Water, Spillovers and Free Riding: Provision of Local Public Goods in a Spatial Network

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Abstract

When public goods are provided locally, investments may be made strategically in the presence of free riding and spillover effects between neighboring communities. I estimate the costs of fragmented provision of water pumps in rural Tanzania by structurally estimating a spatial network model of decentralized pump maintenance decisions. I identify strategic interactions by using exogenous variation in the similarity of pumps as a shifter in the strength of spillovers that are possible between them. Estimation of the model combines maximum simulated likelihood with a clustering algorithm that partitions the data into geographic clusters and allows for multiple equilibria. The results show that free riding and pump maintenance spillovers are important factors in explaining pump functionality. I estimate that standardization to a single pump technology to increase maintenance spillovers would increase pump functionality rates by 6 percentage points. Water collection fees discourage free riding and would increase pump functionality rates by 11 percentage points if adopted universally.

Keywords: local public goods, spatial network, water, spillovers, free rider problem.

JEL Classification: H41, L14, O13

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1 Introduction

Decentralized provision of local public goods can be strategic. If agents free ride on public goods in nearby communities, or if there are spillovers in the costs of providing them, provision of a local public good in one area can affect the incentives to invest in a similar public good in a nearby area. This is particularly relevant in developing countries, where non-governmental organizations often provide public goods alongside local and national governments. I analyze fragmented provision of water in rural Tanzania, where more than 500 organizations have installed hand-powered water pumps and where communities make decentralized pump maintenance decisions. I show that a lack of coordination between organizations installing water sources, combined with strategic pump maintenance decisions of communities, is costly: it decreases the functionality rate of pumps and lowers rates of child survival and school attendance.

I develop and structurally estimate a spatial network model to explain the equilibrium pump maintenance decisions made by rural communities in Tanzania in the presence of spillovers and free riding between nearby communities, given the installation decisions made by water practitioners.[1] I use tools from network economics and industrial organization to contribute towards a better understanding of what determines pump functionality. This paper also includes methodological innovations: first by using a novel empirical strategy to identify network effects, and second by using a clustering algorithm to help overcome multiplicity in the estimation of a network game with binary action space.

Distinguishing social interactions from correlated effects is a major challenge in estimating network models (Manski [1993], Brock and Durlauf [2001], Brock and Durlauf [2007], Bramoullé et al. [2009], De Giorgi et al. [2010]).[2] My identification strategy is motivated by two key facts: pumps are more likely to be functional if there are more pumps of the same technology nearby, but are less likely to be functional if there are more non-pump water sources nearby. These spatial correlations in pump functionality may be driven by either strategic interactions in pump maintenance

[1] I make a conceptual distinction between free riding and spillover effects. In this context, individuals can typically access nearby water sources at the same terms as the community maintaining them, allowing them to free ride on that community's pump maintenance expenditure. Spillover effects occur when the maintenance of one pump affects the costs of maintaining a similar nearby pump.

[2] See Blume et al. [2010] or de Paula [2016] for a recent review of this literature.

or spatially correlated shocks or unobserved variables. However, spatially correlated shocks must be technology-specific to explain these two motivating facts, for example if local physical conditions affect both the technology of pump installed and the probability that it is functional, and I do not find quantitative or qualitative evidence to support such mechanisms. The evidence instead points towards a second explanation, that there are two counter-acting social interactions occurring: free riding and positive spillovers in the maintenance of pumps. When there are many pumps of the same technology nearby, the positive spillover effects are larger, and pumps are more likely to work. However, maintenance spillovers are small when a pump is close to many non-pump water sources, the free riding effect dominates and the pump is less likely to be functional.

To identify spillover effects in the cost of pump maintenance, I assume that the strength of spillovers between neighboring communities depends on exogenous variation in whether they have the same technology of pump, but spatially correlated shocks (e.g. weather) are independent of technology. Evidence from reduced form analysis and a survey of water sector experts in Tanzania and other developing countries supports this assumption. To identify free riding in the maintenance of pumps, I use variation in the availability of community taps, which are typically managed by a centralized authority rather than a rural community, because of their higher costs.[3]

I estimate a structural spatial network model to allow me to disentangle the counter-acting free riding and spillover effects, to test the mechanisms that they work through and to estimate the equilibrium effects of proposed policy changes.[4] In the model, decentralized communities decide whether to maintain their pumps, given the actions of their neighbors and the existing network of installed water sources. The model incorporates free riding by allowing a community to use a neighbor's water source if their own pump is non-functional, with the cost of access depending on the distance they must travel and the characteristics of the alternative water source. Spillovers occur through a community's cost of maintaining its pump, which depends on the maintenance decisions of its neighbors: for each neighbor that maintains its water

[3]There are two main types of improved water source in Tanzania: hand-powered pumps which draw groundwater, and taps ('community standpipes') which typically use a gravity-fed supply of surface water from an upland river or spring, transported to the community by pipes.

[4]Reduced form analysis can only estimate the net effect of spillover and free riding effects of nearby water sources, and cannot evaluate the equilibrium effects of counterfactual policies.

source, the cost of maintenance decreases, and this discount is larger for closer, more similar water sources. These maintenance spillovers may occur through a number of mechanisms, including the creation of markets for spare parts, skill development, or sharing of maintenance costs and information. Health and education outcomes depend on communities' maintenance decisions, which allows me to estimate the effects of pump functionality on child survival and school attendance rates.

I estimate the model using new geo-coded administrative data from Tanzania, which contains rich information on all public rural water points in the country. I supplement this data with information from the National Panel Survey (2007-2008), the Population and Housing Census (2002, 2012), groundwater variables from the British Geological Survey (2012) and a survey of 32 water sector experts that I conducted to inform my modeling decisions and help understand the mechanisms driving the results. Estimation of a network game with binary action space is challenging, because community choices are not independent of each other, and because multiple equilibria are possible. To address these challenges, I use a clustering algorithm to partition the water sources into geographic clusters, and assume that each cluster plays an independent game. In each cluster, I calculate the probability that each action profile is an equilibrium, and estimate the likelihood of the observed action profile by using a probabilistic equilibrium selection rule.[5] I estimate the model by maximum simulated likelihood.

The results indicate that free riding and pump maintenance spillovers are important factors in explaining variation in pump functionality. In particular, positive spillovers are stronger between nearby communities with pumps of the same technology, and I estimate that standardization of pumps to a single technology would increase the pump functionality rate by 6 percentage points. I also estimate that communities free ride on neighboring communities' water sources, but that free riding decreases when users have to pay to collect water from an alternative source. I estimate that

[5]The definition of geographic clusters imposes a restriction on the interactions that the model allows. There is therefore an inherent tradeoff in the choice of the number and size of clusters that are defined. The definition of larger clusters allows more interactions between neighboring communities, but increases the computational burden required to solve the network game. In a cluster of size n, we must consider 2^n possible equilibrium outcomes. Further, each cluster represents a single 'observation', an outcome of a network game. Defining larger clusters therefore reduces the number of observations of the network game, and reduces the power of the estimation. I set the maximum cluster size to 10, and define 3431 clusters in the data.

increasing the proportion of water sources that charge user fees from 37 percent to 100 percent would increase the pump functionality rate by 11 percentage points. Finally, I estimate that this increased functionality of pumps would have a modest positive effect on child survival and school attendance. The increase in school attendance is larger for girls, who traditionally collect water, than for boys.

This paper draws on and contributes to a new literature analyzing the provision of public goods by multiple communities in a network. Most of this research is theoretical and has characterized Pareto efficiency of equilibria (Elliott and Golub [forthcoming]), and uniqueness of equilibria (Bramoullé, Kranton, and D'Amours [2014], Allouch [2015]). Acemoglu, García-Jimeno, and Robinson [2015] apply these uniqueness results to estimate that local investments in state capacity in Colombia are strategic complements. However, these uniqueness results rely on a continuous action space and in my empirical context the decision to maintain a pump is binary, so I require a fundamentally different modeling and estimation approach that allows for multiple equilibria. For this, I exploit the spatial structure of the data to partition observations into clusters, and calculate the likelihood of the observed action profile in each cluster using a probabilistic equilibrium selection rule.[6] My empirical context also allows for a novel approach to identify spillover effects, by using exogenous variation in whether communities have the same technology of pump as a shifter in the strength of spillovers that are possible between them.

This paper also contributes to previous research on decentralized provision of public goods (Khwaja [2004], Lipscomb and Mobarak [2016], Casey [2018]) by estimating the costs of fragmented provision by state and non-state actors. Although the modeling framework developed in this paper is particularly relevant to developing countries, where the provision of public goods is fragmented, it might also be applied to the local provision of public goods in developed countries, such as law and order, transport infrastructure, public schools or the reduction of pollution. Finally, this paper also

[6] Bajari, Hong, and Ryan [2010] and de Paula [2013] give an overview of the use of equilibrium selection mechanisms, and Todd and Wolpin [2018] use one in their estimation. The model is also similar to entry games in the industrial organization literature, where it is common to use a game with complete information and consider Nash equilibria in pure strategies (Berry [1992], Mazzeo [2002], Tamer [2003], Andrews et al. [2004], Jia [2008], Ciliberto and Tamer [2009]). An alternative approach would be to model this as an incomplete information game, consider Bayes-Nash equilibria and estimate the model using non-parametric conditional choice probabilities (Hotz and Miller [1993]). I discuss the reasons for my modeling approach in section 5.

relates to the literature on free provision vs cost sharing of development interventions (Kremer and Miguel [2007], Dupas [2014]). Although I do not fully analyze the costs and benefits of free provision, and do not have strong causal identification for the effects of user fees, I do highlight a new channel through which cost sharing may have an effect, by reducing free riding in the provision of public goods.

