

# Literature Review

## Area of Research

This literature review will treat the existing research on the influence of social network – here termed “network effects” – on technology awareness, knowledge, and uptake, particularly in agricultural settings in developing countries. Drawing on academic peer-reviewed articles, it will focus on the evidence of network effects, evaluating the theories, models, and methods underpinning these studies.

## Motivation

The primary motivation in evaluating this literature is to inform the process of constructing a succinct model to measure the influence of network effects on technology knowledge and uptake amongst Kenyan dairy farmers. This will form part of a model, which I will be constructing as part of my dissertation, to measure how the influence of agricultural extension and network effects vary with farmer, household, and network traits. This review is therefore essential in ensuring that the model is appropriate to the data available, the study’s context, and the technologies considered, whilst reflecting the latest knowledge on network effects.

Furthermore, reliance on social networks for agricultural extension is increasing due to questions surrounding the cost-effectiveness of direct extension and a shift towards

more collaborative, bottom-up extension models, such as farmer-to-farmer extension<sup>1</sup>. Therefore, a review of latest knowledge on network effects serves to inform policy and academia on matters to consider to improve the efficiency and equity of agricultural extension systems.

Papers were collected using a keyword search on *Web of Science* followed by title and abstract scanning using *Covidence*, as well as snowballing from key resources. Papers most relevant to developing agricultural contexts were selected.

## Summary on Area of Research

Since Maertens and Barrett's 2013 review, which laments the “distinctly underdeveloped” literature on the subject, there has been a proliferation in studies looking at social network effects on the spread of knowledge and technology, particularly (but not exclusively<sup>2</sup>) in agricultural settings in developing countries. Much of this literature has studied network effects in relation to the issue of identifying lead-farmers<sup>3</sup> in farmer-to-farmer extension systems (Takahashi, Muraoka and Otsuka, 2020, pp.37–39).

Many studies utilise social network data and subsequent social network analysis<sup>4</sup> as part of their methodology. Almost without exception too is reference to the seminal work by Manski (1993), which treats the methodological difficulties in identifying

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<sup>1</sup> A method of extension whereby lead-farmers are trained and allowed to experiment with a technology, subsequently sharing it with their network (Ochieng, Silvert and Diaz, 2022)

<sup>2</sup> See Barham *et al.* (2018), Genius *et al.* (2014)

<sup>3</sup> See <sup>1</sup>

<sup>4</sup> See Scott (2012, p.1)

network effects – referred to as the *reflection problem*. Krishnan and Patnam (2014) summarise this as differentiating actual network effects from *contextual effects* – that an individual acts the same as their network since they occupy the same environment and experience the same shocks - and *correlated effects* – that an individual's behaviour is correlated with his network's simply because they are likely to have similar characteristics<sup>5</sup>. Addressing this reflection problem is thus at the centre of any study attempting to understand the influence of networks.

There is, however, considerable variation in the literature, in both the approach to addressing this reflection problem, and the theoretical underpinnings and methods used in studying network effects. One distinction is that some studies, such as that by Kim *et al.* (2015), measure network effects on a network or community level – in Kim *et al.*'s case, by measuring the proportion of food vouchers redeemed *in a village*. This approach is particularly common when studying lead-farmer selection. Others model network effects at the individual level, looking at singular farmers' responses to network circumstances specific to them. It is *solely the latter class* that this review will focus on, as they have the potential to capture actual dynamics between individuals which explain how and when network effects operate.

## Key Papers' Review

Krishnan and Patnam (2014) use household panel data on fertiliser and improved seed adoption in Ethiopia to measure network effects. Due to the unavailability of network data, authors use geographical data to infer farmers' networks from their spatial neighbours; despite discussing justifications for this at length, the validity of the

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<sup>5</sup> One's network is generally more likely to consist of similar individuals

approach is contestable. Network effects on technology adoption are modelled by regressing individual farmers' adoption against the proportion of the farmer's direct neighbours<sup>6</sup> adopting technology, controlling for farmer/household and village traits, and extension exposure. The influence of neighbours' adoption is found to be strong and persistent up till when 70% of the *village* adopts, beyond which network effects decrease. While this confirms the presence of network effects, the study says little about *when* network effects occur and practically nothing about *how* they operate.

