The Impact of Social Networks on Electric Pump Adoption and Irrigation Access in Bangladesh's Informal Water Markets

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Abstract

This study examines the role of social networks in the adoption of electric pumps and water buyers' access to irrigation water through electric pumps in Bangladesh. Despite government efforts, adoption rates have remained low (2.5%), especially among small and marginal farmers. Using a "networks within sample" approach, we surveyed 1,225 farmers in 60 villages across Rajshahi and Rangpur divisions of Northwest Bangladesh, gathering information on social interactions among the surveyed farmers within each village. Our analysis reveals significant positive network effects: having an electric pump owner in one's social network increases the likelihood of adoption. Network effects on irrigation market access are more pronounced within the same land size class compared to social interactions across different classes. Notably, the impact on water buyers' access to irrigation through electric pumps is less pronounced when small farmers socially interact with large farmer pump owners in their social network than when the situation is reversed.

Keywords: Social networks, Electric pump, Adoption, Irrigation access

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Introduction

Agricultural activities in the South Asian region substantially depend on rainfall, and approximately half of the farmers lack access to reliable irrigation facilities (Huang et al., 2006; Giordano and Fraiture, 2014). The impact of irrigation access on yield, agricultural production, food security, and poverty alleviation is well-documented in the literature (Giordano et al., 2019; Balana et al., 2020). Additionally, irrigation plays a crucial role in mitigating the impacts of climate change by providing water for crops during periods of water scarcity (Woznicki et al., 2015; Arfanuzzaman et al., 2021; El-Nashar and Elyamany, 2023). However, the cost of irrigation as a proportion of total agricultural input costs is substantial, making it challenging to provide access to the wider farmer community at affordable rates (Dono et al., 2012; Arfanuzzaman et al., 2021; Asian Development Bank, 2023).[1]

In Bangladesh, the majority of farmers rely on diesel pumps for irrigation, with approximately 1.5 million diesel pumps currently in operation. Irrigation costs account for a significant 43% of total agricultural costs in the country (Asian Development Bank, 2023). Bangladesh spends $900 million annually on 1 million tons of diesel to power its irrigation systems (World Bank, 2015). Electric pumps and solar irrigation pumps present reliable alternatives for farmers, helping to reduce costs, decrease reliance on expensive diesel fuel imports, and offer better environmental outcomes compared to diesel pumps (Buisson et al., 2021; Wimmer, 2023). However, adoption rates are only about 2.5%,[2] this is due to uneven electricity distribution, electricity infrastructure, and are mediated by government rules and regulations, which govern the provision of connections, unlike diesel pumps that rely solely on the autonomous decisions of the farmers (Mollik et al., 2016; Varshney et al., 2022a).

The government of Bangladesh has implemented several policies and initiatives to promote the electrification of pumps and enhance their accessibility to small and marginal farmers.[3] As a result of these efforts, there has been an increasing trend in the adoption of electric pumps in Bangladesh over the past decade (Varshney at al., 2022a). Statistics indicate a 26% increase in the number of electric pumps, from 0.268 million to 0.338 million (Minor Irrigation Census, 2010 and 2018).While electric pumps offer cheaper irrigation access to farmers,[4] the adoption and access for smallholders are not well understood (Mottaleb et al., 2019).

At the micro-level, the adoption of new technologies and their accessibility to smallholders depend on various factors, including the diffusion of information about the advantages of new technology over traditional technology, existing infrastructure, education levels, experience, and the financial capacity of farmers (Feder and Umali, 1993; Ali and Behera, 2016; Mottaleb, 2018; Takahashi et al., 2020). On the uptake of new technologies, there is a vast literature that talks about the role of

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[1] Arfanuzzaman et al., 2021 showed that the total irrigation cost is 61% of the total production cost in the Lower Teesta Basin region in Bangladesh.

[2] Appendix Table A2

[3] For example, the National Food Policy Plan of Action (2008-2015) prioritized improving irrigation practices, ensuring an uninterrupted power supply to electric pumps, extending irrigation facilities, and enhancing access to equipment for small and marginal farmers, with a commitment to fair water price regulation. The Integrated Micro-irrigation Policy (2017) highlighted the importance of electric pumps for sustainable irrigation, introducing subsidies and prioritizing electrical connections. The Groundwater Management Act (2018) regulated groundwater use by requiring farmers to obtain permits for tubewell installation, ensuring compliance with spacing and verification criteria to manage groundwater resources sustainably. The act specifies that deep tube wells for a 24-hectare land area cannot exceed 2 cusec units, and for a 6-hectare land area, they cannot exceed 0.5 cusec units.

[4] Varshney et al. (2022) compare the average price paid by water buyers to access irrigation for boro rice cultivation (in taka/acre at 2010 prices) for 2018, the price through electric pump was 3081 taka/acre (18% lower) compared to 3722 taka/acre through diesel pump.

social networking/learning in their adoption and shows that farmers' social networks facilitate adoption (Bandiera and Rasul, 2006; Conley and Udry, 2010; Mekonnen et al., 2018).[5]

In this paper, we study the role of social networks in the adoption of electric pumps and smallholder's access to them through informal water markets. While several attempts have been made to identify best practices for information diffusion regarding the adoption of seed varieties, fertilizer, and types of machinery (Magruder, 2018; Oyinbo et al., 2020; Banerjee et al., 2019; Beaman et al., 2021), the role of social networks in determining access to irrigation facilities through electric pumps, particularly to small and marginal farmers received scant attention.

The study explores two distinct yet interrelated types of networks in agricultural settings: economic networks, exemplified by buyer-seller interactions, and social networks, which encompass relationships forged through advice, trust, or kinship. While these networks often intersect in practice, they remain conceptually distinct. Economic networks are primarily transactional, driven by the exchange of goods and services, whereas social networks are relational, grounded in shared social attributes such as caste, kinship, or community affiliation. Despite their analytical distinction, economic and social networks frequently overlap in agricultural societies. For example, access to irrigation water facilitated through pumps represents an economic interaction. However, the feasibility of such access often relies on social factors, including trust, shared norms, and advisory relationships, which are rooted in social networks(White, 2002; Jackson 2006). This interdependence underscores the necessity of situating economic transactions within the broader context of social structures.

The analysis is warranted for several reasons. Small and marginal farmers depend extensively on informal water markets for irrigation, and their access depends on how these markets operate (Shah, 1993; Palmer-Jones, 2001; Shah, 2010; Mottaleb et al., 2019; Razzaq et al., 2019; Vij et al., 2019). Their access through informal water markets can be shaped by many factors. First, concerns persist regarding elite capture of water resources through these markets, exacerbating inequalities in access (Bardhan, 2000; Modak, 2018; Chatterjee and Pal, 2021). Second, social norms and historical practices also influence interaction between farmers in these markets (Dubash, 2000; Prakash, 2005). Third, poorer farmers are less likely to purchase electric pumps due to shortage of funds for such equipment therefore they cannot take advantage of electricity subsidies(Sarkar, 2011). Kumar and Jaglan (2021) showed that there is variability in accessibility of groundwater across different land sizes—marginal and small farmers have less access to electric pumps compared to large farmers. Therefore, identifying pathways through which irrigation access through electric pumps for poorer farmers can be improved can contribute to agricultural productivity, food security, and poverty alleviation.

In this context, this paper has three objectives. First, we examine the role of social networks in the adoption of electric pumps.[6] Second, we investigate how social networks determine water buyer's access to irrigation water through electric pumps,[7] classifying networks as intra- and inter-class based on the land size. Finally, we explore the heterogeneity in network effects by examining how interactions between small and large farmers in their social networks influence outcomes. This study is based on a primary survey of 1,225 farmers in the Rajshahi and Rangpur divisions of Bangladesh. To assess network effects, we employed a "networks within sample" approach, collecting information to construct a social interaction map of the sample farmers in each of the 60 villages surveyed.

This paper contributes to the literature in several ways. First, it is an incipient study on the role of social networks in adopting electric pumps in the context of Bangladesh. Exceptions include Mottaleb (2019), who showed that social capital (not social networks) increases the likelihood of

[5] This literature largely concentrates on the adoption of agricultural innovations.

[6] Adoption of electric pumps refers to cases where farmer becomes the owner or adopter of electric pumps for irrigation purposes.

[7] Access to irrigation through electric pumps in the water market refers to cases where water buyers obtain irrigation water using electric pumps through the water market.

determining methods and payment for irrigation. Second, the study makes a novel attempt to understand the social interactions between buyers and sellers and their implications for determining access to irrigation sold from electric pumps. There is a vast body of literature analyzing access through social networks in seed, fertilizer, and agricultural machinery (Bandiera and Rasul, 2006; Conley and Udry, 2010; Maertens and Barrett, 2013), and the role of social networks in the job market (Montgomery, 1991; Cingano and Rosolia, 2012). To the best of our knowledge, no study has quantified the network effects in gaining access to irrigation in the water market. Third, the study contributes to the growing literature on social networks by examining heterogeneity in network effects, distinguishing between the varied interactions between small and large farmers (see, for example, Young, 2009; Jackson and Lopez-Pintado, 2013; Magnan et al., 2015; Grzybowski, 2015; Kumar et al., 2021). Finally, the classification of farmers based on land class to study heterogeneity in network effects extends the existing literature, which has primarily focused on classifications such as caste, religion, gender, education, and location (McPherson et al., 2001; Bandiera and Rasul, 2006; DiMaggio and Garip, 2012, Varshney et al., 2022b). Through this approach we provide a nuanced understanding of how social interaction among farmers classified based on land class influences technology adoption.

The rest of the paper is organized as follows: The second section describes the role of policies on the electrification of pumps in Bangladesh, providing the context. The third section details the primary survey of farmers in Bangladesh, outlining the sampling strategy, sample profile, and information on network members. The fourth section discusses the empirical framework for identifying the network effects. The fifth section presents and discusses the study's results. The final section summarizes the findings and concludes with policy implications.