The remainder of this paper is structured as follows. Section 2 provides more detail on the provision of water in rural Tanzania and how this relates to my empirical approach, then section 3 describes the main sources of data. Section 4 establishes key facts about spatial correlations in the functionality of water pumps, and how I use these to identify spillover effects in the network model. Section 5 describes the model, while section 6 gives an overview of the estimation procedure, and how I identify each of the model parameters. Section 7 presents the model estimates, model fit, and evaluates potential policies to improve water provision and the effects this may have on health and education outcomes. Section 8 concludes.

2 Water supply in rural Tanzania

Globally, an estimated one billion people rely on hand-powered pumps as their main water source (Carter, Harvey, and Casey [2010]), but functionality rates are often low, with about one third of pumps broken across sub-Saharan Africa.[7] In rural Tanzania, handpumps have a functionality rate of 63 percent, while only 46 percent of people have access to an improved source of drinking water within 1km of their home (JMP [2015]).[8] This lack of water access is costly: provision of water has been estimated to decrease poverty (Sekhri [2014]), improve health (Jalan and Ravallion [2003], Galiani et al. [2005], Kremer et al. [2011], Ashraf et al. [2017]), increase welfare (Devoto et al. [2012]) and increase school attendance, particularly for girls, who are often responsible for water collection in sub-Saharan Africa (UNDP [2006]).

There are two main types of improved water source in Tanzania: hand-powered pumps which draw groundwater and taps which typically use a gravity-fed supply of surface water from an upland river or spring, transported to the community by pipes. There

[7] Figures A18 to A21 in section A.2 of the Online Appendix show pictures and technical details of the four most common technologies of hand-powered pumps in Tanzania.

[8] According to the classification used by WHO and UNICEF an 'improved' source of drinking water includes piped water, a public tap or standpipe, a handpump, a protected spring or rainwater. 'Unimproved' sources include an unprotected spring, an unprotected dug well and surface water.

are four common handpump technologies in Tanzania: Afridev, India Mark II, SWN 80 and Nira.[9] Each technology can be installed on either a hand dug or machine drilled borehole, and uses a cylinder and plunger to lift groundwater to the surface. However, each technology has a different design, with different internal mechanisms which require different parts.

Provision of handpumps in Tanzania has two main stages: installation and maintenance. Pumps are installed by a large number of 'water practitioners' (local or national government, domestic or international NGOs and aid agencies), with more than 500 installing organizations listed in the data.[10] There is very little coordination between these installing organizations, and they typically install their preferred technology without accounting for community characteristics or preferences.[11]

In rural Tanzania, as in most developing countries, the local community is responsible for the maintenance and repair of handpumps, which reflects the perceived failure of centralized water provision in Tanzania and an international trend towards 'community-based management' (CBM) of water pumps.[12] 'Water point committees' are appointed by the community to maintain the pump, and are typically made up of five to ten women, who replace pump components as they wear out, and carry out repairs if the pump breaks down.[13] 35 percent of pumps require users to pay to collect water and this decision is typically made jointly by the installing organization and water point committee.[14]

[9]For pictures of the pumps, and more technical details on the four technologies, see section A.2 of the Online Appendix.

[10]The capital expenditure required for installation is unaffordable for the vast majority of beneficiary communities, at $20 to $61 per person (IRC [2012]).

[11]See survey evidence in Figure A29 in section A.4 of the Online Appendix.

[12]The policy of decentralization was started with the Tanzania National Water Policy of 1991, and has continued with the Tanzania National Water Policy [2002] and the Tanzania National Water Sector Development Strategy [2008]. The Tanzania National Water Policy [2002] emphasized that communities are responsible for 'full cost recovery for operation and maintenance of services as opposed to the previous concept of cost sharing'. Ongoing costs are estimated at $3 to $6 per person per year (IRC [2012]).

[13]There are many names given to these committees, in Tanzania and other countries. Official Tanzanian government policy refers to 'Community Owned Water Supply Organizations' (COWSOs), Water User Associations and Water Consumer Associations, while other names, including 'water user groups' and 'village water committees', are used in various places. For consistency, I will use 'water point committees', which is commonly used in different countries.

[14]See survey evidence in Figure A34 in section A.4. Payments are usually made per bucket, per month or per year.

The causes of widespread low pump functionality rates are varied and complex. Qualitative studies emphasize a number of causes, including social, institutional and economic factors, as well as hydrological and engineering factors (Prokopy [2005], Schweitzer and Mihelcic [2011], WaterAid [2011], Harvey and Reed [2004]). Statistical analyses estimate that system age, distance to the country's capital and user fee collection are consistent predictors of pump functionality (Foster [2013]) and find strong effects of management and the institutional environment (Fisher et al. [2015]).[15]

My research corroborates these general findings, and presents new evidence that maintenance of pumps is strategic, with strong interdependence between neighboring communities.[16] In particular, I find evidence of free riding between nearby communities, and of maintenance cost-reduction spillovers between communities with pumps of the same technology. These positive maintenance spillovers may occur through a number of channels for which I find evidence in my survey of water sector experts.[17] Neighboring communities may share some costs of maintenance, for example the costs of obtaining spare parts, tools and skilled labor, and areas with many pumps of the same technology are more likely to develop markets for these inputs. Markets in these poor rural settings are often non-existent or thin, so can be affected by the actions of individual communities. Communities may also share information about, or cooperate in, the maintenance of pumps (Pond and Pedley [2011]).

The potential benefits of standardizing pump technology are well known in the water

[15] Foster [2013] uses logistic regressions to estimate predictors of pump functionality in Liberia, Sierra Leone and Uganda. In all three countries, pumps are more likely to be functional if they are closer to the capital, are more recently installed or charge user fees. Other pump and community characteristics predicted pump functionality in one or two of the countries studied. Fisher et al. [2015] uses a Bayesian network model to estimate the effect of different variables, and the synergy between them, in explaining pump functionality.

[16] A number of my findings are consistent with these previous papers. First, descriptive analysis of the data shows that 28 percent of breakdowns in Tanzania are due to hardware problems that cost less than $10 to fix, and 15 percent of pumps are non-functional primarily because they are no longer used, suggesting that economic incentives to maintain a pump are an important determinant of their sustainability (see Figure A22 and Table A2 in section A.2 of the Online Appendix for more details on reasons given for breakdown in the data). Responses to my survey show that water experts believe that a wide variety of factors are important in explaining pump functionality (see Figure A32 in section A.4). Results from the reduced form analysis are consistent with the findings of Foster [2013] and Fisher et al. [2015] (section 4), as are the model estimates (section 7).

[17] My survey of water sector experts indicates that standardization of technologies is likely to increase cooperation and cost sharing between communities, and the availability of spare parts and pump mechanics. See Figure A33 in section A.4 of the Online Appendix.

sector. Since 1982, fifteen countries in sub-Saharan Africa have attempted formal standardization with the support of UNICEF (MacArthur [2015]).[18] The Tanzania National Water Policy [2002] attempted to initiate standardization to two technologies in Tanzania (Nira and SWN 80) but this has had very little impact on the proportion of Nira and SWN 80 pumps installed in Tanzania, which has declined since 2002.[19]

Access to water is often a key part of development strategies, and recent economic research has estimated effects on health, poverty and education.[20,21] In Tanzania, where girls are traditionally responsible for water collection, school attendance is 12 percent higher for girls located within 15 minutes of a water source relative to those who live more than an hour away, with a much smaller effect on boys' school attendance (UNDP [2006]). Consistent with this body of evidence, I find a small but significant effect of improved water access on child mortality and school attendance, with the effect on school attendance larger for girls than boys.

3 Data

3.1 Primary data: water point mapping

The analysis focuses on administrative 'water point mapping' data collected by Geo-Data Consultants Limited on behalf of the Tanzania Ministry of Water and Irrigation.[22] The data were collected between February 2011 and June 2013 to provide a census of all mainland rural water services in the country to help determine investment

[18]Standardization efforts have attempted to decrease market fragmentation, and improve supply chains, quality of installations and communities' ability to effectively manage their pump. Potential costs of standardization include stifling of innovation, and decreased competition in manufacture (MacArthur [2015]).

[19]See Figure A1 in section A.1 of the Online Appendix.

[20]Millennium Development Goal 7.C aimed to halve the proportion of the population without sustainable access to safe drinking water and sanitation. This goal was reached globally, though approximately 45 individual countries failed to meet it (WHO, UNICEF [2014]).

[21]Sekhri [2014] estimates that access to improved water sources reduces rural poverty in India by 10-12 percent, Kremer et al. [2011] estimate a reduction of child diarrhea in Kenya by 25 percent, while Jalan and Ravallion [2003] find that health improvements in India are largest in families with more educated mothers. Galiani, Gertler, and Schargrodsky [2005] find a significant effect of water access on child mortality in Argentina, with the effect largest for children in poorest areas, and Devoto et al. [2012] find evidence of welfare increases in Morocco, though no effect on health or income.

[22]The data can be accessed at `http://wpm.maji.go.tz/`, and many similar datasets are available as part of the Water Point Data Exchange, at `https://www.waterpointdata.org/`

priorities.[23] Enumerators used hand-held computers to collect detailed information about each water point and the community using it, including: GPS coordinates, functional status, the type of water source (tap or pump), the technology of pumps, the type of hole the pump is installed on, how the water source is managed, when the water source was installed, whether users pay to use it, and (when relevant) the date of last breakdown and repair.

