.6	11.1	19.0	75.0	55.2	11.1	19.0	77.0
Network mean education attainment†	2.40	0.52	1.00	3.00	2.41	0.510	1.00	3.00
Network mean economic dependents (#)	5.77	2.64	0.00	15.0	5.62	2.66	0.00	14.0
Network mean farm size^	2.09	0.616	1.00	3.00	2.05	0.618	1.00	3.00
Network mean cows owned (#)	1.84	1.06	1.00	7.50	1.81	1.05	1.00	7.50

Supplementary Table 3: Adjusted generalised standard error inflation factor (aGSIF) values for the regressions on 50%+ dataset – i.e., excluding participants for which less than 50% of their named network members were surveyed,, the results of which are presented in Table 10. The terms involving an interaction - here namely the number and square of the number of technology adopters in network - are boxed in the dotted line.
The value of all variables is below the threshold of 1.6, above which multicollinearity becomes a concern, bar for the case of case of terms involving an interaction (Nahhas, 2023). However, the high aGSIF between the terms involved in interactions can be ignored (Allison, 2012).

Variable	Improved Breed	Improved Forage	Vaccination
Age (years)	1.15	1.20	1.20
Education	1.31	1.38	1.27
Decisionmaker gender	1.29	1.22	1.21
Economic Dependents (#)	1.23	1.25	1.16
Farm size	1.29	1.43	1.18
Cows owned (#)		1.26	
Improved breed cattle (1=yes)		1.37	
Group membership (yes=1)	1.23	1.17	1.14
Named network members (#)	1.41	1.8	1.39
Selling price (KES)	1.31	1.42	1.28
Market Distance (km)	1.29	1.31	1.21
Info. received: Government	1.31	1.3	1.15
Info. received: Other extension	1.11	1.36	1.22
Info. received: Lead farmer	1.16	1.18	1.19
Info. received: Coop	1.33	1.28	1.25
Info. received: Media	1.28	1.54	1.28
Site	1.47	1.66	1.43
Improv. breed users (#)	3.34		
Square of improv. breed users	3.14		
Improv. forage users (#)		3.6	
Square of improv. forage users		3.23	
Vaccine users (#)			3.46
Square of vaccine users			3.43
Network mean age (years)	1.27	1.35	1.22
Network mean education attainment†	1.43	1.47	1.32
Network mean economic dependents (#)	1.30	1.4	1.24
Network mean farm size^	1.48	1.39	1.35
Network mean cows owned (#)	1.36	1.37	1.25

Supplementary Table 4: Estimated Average marginal effects of supplementary logistic regressions for the three technologies. Values are all scaled by 100 to aid readability. "Decisionmaker" refers to those regressions including solely those participants who were the main decisionmaker on dairy farming in the household, and "Excluding Siaya" refers to regressions in from which instances collected for Siaya were excluded.

Variable	Improved Breed Cattle		Improved Forage		Vaccination	
	Decisionmaker	Excluding Siaya	Decisionmaker	Excluding Siaya	Decisionmaker	Excluding Siaya
Age (years)	0.26	0.00	0.15	0.26	0.27	0.29
Education: None	-22.26	-6.23	-43.40 **	-25.22	-15.04	-30.61
Education: Primary	-1.68	1.91	-13.91 *	-9.38	-4.86	1.72
Decisionmaker gender (1=male)	0.23	-3.02	-1.21	-3.41	14.83 *	7.90
Economic Dependents (#)	-1.96 *	-2.11 **	-0.35	-0.06	-1.52	-1.17
Farm size: 0-0.5ha	-1.57	-11.75	-9.92	-9.68	-6.17	-7.48
Farm size: >2.5ha	15.16 *	6.06	-8.64	2.56	-4.90	3.24
Cows owned (#)			4.87	4.69		
Improved breed cattle (1=yes)			5.92	-2.45		
Group membership (yes=1)	4.69	0.67	5.13	13.51	14.33	12.75
Named network members (#)	-3.17	-3.12	-4.62	-3.18	-0.69	-3.18
Selling price (KES)	0.18	-0.13	-0.03	0.29	0.41	-0.08
Market Distance (km)	1.76	2.32	0.24	0.82	-1.47	-0.38
Info. received: Government	14.38	1.93	11.77	1.61	12.20	19.36 **
Info. received: Other extension	19.17 *	16.92 **	8.27	4.93	8.88	5.44
Info. received: Lead farmer	2.49	3.49	11.50	5.45	-8.05	-3.19
Info. received: Coop	-5.02	0.03	10.50	9.48	4.60	1.35
Info. received: Media	-1.99	0.31	-4.60	-11.98	18.55 **	18.03 *
Site: Rongo	-17.28	-25.54 **	26.23 *	15.90	0.35	-10.43
Site: Siaya	-37.49 *		13.84		-5.42	
Site: Vihiga	-8.00	-8.30	29.44 **	26.41 **	33.34 ***	28.39 **
Improv. breed users (#)	16.03	43.59 ***				
Square of improv. breed users	0.02	-7.11 **				
Improv. forage users (#)			17.25 *	8.76		
Square of improv. forage users			-2.44	-1.23		
Vaccine users (#)					24.37 *	22.68 *
Square of vaccine users					-6.63 *	-6.85 **
Network mean age (years)	-0.25	-0.08	-0.61	0.18	-0.30	-0.22
Network mean education attainment†	6.73	8.58	-8.08	-1.69	-6.13	5.15
Network mean economic dependents (#)	-0.82	-0.58	-0.32	-1.50	-2.66 *	-3.21 **
Network mean farm size^	-9.92	-10.79	1.30	-1.05	4.28	8.12
Network mean cows owned (#)	1.34	0.70	3.70	3.85	4.67	3.49
N	169	153	168	152	170.00	152.00
Log Likelihood	-6576.75	-4476.68	-5969.06	-4516.33	-7345.70	-5580.58
McFadden P.R2	0.41	0.52	0.32	0.30	0.29	0.34
AUC	0.89	0.93	0.88	0.87	0.84	0.86

*** p < 0.001; ** p < 0.01; * p < 0.05.