The Context

In Bangladesh, the agriculture sector contributes to 14% of GDP and engages over 40% of the nation's workforce (BBS, 2019). In the 1970s, the country faced significant food security challenges but achieved food self-sufficiency by the late 1990s. This achievement is notable given the country's high population density and low per capita land ownership (Mukherji et al., 2021). The agricultural transformation was largely driven by the Green Revolution technologies, such as high-yield variety (HYV) seeds and irrigation (Mottaleb et al., 2015). Between the 1970s and the 2020s, rice and wheat production doubled due to agricultural intensification, which included both expanding crop areas and increasing crop yields (BBS, 2018; Mottaleb et al., 2019).

Irrigation, particularly from groundwater using diesel-operated shallow tube wells (STWs), played a crucial role in this growth (Mitra et al., 2021). The number of STWs has increased since the mid-1980s, supported by various policies that eased import norms for agricultural machinery. This period also saw the rise of informal water markets, where STW owners provided irrigation services to farmers without STWs, allowing wider access to irrigation benefits without the need for individual investments in groundwater extraction (Rahman et al., 2015).

While diesel-run STWs remain the primary source of irrigation in Bangladesh, the early 2010s marked a significant increase in rural pump electrification. At the same time, the country saw a sharp increase in diesel prices (Sajid, E., 2021). Additionally, this decade also brought concerns about groundwater sustainability (Krupnik et al., 2017; Bhattacharjee et al., 2019), leading to new regulations such as well spacing norms and permits for groundwater wells.

The Data

Sampling strategy

The analysis presented in the paper is based on a primary survey conducted between April and June 2023 in two northern divisions of Bangladesh: Rajshahi and Rangpur. The primary objective of the survey was to collect representative data on irrigation sources at the divisional level. To achieve this, we designed a survey encompassing 900 farmers, with 450 farmers selected from each division. The selection of divisions was purposive.[8] Subsequently, three districts were randomly selected from each of the two divisions, resulting in a total of six districts. From each district, we randomly chose two sub-districts (locally, upazillas), totaling 12 sub-districts. Finally, we selected five villages randomly from each sub-district, resulting in a total of 60 villages.

Within each village, we conducted a census to gather information on 8-10 key indicators, including land owned, and cultivated land for 2022-23.[9] In larger villages, where the number of households exceeded 250, we opted to select one sub-village (or hamlet) randomly. This approach enabled us to collect data from 7,583 households across the 60 villages, of which 6,598 households cultivated land and agreed to participate in the survey. From this pool of 6,598 households, we randomly surveyed 15 households in each village, totaling 900 households. Finally, we encountered 46 missing observations at random, resulting in a final random household sample of 854.

The survey further aimed to gather data on social interactions among farmers to understand the role of social networks in accessing irrigation, particularly through electric pumps. In doing so, we expanded the sample by including those farmers who buy and sell water through electric pumps to the farmers in a representative sample.[10] We then compiled an enumerated list of these water sellers and buyers for each village. Enumerators subsequently selected water seller and buyer through systematic random sampling from this list to form an augmented sample, aiming for approximately 3 (or 2) water sellers and 3 (or 2) water buyers in each village.[11] As a result, our total sample consists of 1,225 households, comprising 854 farmers from the random sample and 371 additional water sellers and buyers who transact with the farmers of the representative sample i.e. augmented sample.

To capture the social interaction of farmers, the survey adopted a "network within sample" approach (Chandrasekhar and Lewis, 2011). This approach involved asking each farmer about their connections to every other person in the sample, along with the duration of their relationship. Additionally, we inquired whether farmers discussed agricultural matters, including whether they sought advice on irrigation energy sources, and whether they engaged in buying or selling water among themselves. This information enabled us to construct a social interaction map for each surveyed farmer within the sample for each of the 60 villages. Although this technique truncates the network and may lead to estimates with a downward bias, it still provides valuable insights into quantifying the network effects.[12]

Sample profile

Table 1 provides a sample profile of surveyed farmers based on the representative sample. On average, nearly all households (98%) are headed by males. The mean age of household heads is approximately 47 years. The mean education level of household heads is relatively low, at around 5 years. The majority

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[8] We chose this geographic area for our investigation due to its reliance on intensive groundwater usage for agricultural intensification.

[9] Additional key variables asked were ownership of electric and diesel pumps, gender of the household head, mobile number, etc.

[10] To accomplish this, we asked all farmers within the representative sample to provide the names of water sellers and buyers from whom they sold and purchased water, respectively, in their village.

[11] Some villages had slightly fewer or more than a total of five water sellers or buyers.

[12] Ideally, a village census would be conducted to identify network beneficiaries, wherein all farmers list their network members, such an approach is time- and budget-intensive, particularly in large villages (Van den Broeck and Dercon, 2011).

of households (88%) follow Islam as their religion. Farming appears to be a significant primary income activity for households, 78% of the households practice agricultural as livelihood. Additionally, households comprise an average of 4.59 members per household.

On average, approximately 20% of households have taken a loan, indicating a moderate level of financial engagement with external sources. Around 30% of households have a bank account, suggesting significant but not universal access to formal banking services. Moreover, about 36% of households own a smartphone, reflecting a notable penetration of digital technology in the area. In terms of land ownership, households possess an average of 103.41 decimals of land. Figure 2 depicts the cumulative distribution curve of land ownership. Notably, the median land size among the surveyed farmers in the representative sample stands at 87 decimals (Fig 3). To further explore disparities in network effects, we categorize farmers into four quartiles, the land size in 1st quartile (calling it marginal farmer) is 19 decimals, 2nd quartile (58 decimals, small), 3rd quartile (118 decimals, medium), and 4th quartile is 311 decimals (large).[13] In terms of soil type, clay and loam soils are prevalent among households, with approximately 26% and 36% of households having these soil types, respectively. Sandy soil is less common, found in only 5% of households, while sandy-clay loam soil is relatively more prevalent, present in about 33% of households.

Lastly, the average distances to various facilities provide insights into accessibility. The average distances to the nearest diesel pump trader and petrol pump station are notably shorter, at 3.81 km and 6.38 km, respectively. The average distances to the nearest electric board office, electric pump trader, and rural or commercial bank are 7.89 km, 20.64 km, and 5.76 km, respectively. However, the average distance to the district headquarters is approximately 27.38 km, while the average distance to the upazila headquarters is about 9.53 km.

However,

Table 1 Column 5 provides a comparison between adopters and non-adopters of electric pumps across various households, plots, and village characteristics. Analyzing the data, it becomes evident that adopters and non-adopters exhibit several differences. Adopters tend to have slightly older household heads with higher education levels, larger household sizes, ownership of smartphones, and bank accounts. Moreover, adopters generally own more land compared to non-adopters. Interestingly, adopters live closer to electric pump traders than non-adopters, indicating potential accessibility advantages. However, no significant differences emerge in terms of religious affiliation, primary income activity, or proximity to government offices and village amenities.

Additionally, Figure 4 plots the electric pump adoption by quartiles of land, which suggests that the percentage of electric pump adoption increases with the land size, from the 1st quartile (3.3%) to the 4th quartile (18.8%).

Network description

Figure 5 provides a visual representation of the sample network map within the village of Madhupur, Thakurgaon, illustrating the social connections among farmers labelled F1 to F20.[14] Each cell within

[13] Based on the government of Bangladesh guidelines, small farmers are defined as those holding less than 2.5 acres of land, while medium and large farmers possess greater than 2.5 acres of land. However, if this cutoff were applied directly to our sample, it would result in a disproportionately large "small farmer" category, comprising 85% of the total sample, and a smaller representation of large farmers. To address this imbalance and ensure a more representative classification, we have decided to categorize our sample based on the distribution of land sizes, specifically using the quartiles of land size.

[14] Social interaction map is constructed based on a sample village to demonstrate the construction of the network data.

the matrix indicates whether there is a social connection (N, Network member) or absence of social connection between each pair of farmers. Notably, F10 is identified as the electric pump owner and is socially connected with 9 other farmers surveyed in the village. In the paper, we argue that farmers socially connected to F10 are more likely to adopt electric pumps or gain access to irrigation through them compared to unconnected farmers. The next section provides an econometric framework to assess whether this is indeed the case.

Figure 6 presents the social interaction dynamics among farmers at the village level. On average, in each village, we surveyed approximately 20 farmers. Among these farmers, they socially interact with 11.4 of their peers, suggesting a robust network of connections. Impressively, the longevity of these social interactions spans an average of 23 years (Figure 7), highlighting the strong social ties. Regarding information exchange, a relatively high percentage of farmers, approximately 45% (Figure 8), seek agriculture-related advice from their network members, while a slightly smaller proportion, around 38%, seek irrigation-related advice (Figure 9). It appears that the information exchange for both agriculture-related advice and irrigation-related advice is relatively less for the bottom quartile and the difference between Q2, Q3 and 4 is small. (Figures 8 and 9). These statistics demonstrate the strong role of social networks in disseminating agricultural knowledge, which can be leveraged for more effective information dissemination strategies.

Empirical Framework

The choice of pumps (electric or diesel) for extracting water for irrigation is influenced by various factors, including electricity infrastructure, the availability of electricity or diesel fuel, previous experiences, and awareness of their relative benefits. Each type of pump comes with its own set of advantages and disadvantages, which vary in terms of costs, benefits, mobility, labor, and capital requirements. Considerations such as natural circumstances—whether the pump is used for extracting groundwater or pulling up surface water—and use intensity (application in water-intensive or water-saving crops) also play a role in this decision. In Bangladesh, where formal sources of agriculture extension services are ineffective,[15] farmers often rely on informal sources such as social networks (Maertens and Barrett, 2013; Beaman and Dillon, 2022). These networks are comprised of friends, neighbors, relatives, progressive farmers, and farmers' groups. In a scenario, when farmers observe and interact with network members who have already adopted electric pumps, they gather valuable information about the practical aspects and challenges, which can help them make more informed decisions. In many cases, these networks serve as the primary source of information for farmers.[16]

However, assessing the effects of social networks in determining the adoption of electric pumps essentially involves identifying what drives the correlation between the adoption of electric pumps by farmers, and their network members. A pioneering study by Manski (1993) distinguishes between endogenous effects, exogenous effects, and correlated effects in identifying the network effects. In our case; the influence of the adoption of electric pumps by network members on farmers' adoption represents endogenous effects, the influence of network members' characteristics on farmers’ adoption represents exogenous effects, and finally, when the farmers and their network members tend to behave similarly because they face similar situations, such as residing in the same village, this represents correlated effects.