Table 1 presents summary statistics for key variables in the data. As noted in section 2, there are four common handpump technologies in Tanzania, and they account for 87 percent of pumps. 89 percent of handpumps are managed by a water point committee (community based management), and about 35 percent of these regularly collect user fees. The observations are plotted on a map of Tanzania in Figure 1, with the colors of the markers corresponding to the functionality of water sources. Water sources are often installed in clusters, with some clusters having a greater variety of type and technology than others (see Figure A2 in the Online Appendix).

3.2 Additional data

I use a number of secondary data sources in the analysis, to control for community characteristics and physical variables that are not observed in the water point mapping data, and to estimate the effect of pump functionality on health and education outcomes. I use the Tanzania Population and Housing Census [2002] to control for additional community and demographic characteristics that might help explain pump functionality in the reduced form analysis, and the 2012 census to estimate the effect of pump functionality on health and education outcomes in the model.[24] I also use detailed community information from the Tanzania National Panel Survey [2008-09] to test whether certain technologies of pump are more likely to be installed in communities with different characteristics.

[23] A 'pilot' water point mapping exercise was carried out between 2005 and 2008 by three international NGOs (WaterAid, Engineers Without Borders and SNV), and mapped water sources in 42 of 132 districts. Other pilot mapping exercises were carried out by Plan International, Concern Worldwide, and AMREF, an African health charity.

[24] The timing of these censuses works well for the analysis: the 2002 census provides plausible explanatory variables for patterns of pump functionality, while the 2012 census was collected at a similar time to the water point mapping data and therefore provides good measures of outcomes to use in the model.

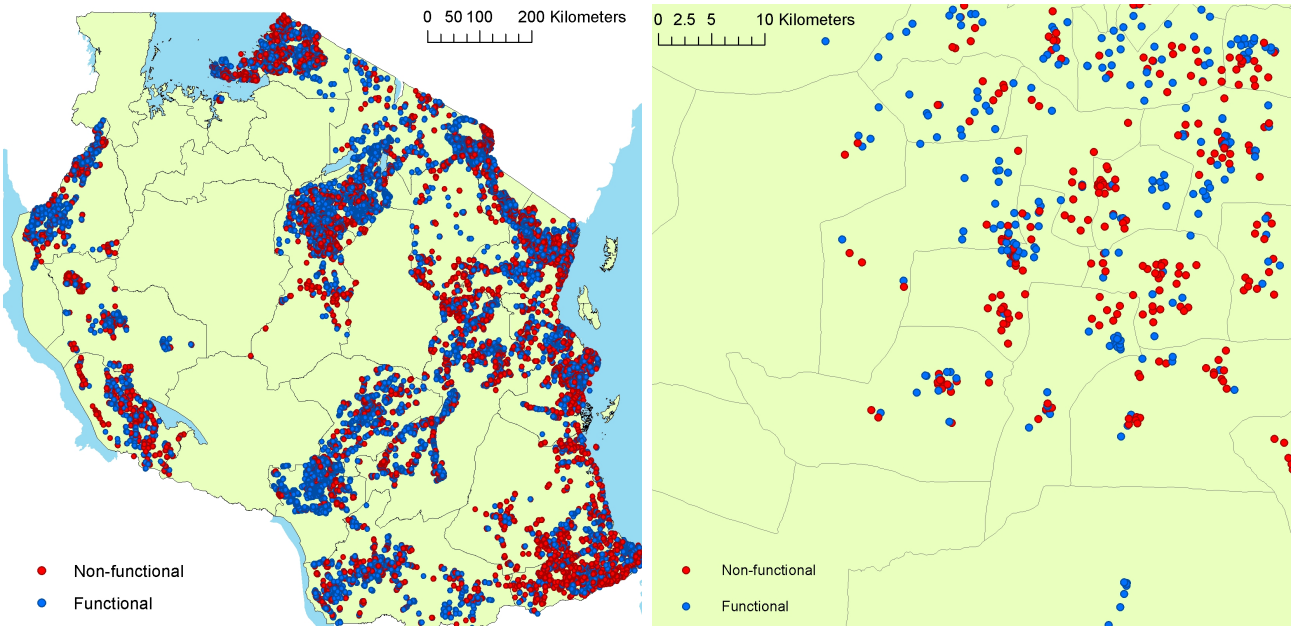
Table 1: Summary statistics, water point mapping data. Key variables in the sample used for reduced form analysis.

	Observations	Percent of obs.	Functionality rate
All water sources	43,441	100%	61.5%
Water source type			
Tap/standpipe	27,776	63.9%	68.3%
Hand pump	10,667	24.6%	62.6%
Other	4,998	11.5%	21.8%
Hand pump technology			
Afridev	1,176	11.0%	69.1%
India Mark II	2,138	20.0%	62.2%
SWN 80	2,722	25.5%	63.1%
Nira/Tanira	3,214	30.1%	67.1%
Other	1,417	13.3%	46.5%
Hand pump hole type			
Machine drilled borehole	3,195	30.0%	60.8%
Hand drilled borehole	505	4.7%	63.8%
Hand dug shallow well	6,775	63.5%	63.6%
Other	192	1.8%	54.7%
Hand pump management			
CBM	9,524	89.3%	62.4%
Parastatal	201	1.9%	74.6%
Private	493	4.6%	55.6%
Other	449	4.2%	47.0%

Other variables	Observations	Mean	Std. dev.
Hand pumps			
Age of pump at record (years)	10,667	12.69	9.50
Pay for use dummy	10,667	0.35	0.48
Non-pump water sources			
Age of water source at record (years)	32,774	16.44	13.26
Pay for use dummy	32,774	0.49	0.5

It is important to control for physical variables that may affect pump functionality, in particular the local availability of groundwater. For this I use data from the British Geological Survey, which has three groundwater variables for the whole of Africa at a 5km resolution. The dataset is constructed using information on geology, geomor-

Figure 1: Location and functionality of water sources in Tanzania. Water point mapping data, Tanzania (2013).



Notes: The left hand side image shows the water sources in the main source of data and their functionality status. The right hand side image zooms in on a specific region, Morogoro. Regions with missing data are excluded. Maps with type and technology of water source are shown in Figure A2 in section A.1.

phology and rainfall.[25] I control for its three variables in the analysis: groundwater storage (measured in mm), groundwater productivity (measured in liters per second), and depth to water (measured in meters). MacDonald et al. [2012] give a thorough overview of how they constructed the data.

I conduct a survey of water sector experts to supplement the quantitative analysis, and help understand the mechanisms driving the patterns of installation and functionality in the data. A wide variety of stakeholders with experience working in the provision of water in rural areas of low income countries responded to the survey, and I followed up with some of these for additional input. A detailed description of the survey methodology and a summary of the responses can be found in section A.4 of the Online Appendix. I refer to these results throughout the paper to help explain the quantitative analysis and justify some of my modeling assumptions.

[25]The data is constructed using direct measures of borehole yields, existing hydrogeological maps and a review of 283 aquifer summaries within 152 publications.

4 Reduced form analysis: spatial correlations in pump functionality

The reduced form analysis establishes two empirical facts about water pump functionality. First, pumps are more likely to be functional if there are more pumps of the same technology nearby. Second, pumps are less likely to be functional if there are more non-pump water sources nearby. I demonstrate these facts using the main specifications in section 4.1, and then show that these spatial correlations are robust to a large number of different specifications in section 4.2. There are multiple explanations for these correlations, and I test these in section 4.3. In section 4.4, I discuss how I use these facts to overcome the identification challenge to estimate spillover and free riding effects in a model of strategic interactions.

4.1 Main specifications

I estimate a probit model with pump functionality as the dependent variable, and the number of water sources of various types within 1.2km as the key explanatory variables of interest.[26] In particular, I am testing the correlation between pump functionality and the number of non-pump water sources, pumps of a different technology, and pumps of the same technology within 1.2km. These variables can be interpreted as a measure of degree centrality of a pump in a spatial network, where pumps are connected if they are within 1.2km of each other. I include various pump and community characteristics as explanatory variables, and present the results in Table 2.

[26]Pump functionality is equal to one if the pump produced any water at data collection, and zero otherwise. I chose 1.2km as the cutoff distance for two reasons. First, it provides good variance in the number of water sources of various types, so allows me to estimate the effect of neighboring pumps. Summary statistics for the number of water sources within 1.2km can be found in Table A1, and the histograms are given in Figure A3. Second, I estimated that approximately 50 percent of households in the Tanzania National Panel Survey [2008-09] reported that they would have to walk 1.2km or less to collect water. I run the same regressions with cutoffs of 0.7km and 1.7km as robustness tests, and discuss these in section 4.2.

Table 2: Main specifications. Probit regressions of pump functionality on the number of water sources within 1.2km, pump and community characteristics. Marginal effects reported, in percentage points.