Maertens (2017) adopts a more elaborate version of this approach in studying BT cotton adoption in India. In seeking to go further than Krishnan and Patnam (2014), the author splits each farmer's network along two lines; whether the farmer could observe the connection's farming practices/decision, and whether the connection is a progressive farmer<sup>7</sup>. The proportion of adopters in each grouping - elicited from household and network data – was regressed against each farmers' BT uptake<sup>8</sup>, controlling for year effects, farmer traits, and other information sources. The hypothesis that adoption by progressive farmers in the learning network decreases the likelihood of a farmer adopting BT cotton is corroborated by results, being explained on the basis of strategic delays by farmers to freeride on others' experimentation; this provides evidence for network effects influencing uptake via *learning*. Links between farmer adoption and proportion adoption in non-progressive networks indicated network effects operating via *social pressure*<sup>9</sup>, as expected, yet evidence for this was weaker. Maertens thus starts to shed light on *how* network effects work.

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<sup>6</sup> See p.313

<sup>7</sup> See p.993

<sup>8</sup> Using a probit model

<sup>9</sup> The tendency to conform to one's network's decision, controlling for other factors

Varshney *et al.* (2022) adopt a similar approach in exploring how network effects vary with farmer and network traits. Given the focus on mustard production in India, caste-based heterogeneities are focussed on, yet such an approach is appropriate in other communities experiencing social/ethnic/racial cleavages. Using household and network data, the *number of* adopters<sup>10</sup> in different castes in the farmers' network, farmers' own cast, and an interaction of the two are regressed<sup>8</sup> against each farmer's adoption of hybrid mustard, controlling for village and farmer traits. There is clear evidence of network effects, albeit not via social pressure, and results support the authors' hypotheses on variation in learning effects by caste. Farmers are more likely to learn from individuals in the same caste, and farmers in lower castes are more influenced by network effects and higher caste farmers than others. This study therefore contributes to a better understanding of *when* network effects operate.

The approach adopted by Fisher *et al.* (2018) differs from those above in that authors construct two models to study the influence of lead-farmer characteristics on farmer awareness and uptake of conservation agriculture techniques, respectively. Using household and network data of lead- and follower-farmers<sup>11</sup> in Malawi, authors simultaneously estimate<sup>12</sup> the influence of lead-farmer familiarity with and adoption of technology, amongst others, whilst controlling for farmer, household, and village traits. Findings indicate that higher lead-farmer familiarity and adoption generally improve others' awareness, as expected, yet of the two only familiarity is found to increase uptake. This may be interpreted as supporting the prominence of learning

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<sup>10</sup> Rather than the proportion, as in Maertens (2017)

<sup>11</sup> Farmers in lead-farmers' networks

<sup>12</sup> Using a bivariate probit model

over social pressure in explaining network effects. Thus, even though this study only measures lead-farmers' influence, it also provides insights about how and when network effects matter.

Fafchamps, Söderbom and van den Boogart's model (2022) is different in that it directly incorporates the flow of *knowledge* through networks, thus explicitly studying *how* network effects operate. This is made possible by using a rigorous dataset of mobile-phone exchanges to study the spread of awareness and use of mobile credit transfer technology, which allows for learning and social pressure to be independently identified from network effects. Findings indicate the former to be significant in terms of both learning about the *existence* and *utility* of the technology, as expected, but once again no evidence is found to support social pressure.

The prohibitive cost of the data collection required for Fafchamps *et al.*'s approach (2022) means it is difficult to reproduce in other settings. Banerjee *et al.*'s study (2013) navigate this by using a Bayesian model to determine the flow of awareness<sup>13</sup>, whereby the probability of information diffusion on the technology from *a* to *b* differs according to whether *a* uses it. Authors used detailed social network and household data to track the spread of microfinance awareness and use in Indian villages, approximating values by bootstrapping and optimising the model's match to the observed spread. They corroborate that awareness of technology is more likely to spread between two individuals when one is an adopter, and again no significant pressure effect is detected; thus, they provide insight into both *how* and *when* network effects operate.

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<sup>13</sup> A form of knowledge – that a technology exists/is available

Wordcount: 1499

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