[15] Afrad et al. (2019) highlight that the national agricultural extension system in Bangladesh is ineffective, with farmers not benefiting due to illiteracy, reluctance, and low technological competency of extension personnel. Dysfunctional public-private-NGO partnerships and a lack of cooperative societies further exacerbate the issue.
[16] Birthal et al. (2015) showed that one-third of all farmers relied on social networks as compared to only one-tenth of farmers who relied on formal agriculture extension services.

In the simple model of social learning,[17] we assume that farmers lack knowledge about the optimal levels of other complementary inputs required for the adoption of electric pumps, such as the availability and timing of electricity, operation and maintenance assistance, and other related factors. In practice, farmers can update their beliefs regarding the requirements of these complementary inputs based on the experiences of their social network members. Therefore, the mechanism of endogenous network effects operates through the members of the social network who have adopted electric pumps, and they can serve as a mechanism to inform about the expected marginal benefits of its adoption.

Analyzing social network effects requires comprehensive data. As noted earlier, we followed a "network within sample" to collect information on social interaction. In this approach, since the network members are part of the surveyed sample, this strategy yields comprehensive data on these individuals, including their adoption of electric pumps, the timing of adoption, and their socioeconomic and demographic characteristics. Although this method limits the network scope, it still effectively mitigates some of the primary econometric issues inherent in network effect analysis.

We estimate the following specification to identify the effects of social networks on the adoption decision of electric pumps.

$$Y_{ivb}=\beta X_{ivb}+\gamma N_{nvb(i)}+\delta X_{nvb(i)}+\Phi Z_{vb}+\eta \underline{a_{vb,2021}}+\lambda G_{vb}+\varepsilon_{ivb} \quad (1)$$

where i is farmer, *v* is a village, *b* is block (or sub-district), Y_i is the adoption of electric pumps by farmer i and takes the value of 1 if the farmer adopts electric pumps and 0 otherwise.[18] X_{ivb} *is the* set of covariates related to farmers (see Table 1 for the list of covariates). $N_{nvb(i)}$ is the adoption decision of a member of the social network *n* corresponding to individual farmer *i*, and it takes the value 1 if at least one network member adopted electric pumps and 0 otherwise.[19] $X_{nvb(i)}$ is the characteristics of social network member *n*, corresponding to individual farmer *i*, which also captures exogenous effects (see Appendix Table A1 for the list of covariates). Z_{vb} represents the village-level characteristics including distance from the district, sub-district headquarters, electric pump dealers, and banks.[20] $\underline{a_{vb,2021}}$ captures the average adoption rate at the village level in the previous year i.e. 2021. *G* represents the district's fixed effects. ε is an error term assumed to be uncorrelated with other covariates.

One of the key problems in estimating network effects is that the behavior of network members influences the farmer, who in turn influences the network members. This issue is known as the reflection problem in social network literature.[21] To address this problem, we adopted a dynamic adoption framework, where an individual farmer is influenced by the behavior of his network member with a lag (e.g., Dong and Saha, 1998; Foster and Rosenzweig, 1995; Manski, 2000; Neill and Lee, 2001). This "seeing is believing" type of learning assumes that a farmer first observes his network members and then decides to adopt it in the next period. To address this, we excluded those farmers who adopted electric pumps before their network members and eliminated cases where a farmer's decision might have influenced the network members' decisions, thus isolating the direction of influence from the network to the farmer.[22]

By incorporating the characteristics of network members, the specification controls for how the attributes of network members (such as socio-economic status, education, or farming experience)

[17] See, for example, Bandiera and Rasul (2006) and Matuschke and Qaim (2009).

[18] The reference period of the survey is 2022-23.

[19] We also perform analysis using the total number of electric pump adopters in the network. Results are available from the authors upon request.

[20] See Table 1, for the complete list of village characteristics.

[21] Manski (1993)

[22] We dropped 59 such observations.

influence the adoption decision of farmers i.e. exogenous effects. Additionally, individual attributes may explain the process of selection into social networks. A growing body of theoretical work explores how individual incentives give rise to networks and, in turn, can be shaped by them (e.g., Jackson, 2006). Although the "network within sample" approach establishes social interactions among farmers in a randomly drawn sample, it is still crucial to incorporate the individual characteristics of social network members. This step addresses the endogenous selection of individual farmers into networks, a well-documented issue concerning sorting into networks. This approach advances our analysis compared to several previous studies in this field (Bandiera and Rasul, 2006).

We adopted a range of strategies in the specification to address correlated effects. By including village-level characteristics, we control for common environmental or infrastructural factors influencing adoption decisions. Second, capturing the previous year's average adoption rate of electric pumps at the village level accounts for temporal and spatial trends affecting all farmers similarly. Finally, incorporating district or sub-district fixed effects controls for broader locational factors could create correlated behaviors among farmers within the same district. Even though the strategy outlined above is robust it may not lend itself to full causal interpretation.

Next, we would like to assess the role of social networks in water buyer’s access to irrigation water through electric pumps. In doing so, we estimate the following specifications:

$$Y_{ivb}=\beta X_{ivb}+\gamma N_{nvb(i)}+\delta X_{nvb(i)}+\Phi Z_{vb}+\eta \underline{a_{vb,2021}}+\lambda G_{vb}+\varepsilon_{ivb} \qquad (2)$$

All notations remain the same except Y_i where it takes a value of 1 if the water buyer access~~ed~~ ~~to~~ irrigation water through electric pumps and 0 if they get access through diesel pumps.

Inter-class and intra-class network effects

To ascertain whether social network effects on irrigation access are more pronounced when farmers interact within the same class (based on the land size) compared to interactions across different classes, we employ the following specification:

$$Y_{ivb}=\beta X_{ivb}+\gamma NA\_SAMECLASS_{nvb(i)}+\delta X_{nvb(i)}+\Phi Z_{vb}+\lambda G_{vb}+\varepsilon_{ivb} \qquad (3)$$

Here, *NA_SAMECLASS* represents the number of same-class social network members who own electric pumps. Recall that, we categorized farmers into four groups based on land size and formed quartiles of network members using the minimum and maximum land size in each group. We then tallied the number of network members with electric pumps in the same category. All other notations remain as defined above. The variable *NA_SAMECLASS* captures the social network effect when farmers interact within the same class.

To explore social network effects when farmers interact outside their class, we implement the following specifications:

$$Y_{ivb}=\beta X_{ivb}+\gamma NA\_DIFFCLASS_{nvb(i)}+\delta X_{nvb(i)}+\Phi Z_{vb}+\lambda G_{vb}+\varepsilon_{ivb} \qquad (4)$$

In this specification, NA_DIFFCLASS represents the number of different-class social network members who own electric pumps.

Heterogeneity in Network Effects

To assess the differential impact of networks/interactions by class, we implement the following specification :

$$Y_{ivb}=\beta X_{ivb}+\gamma NA\_SAMECLASS_{nvb(i)}+\Phi\left(Large_{ivb} * NA\_SAMECLASS_{nvb(i)}\right)+\delta X_{nvb(i)} \quad +\Phi Z_{vb} \quad + \lambda G_{vb}+\varepsilon_{ivb} \tag{5}$$

All notations in the above equation are as defined above. The interaction term *Large*NA_SAMECLASS* captures the differential effect of intra-class networks on large farmers (4th quartile) compared to the other farmers (marginal, small, and medium).[23]

Farmers distinguished by class may have biased interaction patterns (see Jackson and Lpez-Pintado, 2011). For example, when large farmers interact with medium, small, and marginal network members, the effects on them could be very different than when they interact vice versa i.e. heterogeneous effects. To examine such asymmetric or differential effects, we implement the following specification :

$$Y_{ivb}=\beta X_{ivb}+\gamma NA\_DIFFClass_{nvb(i)}+\Phi\left(Large_{ivb} * NA\_DIFFClass_{nvb(i)}\right)+\delta X_{nvb(i)} \quad +\Phi Z_{vb} \quad + \lambda G_{vb}+\varepsilon_{ivb} \tag{6}$$

Here, the interaction term *Large*NA_DIFFClass* captures the differential effect based on land classes.

Unobserved heterogeneity and simultaneity

Identifying the effects of social networks, especially when considering geographical proximity like village-based networks, poses challenges due to unobserved heterogeneity and simultaneity in the adoption decision process. To address this, our study defines social networks based on actual group interactions with farmers within the village. We mitigate the group effect by including district or sub-district fixed effects and village-level characteristics, such as proximity to district or sub-district headquarters, electric pump traders, and banking services. We test the robustness of our findings by estimating specification 1 with village effects.

Individual heterogeneity may arise from two primary sources: first, farmers may adopt electric pumps due to unobserved individual characteristics influencing the adoption decision, such as their ability to process information. To account for this, we include farmer attributes like education and age in the empirical model. Simultaneity presents another challenge in estimating social network effects. Social network members' adoption choices may influence an individual farmer's decision to adopt electric pumps, but the reverse could also be true, where individual farmers' adoption decisions influence their social network members. As discussed above, we assess the extent of the simultaneity problem by testing for simultaneity between the adoption choices of farmers and their social network members. The uniquely collected past adoption data for electric pumps enables us to test the extent of the problem by excluding farmers who adopted electric pumps before their network members.

[23] We designate the 4th quartile as large farmers. 3rd, 2nd, and 1st quartile as medium, small, and marginal farmers, respectively. We also assess the results by comparing large and medium farmers with marginal and small farmers and found similar results in terms of sign of the coefficients.