	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.190	-0.245	-0.291	-0.346	-0.331
	(0.114)	(0.106)	(0.107)	(0.104)	(0.112)
Number of pumps, diff tech within 1.2km	-0.437	0.0822	0.0957	0.0222	-0.156
	(0.232)	(0.185)	(0.194)	(0.191)	(0.243)
Number of pumps, same tech within 1.2km	1.74	1.12	1.06	1.13	1.17
	(0.293)	(0.224)	(0.215)	(0.202)	(0.221)
Age at record		-0.585	-0.587	-0.556	-0.568
		(0.0835)	(0.0839)	(0.0916)	(0.0901)
Pay for use dummy (per bucket/month/year)		18.8	19.8	20.4	19.6
		(1.55)	(1.55)	(1.47)	(1.46)
Installed on hand-drilled borehole			-11.7	-11.7	-14.9
			(7.48)	(7.46)	(7.46)
Installed on machine-drilled borehole			-11.0	-10.5	-13.8
			(6.30)	(6.39)	(6.35)
Installed on shallow well			-7.03	-5.61	-7.63
			(5.65)	(5.75)	(5.72)
Water quality dummy (community perception)			2.57	3.50	3.05
			(1.85)	(1.80)	(1.81)
Managed by a parastatal organization			11.2	12.3	9.02
			(5.96)	(5.80)	(6.09)
Managed by water point committee			-6.58	-5.94	-7.87
			(5.39)	(5.43)	(5.00)
Observations	10,667	10,667	10,667	10,667	10,667
Technology dummies	No	Yes	Yes	Yes	Yes
Groundwater variables	No	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	Yes	Yes	Yes
Month of data collection dummies	No	Yes	Yes	Yes	Yes
Management type dummies	No	No	Yes	Yes	Yes
Installer fixed effects	No	No	No	Yes	Yes
Funder fixed effects	No	No	No	Yes	Yes
Population quintile dummies	No	No	No	No	Yes
Distance to major cities	No	No	No	No	Yes
Ward census variables	No	No	No	No	Yes
Psuedo R^2	0.0118	0.108	0.113	0.128	0.143

Notes: Standard errors clustered at the ward level in parentheses. Missing category for type of hole pump installed on is 'other'; there are 7 categories of payment type; 5 types of management, commercial management is omitted; dummies included for installers with >1% of pumps, (16 largest representing 60% of pumps); dummies included for funders with >1% of pumps (18 largest representing 50% of pumps); distance to the 11 largest cities; Ward census variables include gender ratio, population density, dependency ratio, total population, geographic area, population per water source, number of water sources/pumps in ward and ward nationality fractionalization.

These results show a clear negative correlation between a pump's functionality status and the number of non-pump water sources within 1.2km. The estimated marginal effect in column (5) indicates that a pump is 0.33 percentage points less likely to be functional for every additional non-pump water source within 1.2km, or 2.3 percentage points less likely to be functional for a one standard deviation increase in non-pump water sources (6.8 water sources), a significant but modest effect. The marginal effect is reasonably stable across specifications, controlling for various pump characteristics, groundwater variables, district fixed effects, installer fixed effects, and geographic variables.

There is a clear positive correlation between a pump's functionality status and the number of pumps of the same technology within 1.2km. A pump is 1.2 percentage points more likely to be functional for every additional pump of the same technology within 1.2km, or 4.5 percentage points more likely to be functional for a one standard deviation increase, a fairly large effect. The number of pumps of a different technology within 1.2km is not a significant predictor of whether a pump is functional or not, but pumps that charge user fees are about 20 percentage points more likely to be functional.[27]

4.2 Robustness tests

The main reduced form specifications show two key results: that pumps are less likely to work if there are more non-pump water sources within 1.2km, but more likely to work if there are more pumps of the same technology within 1.2km. To check the robustness of these findings, I estimate a number of other specifications (reported in full in section A.3 of the Online Appendix), and get qualitatively similar results. These two main findings are robust to changing the cutoff distance or using the distance to the nearest (working) water source of various types (rather than a

[27] The effect of user fees does not vary with the frequency of payment (per bucket, per month or per year), or the amount charged (results not reported). A number of other results from the main specifications are relevant to this and previous research. Older pumps are less likely to be functional, as we would expect. However, the rate of breakdown is close to constant in the first 20 years of a pump's life, as shown in Figure A4 in section A.1. There is weak evidence that pumps installed on boreholes are less likely to be functional, perhaps because it is harder for communities to make repairs on pumps installed on deeper holes. There is also weak evidence that pumps with a higher perceived water quality, and those managed by a parastatal organization, are more likely to work. Finally, there is strong evidence that pumps with more users are more likely to be functional, perhaps because these communities have more collective resources for repairs and maintenance.

count variable). I also show that the pump functionality rate is lower in villages and wards that have a higher degree of 'fragmentation' of type or technology of water source.[28] It is not clear from these regressions what is driving these results, but the main pattern remains, that pumps are less likely to be functional when there are fewer pumps of the same technology or more non-pump water sources nearby.

4.3 Correlated effects or social interactions?

There are two main explanations for the fact that pump functionality is positively correlated with the number of pumps of the same technology nearby, but negatively correlated with the number of non-pump water sources nearby. First, there may be spatially correlated shocks or unobservables (Manski's 'correlated effects'). However, the sign and size of the estimated coefficients in sections 4.1 and 4.2 depend upon water source type and technology, so these unobserved variables must have technology-specific effects. Second, social interactions may explain these correlations, if communities free ride on their neighbors' pumps, but also experience pump maintenance cost-reduction spillovers. I assess quantitative and qualitative evidence for a number of 'technology-specific correlated effects' that may explain these results and do not find evidence for them.[29] This section gives a brief overview of the findings (full results are in section A.5 of the Online Appendix).

The first 'correlated effects' explanation that I test is whether pump technologies are chosen based on community characteristics. For example, if pump technology A is typically installed in rich communities, and pump technology B in poor communities, and if rich communities are better able to maintain their pumps and are clustered together, then they will have the same technology and be more likely to have functional pumps, generating the positive spatial correlation seen in the data. However, the survey of water sector experts provides compelling evidence that pump technologies are not chosen based on community characteristics: in Tanzania, the preferences of

[28] The administrative divisions in Tanzania are broken down as follows: 26 regions, containing a total of 132 districts, with further sub-divisions into wards, villages and sub-villages. I calculate fragmentation using the Herfindahl-Hirschman Index (HHI): fragmentation in ward or village k is given by $frag_k = 1 - \sum_j s_{jk}^2$, where s_{jk} is the share of type or technology j in ward or village k.

[29] It is unlikely that the use of these pumps directly affects each other through the availability of groundwater, as they are mainly used for drinking water (less than 1% are used for any agricultural activities), and they are not typically in very close proximity. If this was the case, we would expect the existence of nearby pumps of the same technology to have a negative effect on a pump's functionality status, and this would work against the hypothesis of pump maintenance cost-reduction spillovers.

the installing organization are the most important factor explaining the technology of pump installed, with community characteristics and community preferences among the least important factors (see Figure A29). Installing organizations typically have a preferred technology, so the technology installed in a given community is largely decided by which of the more than 500 installing organizations installs a pump in that community. In addition, community characteristics taken from the Tanzania National Panel Survey [2008-09] are not significant predictors of pump technology when we estimate selection regressions (see Tables A12, A13 and A14).[30]

Given that installing organizations tend to install their preferred technology of pump regardless of community characteristics, it might be installer characteristics that drive these spatial correlations. Suppose one organization makes high quality installations of technology A, and another makes low quality installations of technology B, then this might induce technology-specific spatial correlations in the functionality of pumps. To control for this, I include installer and funder fixed effects in the main specifications, and there is very little change in the key estimated marginal effects.[31] To further test this explanation, I also re-estimate the main specifications but include the number of pumps of the same technology *and* the same installer within 1.2km as an explanatory variable, as well as the number of pumps of the same technology but a different installer, as shown in Table A16. I find no statistically significant difference in the effects, showing that the positive correlation between pump functionality and the number of pumps of the same technology nearby does not depend on whether they are installed by the same organization.

[30] I estimate selection regressions of water source type and pump technology on 36 community characteristics from the Tanzania National Panel Survey [2008-09]. The results are shown in section A.5. Of the 216 estimated coefficients in the type and technology selection regressions, only 31 (14 percent) are significant at the 90 percent confidence level, only slightly greater than we would expect if technology was decided randomly. Note that the 90 percent confidence level is appropriate because the Tanzania National Panel Survey [2008-09] only covers a small subset of communities in the water data, so the sample size is greatly reduced and the power of this test is low.

[31] I cannot include fixed effects for every installer or funder in the data, as there are more than 500 of each. I include fixed effects for every installer or funder that installs or funds more than 1 percent of pumps in the data, representing more than 60 percent and 50 percent of pumps respectively. Of the 34 coefficients tested, only three are statistically significant at the 95 percent level (all negative coefficients), suggesting that the performance of the vast majority of installing organizations is not significantly different to the average. To test whether it is fixed effects of smaller installers driving the results, I restrict the analysis to pumps installed by organizations with more than 1 percent of installations in Table A15, and find that the results are very similar to the main specifications.

The observed correlations may also be explained by the selection of pump technology based on physical conditions, and survey respondents indicate that hydrological factors are fairly important in the selection of technology (Figure A29). If pump technology A is more suitable for installation in certain physical conditions, then in areas with favorable conditions there will be many similar pumps and they will be more likely to work. However, I test this explanation in two ways and do not find evidence for it. First, I estimate a selection regression of pump technology on groundwater variables from the British Geological Survey (Table A17). Although groundwater variables are somewhat predictive of whether a pump or non-pump water source is installed, they are not good predictors of the technology of pump installed.[32] Second, I include interaction terms between technology dummies and groundwater variables in the main specification: if a technology is more suitable for certain groundwater conditions, these interaction terms will account for any effect on pump functionality (Table A18). However, the estimated marginal effects are virtually unchanged, suggesting that selection of technology on physical conditions is not driving these correlations.[33]

I discuss a number of other possible 'correlated effects' explanations, and how I test for them in section A.5 of the Online Appendix. In particular, I show that spatial correlation in the management of water sources (for example if individuals manage more than one pump) is unlikely to explain these correlations (Tables A20 and A21). Similarly, I do not find evidence that spatial correlation in the type of hole that a pump is installed on, the timing of installation of specific technologies, technology-specific water demand, or technology-specific effects of community shocks can explain the observed spatial correlations.

4.4 Identification of network effects

After testing for a number of potential technology-specific correlated effects, I do not find evidence that any of these mechanisms are explaining the key spatial correlations observed in the data. However, the observed correlations can be explained by the ex-

[32] Pumps are more likely to be installed in areas where the depth to groundwater is less than 25m, and taps more likely to be installed in areas with a deeper water table. Conditional on a pump being installed, the evidence that there is selection of technology on groundwater variables is weaker: only 5 of the 40 estimated coefficients are significant at the 95 percent level

[33] Note that the groundwater variables from British Geological Survey incorporate information on geology, geomorphology and rainfall.

istence of free riding and pump maintenance cost-reduction spillover effects between communities. Note that these effects work in the opposite direction: having an additional pump nearby reduces the incentive for a community to maintain their existing pump, but may also reduce the cost of maintaining it. If positive spillovers are larger when neighboring water sources are more similar, this explains why a pump is more likely to work if there are more pumps of the same technology nearby, as spillover effects will dominate free riding effects. However, if there are many non-pump water sources nearby, the spillover effects may be small, free riding effects dominate, and a pump is less likely to be functional.[34]

To overcome the identification challenge and distinguish social interactions from correlated effects, I exploit the decentralized nature of pump installation and use whether two communities have the same technology of pump as a shifter in the strength of pump maintenance spillovers that are possible between them. This shifter is exogenous if spatially correlated shocks or unobservables are independent of pump technology. This condition allows for spatially correlated shocks or unobservables to affect the functionality of pumps, but rules out the possibility of them having technology-specific effects. For example, spatially correlated rainfall shocks may affect pump functionality, but under this condition they cannot affect one technology of pump but not another. To identify network effects, I assume that this condition holds. This is a mild assumption: I tested a number of ways in which it could be violated in section 4.3, and did not find evidence of technology-specific unobservables that might explain the observed spatial correlations in pump functionality. I formally state the identifying assumption in the context of the model in section 5.

5 A spatial network model of strategic interactions

Although the reduced form analysis provides evidence of free riding effects and pump maintenance cost-reduction spillovers, it cannot distinguish these two opposing effects and can only estimate the 'net effect' of having an additional water source nearby. To disentangle these two effects, estimate their magnitude, and test the mechanisms through which they work, I develop and estimate a model of strategic interactions between neighboring communities. The model also allows me to estimate the effects

[34]This can also explain why the number of pumps of a different technology within a certain distance is not a significant predictor of pump functionality: it seems plausible that free riding and positive spillover effects cancel each other out on average in these cases.

of policies designed to reduce free riding and fragmentation of water supply on the functionality of water pumps and on health and education outcomes.

In the model, each community has a single water pump, and must decide whether to maintain it or not, given the actions of its neighbors.[35] The model allows for maintenance cost-reduction spillovers and free riding to occur through separate channels. First, the cost of maintaining a pump may depend on whether a community's neighbors also maintain their water sources, and how similar these water sources are. Second, if a community decides not to maintain its pump and it breaks down, then it may access a neighboring water source at a cost that increases in distance and whether it must pay for water access at the alternative water source. In what follows, I describe the model more formally and in more detail.

Assumption 1. (Game setup) *There are a finite number of communities, each with a fixed, exogenously determined spatial location. Each community has a binary maintenance decision, $m_i \in \{0, 1\}$. Communities play a static network game of complete information and move simultaneously in a pure strategy Nash equilibrium.*

Assumption 1 sets up the game to reflect both how communities make maintenance decisions in reality and the structure of my data.[36] I assume that communities play a game of complete information because neighboring communities interact in their pump maintenance decisions, and are therefore likely to have a good understanding of each others' costs of maintenance. I use Nash equilibria in pure strategies to restrict the number of equilbria I must consider in the estimation of this model, though multiple equilibria are still possible.[37]

[35]The unit of observation is a 'community', as defined by an observed water source in the data. This is a reasonable assumption, as the users of each pump appoint a 'water point committee' to manage and maintain the water source. Using the administrative definition of a village to define a community would not significantly change the nature of the model, though would complicate estimation, as each community would face a different action space. Given that the results of the robustness analysis using the village and ward as the unit of analysis in section A.3 were similar to those in the main specifications, I would expect the results of such a model to be qualitatively similar to the model I estimate.

[36]I make the simplifying assumption that communities move simultaneously in a static game because we don't see the exact timing of maintenance decisions in the data: it gives a 'snapshot' of all (functional and non-functional) water sources in Tanzania at a given point in time. I later use an equilibrium selection rule in the estimation which allows for some of the features of a sequential game in which the first mover (and hence the equilibrium) is chosen randomly by nature (i.e. whose pump requires maintenance first).

[37]As mentioned in footnote 6, an alternative approach would be to model this as an incomplete

Assumption 2. (Perfectly effective pump maintenance) *Community i's pump is functional if and only if $m_i = 1$.*

Under assumption 2, pump functionality is deterministic, conditional on the maintenance decision of a community.[38] However, this is not restrictive because in the model the *cost* of pump maintenance is stochastic. I will formalize this shortly, but the intuition is that a community draws a random cost of maintenance and then decides whether or not to keep its pump functional, given this cost. Conceptually, this implies that there is always some (possibly zero) cost that a community can and must pay to keep its pump functional. This implication is intuitive and mild.[39]

Assumption 3. (Community utility) *The utility of community i is linear in its outcomes, y_i and the net costs of water, c_i, and is given by $u_i = y_i - c_i$, where c_i comprises the cost of pump maintenance and the cost of water collection.*

Outcomes of community i depend on its own maintenance decisions, m_i and the mean maintenance decisions of its neighbors, $\bar{m}_{-i}$, as well as its own community characteristics and the mean characteristics of its neighbors, $\mathbf{X}^a = [\mathbf{X}^a_i, \bar{\mathbf{X}}^a_{-i}]$:

$$y_i = \beta_0 + \beta_1 m_i + \beta_2 \bar{m}_{-i} + \mathbf{X}^a \boldsymbol{\beta}_3 + \xi_i \tag{1}$$

where $\boldsymbol{\beta}_3$ is a vector of parameters and ξ_i is a random outcomes shock.[40] The set $\{-i\}$ represents the communities that are neighbors of community i, and will be defined more precisely in section 6.[41]

information game and consider Bayes-Nash equilibria. This would guarantee a pure strategy equilibrium, but would not rule out multiplicity.

[38] Data enumerators code functionality as equal to one if a pump produces any water when tested, and zero otherwise. This assumption allows us to treat functionality as a community decision.

[39] Even in the case that a pump is badly damaged, a community could pay a (high) cost to ensure that is functional, potentially by essentially reinstalling it. The only cases where this might be impossible is if there is a severe drought and there is no groundwater available at any depth in a given area. My understanding is that this is very rare in general, and in particular in Tanzania in the period in which the data was collected. If there is no pump maintenance required for a given observation in reality, this would be represented by a random draw that sets the cost of pump maintenance to zero.

[40] For ease of exposition, I present the case with a single outcome. It is straightforward to extend this to multiple outcomes, by stacking the outcomes equations. I estimate the model using three outcomes (child mortality, school attendance of boys and girls) and therefore for each β term I define $\beta = [\beta^s, \beta^g, \beta^b]$.

[41] As part of the estimation, I partition the data into clusters of communities, and I restrict interactions to be between communities in the same cluster. $\{-i\}$ is the set of communities that are

The effects of $\bar{\mathbf{X}}^a_{-i}$ on the outcomes of community i are 'contextual' effects in the terminology of Manski [1993]. Given that I distinguish between actions and outcomes, and therefore between pure spillovers and strategic interactions (endogenous effects), the effect of i's neighbors' actions, m_{-i}, on its outcomes are 'pure spillover' effects, and the effects of m_{-i} on m_i are strategic interactions.

The net cost of water consists of two terms, which I will discuss in turn:

$$c_i = m_i \left(\frac{\mathbf{X}^b_i \boldsymbol{\psi}}{1 + \mathbf{N}_i(\boldsymbol{\delta})\mathbf{m}} + \epsilon_i \right) + (1 - m_i) \sum_{r \in \mathcal{R}} \left(\lambda_r \mathbb{1}(j = i^r) g^{ij}(d_{ij}, m_j, \mathbf{X}^c_j) \right) \tag{2}$$

If a community chooses to maintain its pump, by setting $m_i = 1$, it must pay a cost of maintenance, given by the first term in equation (2). The numerator is a linear function of pump and community characteristics and represents the baseline cost of pump maintenance. $\mathbf{N}(\boldsymbol{\delta})$ is a matrix of network connections with the ij^{th} element giving the strength of network connection between communities i and j. $\mathbf{N}_i(\boldsymbol{\delta})$ represents the ith row of the network connections matrix and $\mathbf{m}$ represents the full column vector of maintenance decisions.[42] Intuitively, i's cost of maintenance is discounted for each of its neighbors that maintains its pump, with the size of the discount dependent on the strength of network connection between the two communities.