Results

Effect of social networks on the adoption of electric pumps

Table 3 presents the results based on Specification 1. It assesses the effects of social networks on the adoption of electric pumps. We run two different variants of Specification 1. The first variant includes all observations (Column 1), while the second variant drops those observations where farmers adopt electric pumps before their network members (Column 2). The dependent variable is whether the farmer owns an electric pump. The key explanatory variable of interest is at least one network member owns an electric pump. Results from both columns 1 and 2 reveal a strong social network effect on the adoption of electric pumps. Column 2, which addresses the reflection problem by excluding farmers who adopted before their network members, indicates that the presence of an electric pump with at least one network member significantly increases the likelihood of adoption by 3.2 percentage points. In another metric, the presence of an electric pump with at least one network member significantly increases the likelihood of adoption by 17 percent.[24] The R-squared values (0.24 and 0.21) in both columns suggest that the specifications explain a substantial proportion of the variation in electric pump adoption, highlighting the importance of social networks in influencing farmers' adoption decisions.

By including farmer and their network member characteristics, village-level characteristics, and district-fixed effects in our specification, we ensure that our results are not influenced by exogenous factors (such as similarity in attributes) or correlated effects (stemming from shared external conditions).

Effect of social networks on water buyers accessing irrigation water through electric pumps

Table 4 presents the results based on Specification 2, assessing the effects of social networks on water buyers accessing irrigation through electric pumps. We run two variants of Specification 2: the first (column 1) excludes the village-level adoption of electric pumps in 2021, while the second (column 2) includes it. Estimating these two different specifications allows us to understand the influence of how adoption at the village-level influences individual decisions. Both columns show a significant impact of social networks on water buyers accessing irrigation through electric pumps. In column 2, if at least one member of the social network owns an electric pump, the likelihood of accessing irrigation water through electric pumps increases by 2.7 percentage points. In another metric, the presence of an electric pump with at least one network member significantly increases the likelihood of water buyers accessing irrigation water through electric pumps by 4 percent.[25] The models control for household, network member, and village characteristics, as well as district fixed effects, addressing potential econometric concerns related to exogenous, and correlated effects. Additionally, the village-level adoption rate is not significant, suggesting individual peer effects are more crucial than broader village trends. The R-squared value of 0.26 indicates that the models explain a substantial portion of the variation in accessing irrigation water through electric pumps.

Inter-class and intra-class network effects on water buyers accessing irrigation water through electric pumps

[24] The share of farmers who own/adopt electric pumps is 0.19. Therefore, the percentage increase is equivalent to ((0.032/0.19) * 100 = 16.84%.

[25] The share of water buyers who are accessing irrigation water through electric pumps is 0.70. Therefore, the percentage increase is equivalent to ((0.70/0.027) * 100 = 4%.

Tables 5 and 6 present the network effects to assess intra-class and inter-class peer influences, respectively.[26] The estimations are based on the specifications 3 and 4. In both tables, we run two variants of Specification 2: the first (column 1) excludes the village-level adoption of electric pumps in 2021, while the second (column 2) includes it.

In Table 5, across both columns, an increase in network members in the same land class owning electric pumps translates to a notable rise in adoption likelihood of water buyers accessing irrigation water through electric pumps, with estimates ranging from 3.7 to 4.0 percentage points. In other words, when farmers from the same land class own electric pumps, it increases the probability of water buyers accessing irrigation water. This result is consistent with empirical research in the social network literature, which assesses intra-class network effects where class is defined by the same social group, religion, and educational background (Wang et al., 2015; Varshney et al., 2022b). Notably, the lack of significance in the village-level adoption rate for 2021, exclusive to the second model, suggests that individual network effects within the same land class hold greater influence than broader village trends.

This phenomenon can be understood through several contextual lenses. Firstly, pioneering work by McPherson et al. (2001) demonstrates that social interaction among individuals with similar characteristics improves the likelihood of understanding the information they receive and the interactions they experience. Additionally, empirical literature on intra-class network effects shows that these effects are more pronounced when individuals interact socially within the same class (Varshney et al., 2022b). Secondly, the survey asked water sellers about their criteria for choosing water buyers, revealing that 60% base their decisions on distance from the field site, while the remaining 40% rely on social networks. Further inquiry into why social networks are used revealed factors such as timely payment and reliability. Lastly, Pedula and Pager (2019) theoretically argue that "network placement" can serve as a key mechanism to increase the likelihood of gaining access to irrigation by leveraging well-placed contacts, such as friends or relatives with water sellers.

In Table 6, across both columns, the findings reveal that while having network members from different land classes who own electric pumps positively influences water buyer's accessing irrigation water through electric pumps, the magnitude of this effect is lesser (compared to intra-class effects), ranging from 1.6 to 1.9 percentage points. Once more, the village-level adoption rate in 2021 does not wield significant influence, reinforcing the prominence of network members' influences over village-wide trends.

Intra-class networks exhibit stronger influence compared to inter-class networks, with network members within the same land class showing a more pronounced impact on water buyer's accessing irrigation water through electric pumps. The substantial effect sizes observed in intra-class networks underline the significance of socio-economic similarities among network members in fostering technology diffusion.

Intra-class, inter-class, and heterogeneity in network effects

Table 7 presents the results of Specification 5, with two variants. The first variant (Column 1) excludes the village-level adoption of electric pumps in 2021, while the second variant (Column 2) includes it. In Specification 5, the key variables of interest are the interaction between large farmers and the number of same-class members who own electric pumps. This interaction term captures the

[26] We have classified farmers into four categories by defining quartiles. Additionally, we tested our results by classifying farmers into three categories by defining terciles and found the results to be qualitatively similar. These results are available upon request.

differential effect of same-class affiliations on large farmers compared to other farmers.[27] The coefficients of interest in both columns are insignificant, suggesting that within-class interactions do not have a differential impact on large farmers compared to other farmers (marginal, small, and medium). In other words, when large farmers interact with other large farmers in their network, the effect is similar to when small farmers interact with other small farmers in their network.

Table 8 presents the results of Specification 6, also with two variants as described above. Here, the key variables of interest are the interaction between large farmers and the number of different-class members who own electric pumps. The coefficients of interest in both columns are significant. The magnitudes suggest that there is a 4.7 percentage point (Column 1) and a 4.6 percentage point (Column 2) higher likelihood of water buyer's accessing irrigation water through electric pumps when large farmers interact with network members from different classes (marginal, small, and medium) who own electric pumps. In other words, when large farmer water buyers interact with farmers from other classes (marginal, small, and medium) who own electric pumps, the likelihood accessing irrigation water is greater compared to when water buyer from other classes (marginal, small, and medium) engage with large farmers who own electric pumps. This implies that cross-class interactions are particularly beneficial for large farmers, enhancing their access to irrigation water through the social networks they maintain with farmers from different land classes.

One concern is that the observed effect might be attributed to sellers' preference for larger buyers rather than a true network effect. To mitigate this concern to some extent, we have attempted to control for it by including the land size of both network members and farmers in our specification. Additionally, water markets are influenced by factors such as topography and distance. However, when selecting farmers from the same topography and distance, other factors like social networks can also play a crucial role.

Limitations of the study

While our study provides valuable insights into the role of social networks in influencing farmers' decisions regarding electric pump adoption and access to irrigation, several limitations warrant consideration. Firstly, our approach to measuring social networks, while practical, may not capture the full complexity of farmers' interactions and influence networks. Factors such as network strength and centrality were not explicitly accounted for in our analysis. Although, we have attempted to test the robustness of our results by including the average duration of relationships as a proxy for network strength. Secondly, despite efforts to address endogeneity through rigorous controls, past adoption data, and fixed effects, the possibility of unobserved factors influencing both network structure and adoption decisions remains a concern. Factors such as unmeasured social or cultural norms could confound the observed relationships. Although our methodological framework is robust, we exercise caution in providing a full causal interpretation of the estimates. Thirdly, the cross-sectional nature of the data limits our ability to infer causality or assess the dynamic evolution of social networks and adoption decisions over time. Here, we attempted to overcome this limitation by collecting past adoption data based on recall, which may be subject to measurement error.

Discussion

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[27] We designate the 4^{th} quartile as large farmers. 3^{rd}, 2^{nd}, and 1^{st} quartile as medium, small, and marginal farmers, respectively. We also assess the results by comparing large and medium farmers with marginal and small farmers and found similar results in terms of sign of the coefficients.

The effects of social networks and the heterogeneity therein, have implications for equity considerations in access to groundwater irrigation. Given the capital-intensive nature of groundwater irrigation, requiring ownership of tubewells and pumps and investments in energy sources, groundwater access through adoption and ownership of these infrastructure required for irrigation access tends to be skewed in favour of large landowners. Small and marginal farmers are therefore largely dependent on informal groundwater markets for accessing groundwater irrigation, buying groundwater from those with ownership of tubewells and pumps. Depleting groundwater levels tend to intensify this inequality in groundwater irrigation as smallholders get further excluded from ownership of groundwater extracting mechanisms as greater investments are made necessary for deeper tubewells and higher power of pumps. While smaller number of farmers who can afford to own deep tubewells and pumps, groundwater markets work mainly towards monopolistic structures with fewer sellers (Reference). . In turn, the bargaining power of the irrigation sellers to dictate water prices, contractual arrangements, and prioritisation of water buyers (Mottaleb, et al., 2019). Literature on groundwater markets has often alluded to these processes leading to elite capture in groundwater markets with the creation of 'water lords' through a 'tubewell capitalism'. While unequal adoption and ownership of tubewells and pumps due to constraints of affordability create a base condition of unequal groundwater access, strong intra-class effects in the social networks would play a key role in further entrenching these inequalities and tendencies for elite-capture by concentrating the irrigation markets within sellers and buyers of the same class.