There is a random shock to the cost of maintenance for community i, given by ϵ_i, and this is potentially spatially correlated. As discussed in section 4.4, I assume that spatially correlated shocks are independent of technology:

Assumption 4. (Spatial correlation of shocks) *If shocks to the cost of maintenance of a water source i of technology j in location k are given by $\epsilon^j_{ik} = \eta_i + \eta^j_k$ where η_i is an idiosyncratic shock, and η^j_k is a spatially correlated shock specific to water sources of technology $j \in \{1, 2, ..., J\}$, then $\eta^1_k = \eta^2_k = ... = \eta^J_k = \eta_k \ \forall k$.*[43]

This assumption allows me to use variation in whether two communities have the

in i's cluster.

[42] $\mathbf{N}_i(\boldsymbol{\delta})\mathbf{m}$ therefore gives the sum of the product of maintenance decisions and strength of network connections between i and other communities.

[43] This assumption is actually slightly stronger than what is required to identify spillover effects. A weaker assumption (implied by Assumption 4) is that η^j_k is independent of the number of other pumps of technology j in cluster k. This allows there to be technology-specific spatially correlated shocks, but assumes that these do not depend on the number of pumps of the same technology nearby. I use Assumption 4 in my explanations as it is more intuitive.

same technology of pump as a shifter in the strength of spillovers possible between them, in a way that I make more precise shortly. As this is a game of complete information, ϵ_i is known by community i and its neighbors, but is unobserved by the econometrician. The cost of maintenance shock, ϵ_i and outcomes shocks, ξ_i, are possibly correlated.

If a community chooses not to maintain its pump, by setting $m_i = 0$, it faces a cost of accessing alternative water sources, given by the second term in equation (2). $g^{ij}(\cdot)$ represents community i's cost of accessing community j's water source, which depends on the distance between them, d_{ij}, whether community j maintains its pump, and some characteristics of community j, $\mathbf{X}_j^c$:

$$g^{ij}(d_{ij}, m_j, \mathbf{X}_j^c) = min\{C_0, (1 - m_j)C_0 + m_j \exp(\gamma_0 + \gamma_1 d_{ij} + \mathbf{X}_j^c \boldsymbol{\gamma}_2)\} \tag{3}$$

where C_0 is the cost of collecting water from an outside option, an unimproved water source not in the data (e.g. a stream, lake or river). Community i can therefore only access the water source in community j if it is functional ($m_j = 1$), and will only do so if the cost of access is lower than the cost of the outside option. The index i^r represents the community with the rth 'cheapest' alternative water source that community i can access. $\mathcal{R} \subset \mathbb{Z}_{>0}$ gives the number of alternative water sources that are relevant to i's maintenance decision. For example, if $\mathcal{R} = \{1, 2\}$ then the costs of the cheapest and second cheapest alternative affect i's decision. λ_r gives the weight of the rth cheapest alternative water source in the calculation of the overall cost of access. λ_1 is normalized to one as it is not separately identified to the parameters in $g(\cdot)$, while subsequent λ terms are estimated. In the estimation, I set $\mathcal{R} = \{1, 2\}$, but estimate that $\lambda_2 \approx 0$, suggesting that only the cheapest alternative water source is relevant to i's maintenance decision.

$\mathbf{N}(\boldsymbol{\delta})$ is a fixed, weighted, undirected, symmetric matrix, with each element, n_{ij}, representing the strength of network connections (and therefore the strength of maintenance cost-reduction spillovers that are possible) between communities i and j:

$$\begin{aligned} n_{ij} = \exp(&\delta_0 - \delta_1 d_{ij} - \delta_2 \mathbb{1}(TY_i \neq TY_j) \\ &- \delta_3 \mathbb{1}(TE_i \neq TE_j) - \delta_4 \mathbb{1}(HT_i \neq HT_j))\mathbb{1}(d_{ij} < c) \end{aligned} \tag{4}$$

where TY_i is the type of water source i (e.g. pump, tap), TE_i is the technology of pump i (e.g. Nira, Afridev), and HT_i is the hole type for pump i (e.g. machine drilled borehole or hand dug well).[44] d_{ij} gives the distance between communities i and j, and c is a distance cutoff for i's network, which controls the density of the network and ensures that there are partially overlapping peer groups, or 'excluded peers'.[45] The exponential function ensures that all network connections are non-negative.

Community i will maintain its pump if and only if its utility from maintaining the pump, u_i^1, is greater than its utility from letting it fail, u_i^0, giving the best response function:

$$m_i = 1 \text{ iff } u_i^1 > u_i^0 \Leftrightarrow \underbrace{\beta_1 - \frac{\mathbf{X}_i^b \boldsymbol{\psi}}{1 + \mathbf{N}_i(\boldsymbol{\delta})\mathbf{m}} + \sum_{r \in \mathcal{R}} \lambda_r \mathbb{1}(j = i^r) g^{ij}(d_{ij}, m_j, \mathbf{X}_j^c)}_{\bar{u}_i} > \epsilon_i \quad (5)$$

$$m_i = 0 \text{ otherwise}$$

Therefore, each community plays a cutoff strategy, in which they maintain their pump only if the cost of maintenance shock, ϵ_i is smaller than a cutoff value, $\bar{u}_i$, which depends on the maintenance decisions of i's neighbors.

In section 6, I discuss estimation of the model, the data that I use, and how I identify the model parameters. I formally show identification of the parameters *after* I discuss estimation, because the estimation procedure, which includes partitioning the water sources in the data into geographic clusters, affects the identification of certain parameters. Therefore, to aid the reader, I provide a brief overview of the intuition behind the identification of parameters here, before showing this formally in section 6.2.

The intuition behind identification of the model parameters proceeds in a few steps. First, note that there are two equations to jointly estimate: the outcomes equation (1) and the best response equation (5). Variation in outcomes and the variables that explain them identifies $\boldsymbol{\beta} = [\beta_0, \beta_1, \beta_2, \boldsymbol{\beta_3}]$ in equation (1). Second, turning to

[44] Having a different water source type implies having different technologies and hole types.

[45] The existence of excluded peers can help overcome the simultaneity problem inherent in the identification of social interactions (Bramoullé, Djebbari, and Fortin [2009] and De Giorgi, Pellizzari, and Redaelli [2010]). I use a cutoff of 1.7km in the estimation. I choose a cutoff greater than the 1.2km used in the reduced form analysis because the strength of connection is now a decaying function rather than a binary function.

equation (5), I make the common assumption that the cost of maintenance shocks, ϵ_i, have a mean of zero, which normalizes the location of the parameters in the best response equation, and their scale is pinned down by β_1. Third, the cost of maintenance parameters, $\boldsymbol{\psi}$, are identified by communities for which $\mathbf{N}_i(\boldsymbol{\delta})\mathbf{m} = 0$ (i.e. communities that have no neighbors maintaining their water sources so receive no discount). Similarly, the cost of accessing an outside option, C_0, is identified by communities with no working alternative water source.[46] Fourth, the cost of access parameters, $\boldsymbol{\gamma} = [\gamma_0, \gamma_1.\boldsymbol{\gamma_2}]$, are identified by communities that have exactly one working alternative water source, and λ_2 is identified by communities with at least two working alternatives. Finally, the strength of spillover parameters, $\boldsymbol{\delta}$, are identified through variation in whether communities have the same water source type, technology and type of hole.

6 Estimation: maximum simulated likelihood

There are two equations to jointly estimate in the model, the outcomes equation (1) and the best response function (5), and I do this by maximum simulated likelihood. I estimate the best response function using pump-level data from the water point mapping data, and I use the Tanzania Population and Housing Census [2012] to estimate the outcomes equation. Due to privacy restrictions, the census data is only available at the ward level, rather than the community level, so I estimate the joint likelihood as the product of ward likelihoods.[47]

$$\mathcal{L} = \prod_{w=1}^{W} \mathcal{L}^w = \prod_{w=1}^{W} f(y_w, E_0^w | \mathbf{X}_w; \boldsymbol{\theta}) \tag{6}$$

$$= \prod_{w=1}^{W} f(y_w | E_0^w, \mathbf{X}_w; \boldsymbol{\theta}) f(E_0^w | \mathbf{X}_w; \boldsymbol{\theta}) \tag{7}$$

The second term in equation (7) is the marginal probability of E_0^w, the observed action profile of maintenance decisions in ward w, given community characteristics

[46] Note that to separately identify C_0 from ψ_0 the constant term in $\mathbf{X}_i^b \psi$, the set of communities without neighbors investing in maintenance must not be equal to the set of communities without an alternative working water source. The cutoff distance, c, ensures that these two sets are distinct, by limiting the set of communities from which a community may receive maintenance spillovers, but imposing no cutoff distance to alternative water sources.

[47] As I discuss in more detail in section 6.1, there are 789 wards with outcomes data in the model, containing an average of 11 pumps and 15 non-pump water sources.

in the ward, $\mathbf{X}_w$, and a vector of parameters, $\boldsymbol{\theta}$. The first term is the conditional density of y_w, the observed outcomes in community w, given $E_0^w, \mathbf{X}_w, \boldsymbol{\theta}$. I discuss how I estimate each of these parts of the ward likelihood in turn.

There are two key challenges in estimating the best response section of the likelihood, $f(E_0^w|\mathbf{X}_w;\boldsymbol{\theta})$. First, community choices are not independent of each other: community i's optimal choice of m_i depends on the choices made by other communities in i's network. Therefore we cannot simply calculate the ward likelihood as the product of the individual likelihoods.[48] Second, because actions of each community are binary, multiple equilibria are possible. To overcome these challenges, I partition each ward into non-overlapping clusters and assume that each cluster plays an independent game. I can estimate the probability that each possible action profile is an equilibrium in each cluster, and use this to estimate the likelihood of the observed action profile. The ward likelihood is then the product of the cluster likelihoods defined in that ward.

Assumption 5. (Within-cluster strategic interactions) *Strategic interactions only occur within non-overlapping geographic clusters.*

Although assumption 5 allows me to overcome the two key identification challenges, it restricts the set of communities between which strategic interactions may occur in the model. To minimize the cost of placing these restrictions on interactions, I use a simple machine learning algorithm (k-means clustering) to define clusters of nearby communities, as I will discuss in more detail in section 6.1.[49]

I partition each ward, w, into K^w clusters, $k = 1, ..., K^w$, each containing N_k communities, $i = 1, ..., N_k$. Each community has two possible actions, so there are 2^{N_k} possible action profiles in each cluster, which I denote as $E_0^k, E_1^k, ..., E_{(2^{N_k}-1)}^k$, where E_0^k is the observed action profile. To calculate the likelihood of the observed action profile in a cluster, we cannot simply calculate the probability that the observed action profile is an equilibrium because multiple equilibria are possible, so the probability of an action profile being an equilibrium is not equivalent to the probability

[48] Similarly, in a moment conditions approach, individual moment conditions will not be independent and this would violate Assumption 2 in Pakes, Porter, Ho, and Ishii [2015].

[49] There is an inherent tradeoff in the choice of the number and size of clusters that are defined. Definition of larger clusters allows interactions between a greater number of communities, but increases the computational burden required to solve the network game, and reduces the number of cluster 'observations' of the network game, and therefore the power of the estimation.

that this equilibrium is the one that is actually played.[50] Therefore, to calculate the cluster likelihood, I use a probabilistic equilibrium selection rule to weigh the probability that the observed action profile is an equilibrium against the probability that all other possible action profiles are equilibria. I allow within-cluster spatial correlation in the cost of maintenance shocks, ϵ_{ic}, and correlation between ϵ_{ic} and the outcomes shocks, ξ_i.[51]

The procedure to estimate $f(E_0^w|\mathbf{X}_w;\boldsymbol{\theta})$ is as follows:

1. Choose a set of parameter values: $\boldsymbol{\theta} = \{\boldsymbol{\delta}, \boldsymbol{\psi}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\sigma}\}$
2. For each possible action profile, l, in each cluster, k, calculate cutoff values of ϵ_{ic} for each community, $\bar{u}_{il}$
3. Simulate a large number of shocks, (ϵ_{ic}, ξ_i)
4. For each cluster, k, estimate the probability that each action profile, l, is an equilibrium: $\Pr(E_l^k) = \prod_{\{i\in k:m_{il}^k=0\}} \Pr(\epsilon_{ic} > \bar{u}_{il}) \prod_{\{i\in k:m_{il}^k=1\}} \Pr(\epsilon_{ic} \leq \bar{u}_{il})$.[52]
5. Using a parametric probabilistic equilibrium selection rule, $h(\cdot)$, calculate the likelihood of the observed equilibrium action profile:[53]

$$f(E_0^k|\mathbf{X}_k;\boldsymbol{\theta}) = h(\Pr(E_0^k), \Pr(E_1^k), ..., \Pr(E_{(2^{N_k}-1)}^k);\boldsymbol{\theta})$$

6. Calculate $f(E_0^w|\mathbf{X}_w;\boldsymbol{\theta}) = \prod_{k=1}^{K^w} f(E_0^k|\mathbf{X}_k;\boldsymbol{\theta})$

To estimate the outcomes section of the likelihood, $f(y_w|E_0^w, \mathbf{X}_w;\boldsymbol{\theta})$, I must aggregate

[50] To ensure that all observed action profiles are possible, and that the likelihood is well defined, I specify an unbounded distribution for the cost of maintenance shocks, ϵ_i. However, this implies that for any finite set of parameters, any action profile can be supported as an equilibrium if every community assigned to $m_i = 1$ receives a large negative cost of maintenance shock, ϵ_i, and if every community assigned to $m_i = 0$ receives a large positive ϵ_i.

[51] The cost of maintenance and outcomes shocks have the following structure: $\epsilon_{ic} = \eta_{1c} + \eta_{2i} + \eta_{3i}$ and $\xi_i = b\eta_{2i} + \eta_{4i}$, where ϵ_{ic} is the shock to community i in cluster c, and $\eta_{1c}, \eta_{2i}, \eta_{3i}, \eta_{4i}$ are independent normal distributions with variances $\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2$ respectively. Therefore, η_{1c} is a shock that is common to cluster c, and $\eta_{2i}, \eta_{3i}, \eta_{4i}$ are all idiosyncratic shocks. b determines whether cost of maintenance shocks are positively or negatively correlated with outcomes shocks, though its magnitude is not separately identified to σ_2^2, so $b \in \{-1, 1\}$. I estimate $\boldsymbol{\sigma} = \{\sigma_1, \sigma_2, \sigma_3, \sigma_4, b\}$.

[52] I use the smoothed logistic estimator to calculate these probabilities, with a smoothing parameter of 0.3: $\frac{1}{S}\sum \frac{\exp((\bar{u}_{il}-\epsilon_i)/0.3)}{1+\exp((\bar{u}_{il}-\epsilon_i)/0.3)}$ where I average over the number of simulated shocks, S.

[53] In the main analysis, I use a simple 'weighted average' equilibrium selection rule, $f(E_0^k|\mathbf{X}_k;\boldsymbol{\theta}) = \frac{\Pr(E_0^k)}{\sum_{l=0}^{2^{N_k}-1}\Pr(E_l^k)}$. To check the robustness of the results, I use two other equilibrium selection rules, the logistic function, with a smoothing parameter of 0.1, $f(E_0^k|\mathbf{X}_k;\boldsymbol{\theta}) = \frac{\exp(\Pr(E_0^k)/0.1)}{\sum_{l=0}^{2^{N_k}-1}\exp(\Pr(E_l^k)/0,1)}$ and simply maximizing the probability that the observed action profile is an equilibrium, $f(E_0^k|\mathbf{X}_k;\boldsymbol{\theta}) = \Pr(E_0^k)$. In both cases the results are qualitatively similar.

the outcomes equation to the ward level, as this is the level at which I have outcomes data from the Tanzania Population and Housing Census [2012]. Averaging equation (1) over all communities in a ward gives:[54]

$$y_w = \beta_0 + \beta_1 \frac{1}{n_w} \sum_{i=1}^{n_w} m_i + \beta_2 \frac{1}{n_w} \sum_{i=1}^{n_w} m_{-i} + \mathbf{X}_w^a \boldsymbol{\beta}_3 + \xi_w \tag{8}$$

where $\xi_w = \sum_{i=1}^{n_w} \xi_i$ and n_w is the number of communities in ward w.

To calculate the density of the observed outcomes, given the observed action profile and community characteristics in a ward, I rearrange the density expression and define $\bar{v}_w$:

$$f(y_w|E_0^w, \mathbf{X}_w; \boldsymbol{\theta}) = f(\xi_w = \underbrace{y_w - \beta_0 - \beta_1 \frac{1}{n_w} \sum_{i=1}^{n_w} m_i - \beta_2 \frac{1}{n_w} \sum_{i=1}^{n_w} m_{-i} - \mathbf{X}_w^a \boldsymbol{\beta}_3}_{\bar{v}_w} | E_0^w)$$

Conditioning on the observed action profile of maintenance decisions, E_0^w, is equivalent to conditioning on having cost shocks in ward w, $\boldsymbol{\epsilon}_w$, that rationalize E_0^w as the observed action profile, and these may be correlated with ξ_w. To calculate this density, I integrate over all possible $\boldsymbol{\epsilon}_w \in \mathcal{E}$, where $\mathcal{E}$ is the superset of shocks that may rationalize E_0^w as the observed action profile.

$$f(y_w|E_0^w, \mathbf{X}_w; \boldsymbol{\theta}) = \int_{\boldsymbol{\epsilon}_w \in \mathcal{E}} f_{\xi_w}(\bar{v}_w|\boldsymbol{\epsilon}_w) f(\boldsymbol{\epsilon}_w) d\boldsymbol{\epsilon}_w \tag{9}$$

To estimate this integral, I make repeated draws of $\boldsymbol{\epsilon}_w$ from the set of shocks that rationalized the observed action profile as an equilibrium in the calculation of $f(E_0^w|\mathbf{X}_w; \boldsymbol{\theta})$, and for each draw I calculate the conditional density of ξ_w at $\bar{v}_w$.[55]

I perform a series of simulation exercises to test how this estimation procedure performs with different sample sizes and different levels of variation in the key variables.

[54] For ease of exposition, I present ward averages as if each community is the same size. In practice, I must weight by the number of individuals in each community when calculating ward averages to make them comparable to the outcomes data, which averages over all individuals in a ward.

[55] The density of ξ_w at $\bar{v}_w$ is given by $f_{\xi_w}(\bar{v}_w|\epsilon_w) = \frac{1}{\sigma_{\xi_w}\sqrt{1-\rho_w^2}} \phi\left(\frac{\bar{v}_w - \rho_w \frac{\sigma_{\xi_w}}{\sigma_{\epsilon_w}} \epsilon_w}{\sigma_{\xi_w}\sqrt{1-\rho_w^2}}\right)$, where $var(\xi_w) = \sigma_{\xi_w}^2$, $var(\epsilon_w) = \sigma_{\epsilon_w}^2$, $corr(\xi_w, \epsilon_w) = \rho_w$, all of which are functions of structural model parameters. I derive this result and the terms for $\sigma_{\xi_w}^2$, $\sigma_{\epsilon_w}^2$ and ρ_w in section A.7 in the appendix.