Notably, the electricity-based groundwater irrigation is accessed at lower average prices by water buyers in the water market than irrigation from diesel pumps, thus benefitting smallholders with access to cheaper irrigation. However, in northwest Bangladesh, from the same study area and period as the present analysis, Kishore et.al (2023) finds a significant relationship between landsize and adoption of electric pumps, with ownership of these pumps being largely concentrated among larger landowners. Further, electric pump owners were more likely to sell water than diesel pump owners, making these electric pumps owners more significant players in the groundwater markets. The study also finds that the likelihood of water selling is lower among farmers operating lesser land or smallholders. Together these findings skew the electricity-based groundwater irrigation ownership. Additionally, in conjunction with the findings from Kishore et.al (2023), our result on the intra-class network effects presented in earlier sections above, showing a stronger likelihood of water selling by pump owners within their same landsize class of farmers, have implications for further limiting access to irrigation from groundwater markets for smallholders and concentrating groundwater access among larger landholders. Further the inter-class network effects that is weaker for smallholders buying water from large landsize pump owners contribute further to this concentration of electricity-based groundwater irrigation access among larger landsize classes of farmers. This pathway of elite capture of the groundwater markets alludes to the accumulation the benefits of electrification of irrigation among the larger landholders.

Further, The Underground Water Management Law of 2018, delegating authority to issue licenses to local government bodies (Mitra et.al., 2021). The Upazilla Parishad is required to form the Upazilla Irrigation Committee (UIC) to conduct field inspections and ensure irrigation pump-sets meet eligibility criteria for licensing. The policy also mandates that existing pump-set owners obtain licenses and specifies the minimum area each pump must service based on its discharge capacity. Groundwater licensing can often be captured by local elites given the social and political capital that is mobilised to influence these processes (Molle and Closas, 2020). Therefore, licensing processes favouring large scale producers as powerful groundwater users, would lead to systemic concentration of electric pumps among large landholders, intensifying the already unequal distribution of groundwater infrastructure. Following the pathway discussed earlier, this concentration of electric pumps in conjunction with network effects, can strengthen processed of elite capture in groundwater irrigation markets. Ensuring transparent licensing along with targeting towards smallholder farmers strengthen the equitable distribution of entitlements is thus important to ensure improved access to groundwater irrigation among smallholders, and more equitable distribution of benefits of electrification of irrigation in Bangladesh.

Conclusion and Implications

This study highlights the critical role of social networks in the adoption of electric pumps and access to irrigation among smallholder farmers in Bangladesh's informal water market. Our findings indicate that having an electric pump owner within one's social network significantly increases the likelihood of adoption, underscoring the importance of peer influence and information diffusion in technology uptake. Furthermore, the impact of social networks on water buyer's accessing irrigation water through electric pumps is more pronounced within the same land size class, revealing intra-class dynamics as a crucial factor in resource distribution. The heterogeneity in network effects observed in this study provides valuable insights: interactions between different class affiliations within social networks have different implications for irrigation access. Specifically, while large farmer water buyer's benefit more in terms of accessing irrigation water through electric pumps from their social ties, while marginal, small, and medium-class farmers gain less from interactions with larger landholders, highlighting potential disparities, facilitated by social connections.

Despite government efforts to promote electric pump adoption through policies and initiatives, our research underscores that social networks play a pivotal role in overcoming barriers to adoption and improving irrigation access for marginal and smaller farmers. Our findings are particularly relevant in the context of informal water markets, where elite capture of resources and market linkages can exacerbate inequalities (Bardhan, 2020; Platteau, 2004; Sim et al., 2015).

In particular, the findings on intra-class network effects suggest that water buyers are more likely to gain access to irrigation when farmers of the same land class category own electric pumps. This means that the pathway to improving access to irrigation for marginal and small farmers, for example, is to increase pump ownership within their own land class. In other words, as pump ownership rises among marginal and small farmers, water sellers from this group are more likely to sell water within their community. Both supply-side and demand-side constraints must be addressed to improve ownership of pumps for marginal and smaller farmers. Supply-side constraints can be mitigated through targeted policy interventions, such as prioritizing the allocation of groundwater permits and electricity connections to such farmers (Bardhan and Mookherji, 2005). On the demand side, improving access to information (exploiting social interactions), credit, and other financial resources is essential to empower these farmers to invest in electric pumps.

Additionally, our findings highlight the crucial contextual heterogeneity of social networks in accessing irrigation through electric pumps. The role of social networks in this context is complex. While individual affiliations are predetermined, interactions can be influenced by policy. The promotion of interactions beyond one's class can be a valuable source of information and learning. Therefore, policymakers should create opportunities for such social interactions, such as agricultural fairs and exhibitions, to facilitate the exchange of knowledge and experiences among different farmers.

With the nuances of social interactions and network heterogeneity addressed in this study, targeted interventions can be designed to support marginal and smaller farmers, ultimately contributing to agricultural productivity, food security, and poverty alleviation in Bangladesh.

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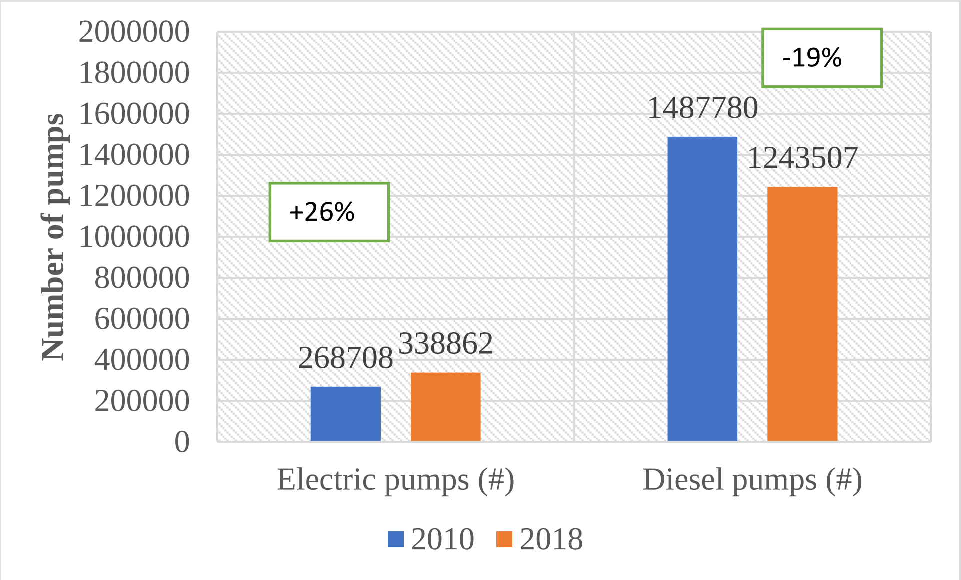
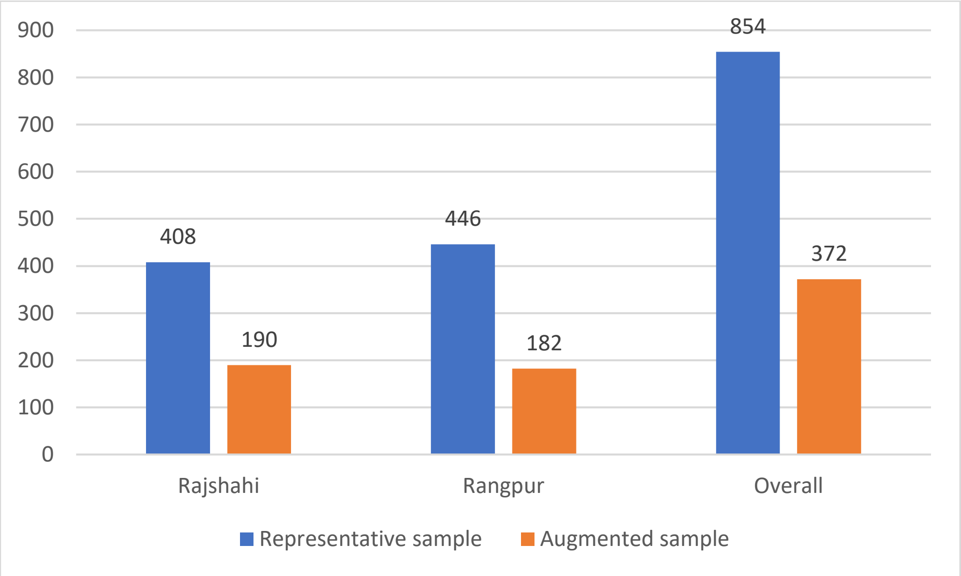
Tables and figures

Figure 1 : Trends in diesel and electric pumps in Bangladesh



Source: Minor Irrigation Census Report, 2010 and 2018

Figure 2: Sample size of representative and augmented sample



Source: IWMI-IFPRI Bangladesh survey (2023)

Table 1: Sample profile of electric pump adopters vs non-adopters, representative sample

Variables	Overall		Non adopter	Adopter	Difference(5=3-4)	T stat
HH characteristics	Mean(1)	S.D(2)	Mean(3)	Mean(4)		
Male head of household (yes = 1)	0.975	0.155	0.973	1.000	-0.027	(-1.44)
Household head's age (in years)	47.192	11.689	46.924	49.973	-3.049*	(-2.16)
Household head's education (in years)	5.083	4.375	4.955	6.413	-1.458**	(-2.77)
Religion is Islam (yes = 1)	0.884	0.320	0.882	0.907	-0.0249	(-0.64)
Primary income activity is farming (yes = 1)	0.777	0.416	0.779	0.760	0.0189	(-0.38)
Household size	4.594	1.813	4.528	5.280	-0.752***	(-3.45)
Borrowed loan (yes = 1)	0.196	0.397	0.199	0.160	0.0392	(-0.82)
Bank account (yes = 1)	0.302	0.460	0.270	0.640	-0.370***	(-6.84)
Own smartphone (yes = 1)	0.359	0.480	0.335	0.600	-0.265***	(-4.61)
Land Ownership (in Decimals)	103.412	124.066	93.767	203.453	-109.7***	(-7.55)
No. of observations	853		778	75	853	
Plot characteristics						
Soil type clay(yes=1)	0.263	0.441	0.260	0.293	-0.033	(-0.62)
Soil type loam(yes=1)	0.365	0.482	0.363	0.387	-0.0233	(-0.40)
Soil type sandy(yes=1)	0.047	0.212	0.049	0.027	0.0223	(-0.87)
Soil type sandy-clay loam(yes=1)	0.324	0.468	0.327	0.293	0.034	(-0.6)
No. of observations	851		776	75	851	
Village characteristics						
Distance to district headquarters (in km)	27.276	16.441	27.121	28.880	-1.759	(-0.88)
Distance to upazilla headquarters (in km)	9.201	5.319	9.082	10.440	-1.358*	(-2.12)
Distance to nearest electric board office (in km)	7.495	4.656	7.520	7.240	0.28	(-0.5)
Distance to nearest electric pump trader (in km)	9.914	76.180	10.425	4.613	5.812	(-0.63)

Distance to nearest diesel pump trader (in km)	3.904	4.142	3.898	3.967	-0.0682	(-0.14)
Distance to nearest petrol pump station (in km)	6.189	6.038	6.297	5.067	1.23	(-1.69)
Distance to the nearest rural or commercial bank (in km)	5.553	4.747	5.623	4.820	0.803	(-1.4)
Number of observations	853		778	75	853	

Source: IWMI-IFPRI Bangladesh survey (2023)

Note: 'S.D' denotes standard deviation. The above table is based on the representative sample. To produce village-level statistics, we have used the village-level module and brought it to the household-level files. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 2: Sample profile of electric pump adopters vs non-adopters, augmented sample

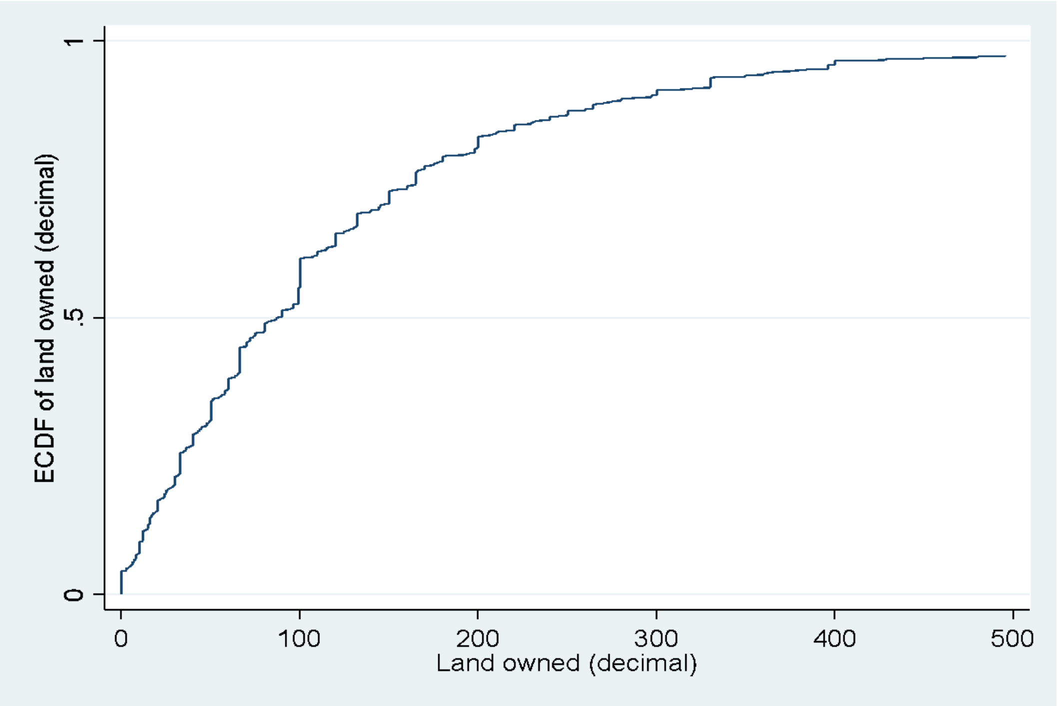
Variables	Overall		Non-adopter	Adopter	Difference(5=3-4)	T stat
HH characteristics	Mean(1)	S.D.(2)	Mean(3)	Mean(4)		
Male head of household (yes = 1)	0.992	0.090	0.995	0.988	0.00729	(-0.78)
Household head's age (in years)	49.108	11.241	47.778	50.776	-2.998*	(-2.57)
Household head's education (in years)	5.957	4.579	5.140	6.982	-1.842***	(-3.93)
Religion is Islam (yes = 1)	0.909	0.289	0.928	0.885	0.0427	(-1.42)
Primary income activity is farming (yes = 1)	0.841	0.366	0.865	0.812	0.0526	(-1.38)
Household size	4.879	1.622	4.845	4.921	-0.0758	(-0.45)
Borrowed loan (yes = 1)	0.183	0.387	0.169	0.200	-0.0309	(-0.77)
Bank account (yes = 1)	0.470	0.500	0.338	0.636	-0.298***	(-5.98)
Own smartphone (yes = 1)	0.487	0.500	0.391	0.606	-0.215***	(-4.20)
Land Ownership(in Decimals)	175.395	163.086	140.174	219.582	-79.41***	(-4.80)
No. of observations	372		207	165	372	
Plot characteristics						
Soil type clay(yes=1)	0.261	0.440	0.232	0.297	-0.0651	(-1.42)
Soil type loam(yes=1)	0.360	0.481	0.348	0.376	-0.0279	(-0.56)
Soil type sandy(yes=1)	0.073	0.260	0.101	0.036	0.0651*	(-2.42)
Soil type sandy-clay loam(yes=1)	0.306	0.462	0.319	0.291	0.0279	(-0.58)
Number of observations	372		207	165	372	
Village characteristics						
Distance to district headquarters (in km)	28.164	16.208	28.797	27.370	1.427	(-0.84)
Distance to upazilla headquarters (in km)	10.306	6.146	10.598	9.939	0.658	(-1.03)

Distance to nearest electric board office (in km)	8.792	6.103	10.035	7.233	2.801***	(-4.51)
Distance to nearest electric pump trader (in km)	43.847	196.294	75.763	3.806	71.96***	(-3.57)
Distance to nearest diesel pump trader (in km)	3.315	3.923	3.199	3.460	-0.261	(-0.64)
Distance to nearest petrol pump station (in km)	6.324	5.723	6.907	5.592	1.315*	(-2.21)
Distance to the nearest rural or commercial bank (in km)	6.374	6.111	7.467	5.002	2.464***	(-3.94)
Number of observations	372		207	165	372	

Source: IWMI-IFPRI Bangladesh survey (2023)

Note: This table is based on the augmented sample. To produce village-level statistics, we have used the village-level module and brought it to the household-level files. *p < 0.1, **p < 0.05, ***p < 0.01.

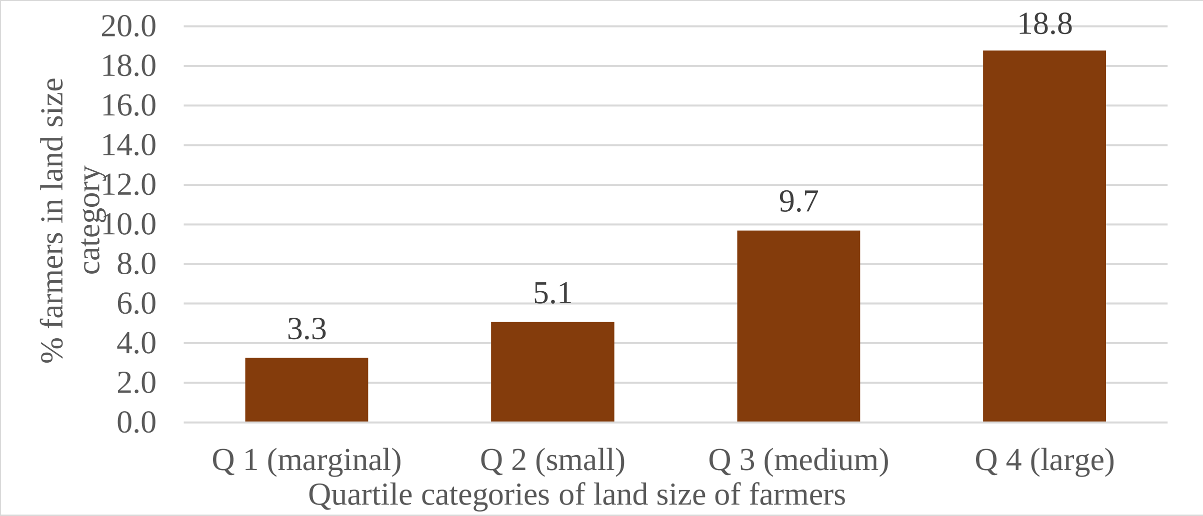
Figure 3: Land ownership cumulative distribution curve



Source: IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the representative sample.

Figure 4 : Electric pump ownership, by land size



Source: IWMI-IFPRI Bangladesh survey (2023)

Note : The analysis is based on the representative sample.

Figure 5: Sample network map distribution (village: Madhupur, district : Thakurgaon),

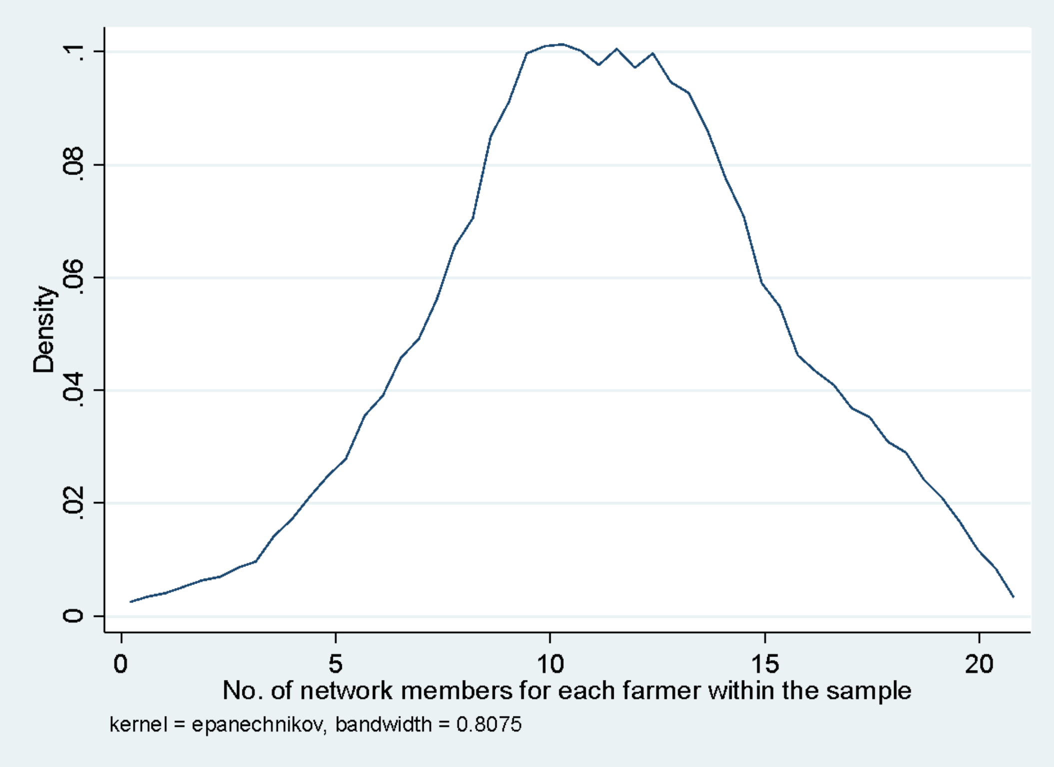
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20
F1		N	N	N		N	N	N	N	N										
F2	N		N	N		N	N	N	N	N										
F3	N	N		N		N	N	N	N	N										
F4	N	N	N			N	N	N	N	N										
F5		N	N	N		N	N	N	N	N	N									
F6	N	N	N	N			N	N	N	N										
F7	N	N	N	N		N		N	N	N										
F8	N	N	N	N			N		N	N										
F9	N		N	N		N	N	N		N										
F10	N		N	N		N	N	N												
F11		N	N	N	N	N	N		N	N										
F12													N	N	N	N	N	N	N	N
F13												N		N	N	N	N	N	N	N
F14												N	N		N	N	N	N	N	N
F15												N	N	N		N	N	N	N	N

F16												N	N	N	N		N	N	N	N
F17												N	N	N	N	N		N	N	N
F18												N	N	N	N	N	N		N	N
F19												N	N	N	N	N	N	N		
F20												N	N	N	N	N	N	N		

Source: IWMI-IFPRI Bangladesh survey (2023)

Code	Meaning
	Pump owner(others)
	Electric pump owner
	Not a pump owner

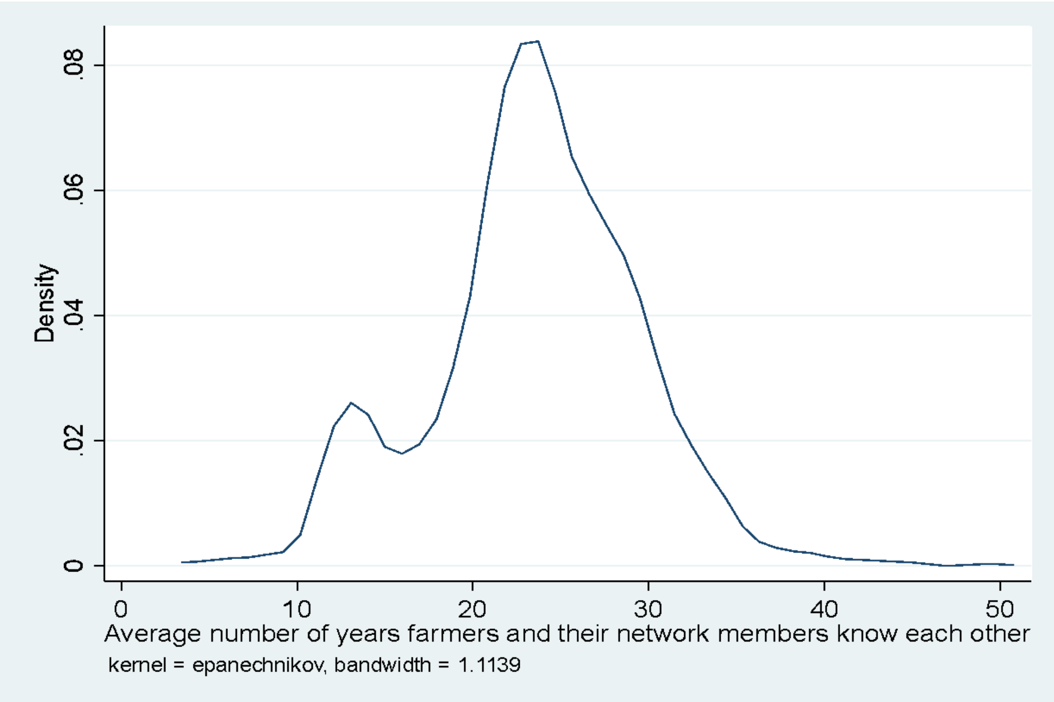
Figure 6: Number of network members for each farmer within the sample



Source: IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the whole sample.

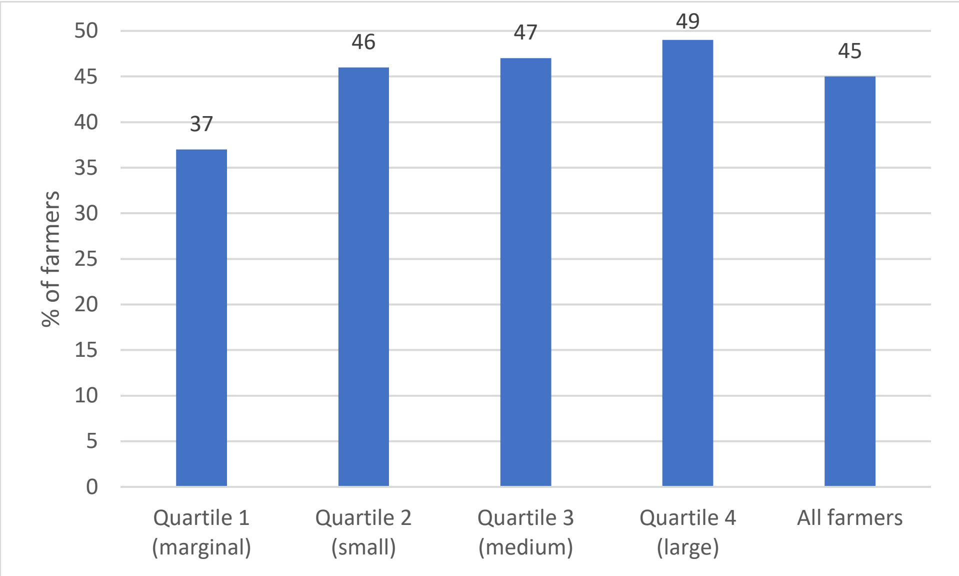
Figure 7: Number of years farmers and their network members know each other



Source: IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the whole sample.

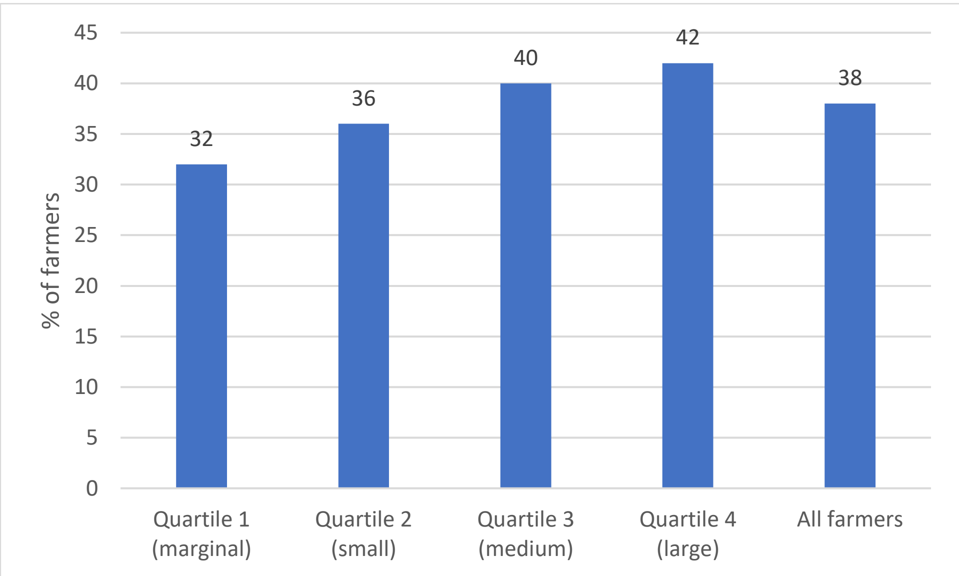
Figure 8: Percentage of farmers who take advice on agriculture-related matters from their network members



Source: IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the whole sample.

Figure 9 : Percentage of farmers take advice on choice of energy for irrigation from their network members



Source: IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the whole sample.

Table 3: Network effects of electric pump adoption

Explanatory variables	Farmer owns electric pump(yes =1)	Farmer owns electric pump(yes =1)
Network member owns electric pump (yes=1)($\gamma (eq\ 1)$	0.028*** (0.009)	0.032*** (0.009)
Share of farmers who own electric pumps at the village level in 2021	Yes	Yes
HH characteristics	Yes	Yes
Network member characteristics	Yes	Yes
Village characteristics	Yes	Yes
District fixed effect	Yes	Yes
Keeping observations only when HH adopts electric pumps after their network members		Yes
R-Squared	0.24	0.21
Number of observations	1208	1149

Source: Author's estimation based on the IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the whole sample. The specification has been provided in the text (ref. equation 1) The dependent variables takes value 1 if farmer owns electric pump and otherwise zero. The key independent variable of interest takes value 1 if at least one network member owns an electric pump and otherwise zero. The characteristics of the household and its network members comprise the following: gender, age, education,, religion, primary income activity in farming, household size, access to loans, access to bank account, ownership of a smartphone, land ownership (measured in decimals), reliance on rainfed agriculture, soil composition including clay, loam, sandy, and sandy-clay loam. The village characteristics encompass Distance (in kilometers) : district headquarters , upazilla headquarters, nearest electric board office, nearest electric pump trader, nearest diesel pump trader, nearest petrol pump station, and nearest rural or commercial bank. In column 2, we keep those observations only when HH adopts electric pumps after their network members. Robust standard errors in the parenthesis. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 4 : Network effects of water buyer's accessing irrigation water through electric pumps

Explanatory variables	Farmer buys irrigation through electric pump (yes=1)	Farmer buys irrigation through electric pump (yes=1)
Network member owns electric pump (yes=1) $\gamma(eq\ 2)$	0.027** (0.009)	0.027** (0.01)
Share of farmers who own electric pumps at the village level in 2021	No	0.027 (0.268)
Household Characteristics	Yes	Yes
Network member Characteristics	Yes	Yes
Village characteristics	Yes	Yes
District fixed effects	Yes	Yes
R-Squared	0.26	0.26
Number of observations	681	681

Source: Author's estimation based on the IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the representative sample. The specification has been provided in the text (ref. equation 2)The dependent variables takes value 1 if farmer buy irrigation through electric pump and otherwise zero. The key independent variable of interest takes value 1 if at least one network member owns an electric pump and otherwise zero. The characteristics of the household and its network members comprise the following: gender, age, education,, religion, primary income activity in farming, household size, access to loans, access to bank account, ownership of a smartphone, land ownership (measured in decimals), reliance on rainfed agriculture, soil composition including clay, loam, sandy, and sandy-clay loam. The village characteristics encompass Distance (in kilometers) : district headquarters , upazilla headquarters, nearest electric board office, nearest electric pump trader, nearest diesel pump trader, nearest petrol pump station, and nearest rural or commercial bank. Robust standard errors in the parenthesis. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 5: Intra-class network effects of water buyer's accessing irrigation water through electric pumps

Explanatory variables	Farmer buys irrigation through electric pumps (yes=1)	Farmer buys irrigation through electric pumps (yes=1)
Number of farmers with the same land class in the network own electric pumps $\gamma(eq\ 3)$	0.040** (0.013)	0.037** (0.013)
Share of farmers who own electric pumps at the village level in 2021	No	0.209 (0.257)
Household characteristics	Yes	Yes
Network member characteristics	Yes	Yes
Past adoption		
Village characteristics	Yes	Yes
District fixed effects	Yes	Yes
R-Squared	0.26	0.26
Number of observations	681	681

Source: Author's estimation based on the IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the representative sample. The specification has been provided in the text (ref. equation 3). The dependent variables takes value 1 if farmer buy irrigation through electric pump and otherwise zero. The key independent variable of interest is the number of network members having the same land class as farmer had. The characteristics of the household and its network members comprise the following: gender, age, education,, religion, primary income activity in farming, household size, access to loans, access to bank account, ownership of a smartphone, land ownership (measured in decimals), reliance on rainfed agriculture, soil composition including clay, loam, sandy, and sandy-clay loam. The village characteristics encompass Distance (in kilometers) : district headquarters , upazilla headquarters, nearest electric board office, nearest electric pump trader, nearest diesel pump trader, nearest petrol pump station, and nearest rural or commercial bank. Robust standard errors in the parenthesis. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 6: Inter-class network effects of water buyer's accessing irrigation water through electric pumps

Explanatory variables	Farmer buys irrigation through electric pumps (yes=1)	Farmer buys irrigation through electric pumps (yes=1)
Number of farmers with different land class in the network own electric pumps $\gamma (eq\ 4)$	0.019** (0.008)	0.016** (0.008)
Share of farmers who own electric pumps at the village level in 2021	No	0.161 (0.264)
Household characteristics	Yes	Yes
Network member characteristics	Yes	Yes
Village characteristics	Yes	Yes
District fixed effects	Yes	Yes
Sub-district fixed effects		
R-Squared	0.255	0.255
N	681	681

Source: Author's estimation based on the IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the representative sample. The specification has been provided in the text (ref. equation 4) The dependent variables takes value 1 if farmer buy irrigation through electric pump and otherwise zero. The key independent variable of interest is the number of network members having the different land class as farmer had. The characteristics of the household and its network members comprise the following: gender, age, education,, religion, primary income activity in farming, household size, access to loans, access to bank account, ownership of a smartphone, land ownership (measured in decimals), reliance on rainfed agriculture, soil composition including clay, loam, sandy, and sandy-clay loam. The village characteristics encompass Distance (in kilometers) : district headquarters , upazilla headquarters, nearest electric board office, nearest electric pump trader, nearest diesel pump trader, nearest petrol pump station, and nearest rural or commercial bank. Robust standard errors in the parenthesis. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 7: Heterogeneity in Intra-class network effects of water buyer's accessing irrigation water through electric pumps

Explanatory variables	Farmer buys irrigation through electric pumps (yes=1)	Farmer buys irrigation through electric pumps (yes=1)
Number of farmers with same land class in the network own electric pumps $\gamma(eq\ 5)$	0.052** (0.021)	0.047** (0.021)
Large farmer(yes=1)	0.019 (0.054)	0.018 (0.054)
Number of farmers with same land class in the network own electric pumps*Large farmers	-0.023 (0.026)	-0.019(0.026)
Share of farmers who own electric pumps at the village level in 2021	No	0.194 (0.259)
Household characteristics	Yes	Yes
Network member characteristics	Yes	Yes
Village characteristics	Yes	Yes
District fixed effects	Yes	Yes
R-Squared	0.257	0.258
N	681	681

Source: Author's estimation based on the IWMI-IFPRI Bangladesh survey (2023)

Note: The analysis is based on the representative sample. The specification has been provided in the text (ref. equation 5).The dependent variables takes value 1 if farmer buy irrigation through electric pump and otherwise zero. The key independent variable of interest is interaction of the number of network members having same land class as farmer had and large farmer dummy. Large farmer is defined as the top quartile defined based on the land owned. The characteristics of the household and its network members comprise the following: gender, age, education,, religion, primary income activity in farming, household size, access to loans, access to bank account, ownership of a smartphone, land ownership (measured in decimals), reliance on rainfed agriculture, soil composition including clay, loam, sandy, and sandy-clay loam. The village characteristics encompass Distance (in kilometers) : district headquarters , upazilla headquarters, nearest electric board office, nearest electric pump trader, nearest diesel pump trader, nearest petrol pump station, and nearest rural or commercial bank. Robust standard errors in the parenthesis. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 8 : Heterogeneity in Inter-class network effects of water buyer's accessing irrigation water through electric pumps

Explanatory variables	Farmer buys irrigation through electric pumps (yes=1)	Farmer buys irrigation through electric pumps (yes=1)
Number of farmers with different land classes in the network own electric pumps $\gamma(eq\ 6)$	0.017* (0.008)	0.014* (0.008)
Large farmers (yes=1)	-0.014 (0.058)	-0.014 (0.058)
Number of farmers with different land classes in the network own electric pumps* Large farmers	0.047* (0.028)	0.046* (0.028)
Share of farmers who own electric pumps at the village level in 2021	No	0.153 (0.265)
Household characteristics	Yes	Yes
Network member characteristics	Yes	Yes
Village characteristics	Yes	Yes
District fixed effects	Yes	Yes
R-Squared	0.257	0.257
N	681	681

Note: The analysis is based on the representative sample. The specification has been provided in the text (ref. equation 6). The dependent variables takes value 1 if farmer buy irrigation through electric pump and otherwise zero. The key independent variable of interest is interaction of the number of network members having different land class as farmer had and large farmer dummy. Large farmer is defined as the top quartile defined based on the land owned. The characteristics of the household and its network members comprise the following: gender, age, education,, religion, primary income activity in farming, household size, access to loans, access to bank account, ownership of a smartphone, land ownership (measured in decimals), reliance on rainfed agriculture, soil composition including clay, loam, sandy, and sandy-clay loam. The village characteristics encompass Distance (in kilometers) : district headquarters , upazilla headquarters, nearest electric board office, nearest electric pump trader, nearest diesel pump trader, nearest petrol pump station, and nearest rural or commercial bank. Robust standard errors in the parenthesis. *p < 0.1, **p < 0.05, ***p < 0.01.

Appendix Tables

Table A1: Sample profile of network members

Network Profile characteristics	Overall		Representative sample		Augmented sample	
	Mean(1)	S.D.(2)	Mean(3)	S.D.(4)	Mean(3)	S.D.(4)
Male head of household (yes = 1)	0.99	0.04	0.98	0.04	0.99	0.04
Household head's age (in years)	47.48	4.23	47.40	4.28	47.69	4.09
Household head's education (in years)	5.23	2.04	5.26	1.97	5.16	2.19
Religion is Islam (yes = 1)	0.89	0.24	0.88	0.25	0.91	0.22
Primary income activity is farming (yes = 1)	0.79	0.19	0.78	0.19	0.80	0.19
Household size	4.62	0.75	4.59	0.76	4.69	0.70
Borrowed loan (yes = 1)	0.19	0.19	0.19	0.18	0.18	0.19
Bank account (yes = 1)	0.31	0.23	0.31	0.23	0.32	0.24
Own smartphone (yes = 1)	0.36	0.20	0.36	0.20	0.37	0.20
Land Ownership(in Decimals)	109.88	51.68	105.44	51.66	120.14	50.33
Own electric pump (yes = 1)	1.66	2.00	1.44	1.79	2.17	2.34
Own diesel pump (yes = 1)	1.17	1.88	0.97	1.68	1.62	2.21
N	1210		845		365	

Source: IWMI-IFPRI Bangladesh survey (2023)

Appendix Table A2 : Adoption of electric pumps in Bangladesh, 2019

Variable	Figures	Source
Agricultural household	1,68,81,757	Agriculture Census 2019
Household have electric pumps and electricity connection	398753	Bangladesh Rural Electrification Board
Electric pump adoption (%)	2.36%	Authors calculation

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