I present a brief selection of results from these exercises in section A.6 of the Online Appendix. Figure A36 shows that the simulated likelihood has a maximum at the true parameters and is well behaved around this point.[56] Figure A37 shows selected results of Monte Carlo exercises to test the performance of the estimation procedure as we increase the sample size. In general, the procedure produces accurate estimates of the true model parameters when there are more than 3,000 observations and variation in the key variables is similar to the level observed in the data.

6.1 Data used to estimate the model

I estimate the model of strategic interactions using communities with pumps as the decision-making agents, and make two adjustments to the subsample used for the reduced form analysis in section 4. First, I drop all water sources that broke down more than five years before data collection, as these water sources are not relevant to recent maintenance decisions.[57] Second, instead of dropping individual observations with key missing data, I drop entire wards, to ensure that there are no 'holes' in the network model. These two adjustments reduce the sample size from 10,667 handpumps in the reduced form to 8,514 pumps in estimating the model. In addition, the sample includes 11,890 non-pump water sources (mostly taps), the functionality of which is exogenous to the decentralized maintenance game, though communities may free ride upon or receive maintenance spillovers from these alternative water sources.[58,59]

I use three outcome variables for the 789 wards covered by the water source data, which I take from the Tanzania Population and Housing Census [2012]: the child

[56]The simulated likelihood is generally well behaved and attains a maximum around the true parameter values when I use the 'weighted average' equilibrium selection rule (as I do in the main estimation). When I use the logistic function for the equilibrium selection rule (as in the robustness estimation), the behavior of the simulated likelihood is sensitive to the choice of smoothing parameter. For each of the equilibrium selection rules, the simulated likelihood is 'more smooth' as we increase the number of simulations used, as we would expect.

[57]Dropping these observations means that the pump functionality rate in the model estimation subsample is higher than that in the overall data, at 70.8 percent rather than 62.6 percent.

[58]Taps are typically maintained centrally, by national or local government, rather than by community-based management. They are also typically gravity-fed, piped systems, that take surface water from rivers or streams in areas with less flat terrain, in contrast to handpumps, which extract groundwater. I therefore take their functionality to be exogenous to the maintenance decisions faced by communities.

[59]I estimate that functional non-pump water sources create a maintenance spillover for neighboring pumps that is very close to zero, though they provide important free riding opportunities.

survival rate, girls' school attendance rate and boys' school attendance rate.[60] To estimate the ward outcomes equation (8) of these three variables on pump maintenance and neighbors' pump maintenance, I control for the adult literacy rate, a rural ward dummy, and the distance to the nearest of Tanzania's eleven largest cities.[61] The baseline cost of pump maintenance, given in equation (2), is a linear function of the age of a pump, whether users must pay to use it, and dummies for the four most common technologies. Finally, the cost of community i accessing water from community j in the case that i's pump is non-functional (see equation (3)) depends on the distance they have to travel, whether they have to pay to use the alternative water source, and whether it is a pump or a tap. These functions can be seen in full in section A.8 of the Online Appendix.

I use k-means clustering, a simple machine learning algorithm, to partition the data into clusters. In each ward, I define clusters, $S = \{s_1, ..., s_k, ..., s_K\}$ to solve $\underset{S}{\operatorname{argmin}} \sum_{k=1}^{K} \sum_{\mathbf{x} \in s_k} \|\mathbf{x} - \mu_k\|^2$ where $\mathbf{x}$ are GPS coordinates of observations assigned to cluster k, and μ_k gives the GPS coordinates of the centroid of cluster k. Figure 2 gives a visual example of the clusters defined in the data, and the distribution of the number of pumps and water sources in each cluster.[62]

6.2 Identification of model parameters

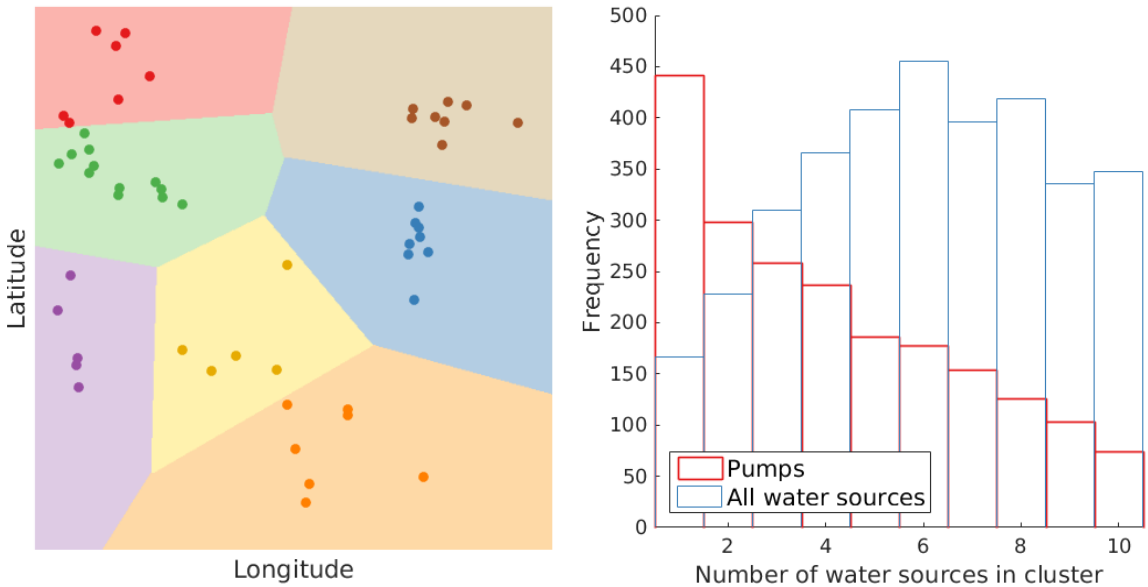
Consider the parameters in the best response equation (5). β_1 normalizes the scale of these parameters because it is separately identified in the outcomes equation (8),

[60] The child survival rate can be interpreted as one minus the child mortality rate, but for ease of interpretation I use the survival rate so that higher numbers in all three outcomes indicate 'better' outcomes. The child survival rate calculated using the census is a fairly crude measure, as the census does not record the age of deaths. Each household is asked how many children have ever been born in the household and how many of these children have survived until the time that the census is taken. I divide the number of children that have survived by the number ever born to get a crude survival 'rate'.

[61] It is straightforward to extend the model to three outcomes. The best response equation will now contain $\beta_1^s + \beta_1^g + \beta_1^b$ instead of just β_1, and there are now 18 parameters to estimate.

[62] I have to limit the size of each cluster because the estimation procedure requires me to calculate the probability of 2^{N_k} action profiles being an equilibrium. Therefore I set the maximum cluster size at 10, and create 3431 clusters with an average of 4.1 pumps in a cluster. Note that the standard k-means clustering algorithm does not set a maximum size of cluster. Therefore to impose the maximum, I adapt the algorithm to redefine clusters with an initial size greater than 10. A significant minority of clusters are defined without a pump water source, so I do not estimate the model for these clusters, but treat the functionality of their non-pump water sources as exogenous.

Figure 2: Definition of clusters using k-means clustering. Example of cluster definitions using k-means clustering (left), and distribution of cluster sizes, by number of pumps and number of all water sources in each cluster (right).



as the treatment effect of having a functional water source on outcomes.[63] The common assumption that $\mathbb{E}[\epsilon_i] = 0$ normalizes the location of these parameters. The $\boldsymbol{\psi}$ terms, which govern the baseline cost of maintenance of a pump, are identified by communities that do not receive a cost of maintenance discount ($\mathbf{N}_i(\boldsymbol{\delta})\mathbf{m} = 0$), but which have access to working alternative water sources.[64,65] Given identification of the $\boldsymbol{\psi}$ parameters and assuming that we have significant variation in the distances, types, technologies and hole types between pumps in clusters, it is straightforward to see that we can identify the $\boldsymbol{\delta}$ parameters for communities that have at least one

[63]Identification of the $\boldsymbol{\beta}$ terms in the outcomes equation, (8), is straightforward when there is sufficient variation in the explanatory variables. Note that $\frac{1}{n_w}\sum_{i=1}^{n_w} m_i \neq \frac{1}{n_w}\sum_{i=1}^{n_w} \bar{m}_{-i}$ in wards where there are clusters with only a single functional water source. In the data approximately 35 percent of wards have different values for these explanatory variables, allowing us to separately identify β_1 and β_2.

[64]There are 1347 such communities in the data used to estimate the model. The best response of these communities is to maintain their pump if and only if $\beta_1 - \mathbf{X}_i^b\boldsymbol{\psi} + \sum_{r\in\mathcal{R}} \lambda_r \mathbb{1}(j = i^r) g^{ij}(d_{ij}, m_j, \mathbf{X}_j^c) > \epsilon_i$. This best response allows us to identify the $\boldsymbol{\psi}$ terms, including the constant term ψ_0 because we already have identification of β_1.

[65]Note that a community receiving no discount in its cost of maintenance, $\mathbf{N}_i(\boldsymbol{\delta})\mathbf{m} = 0$, may still free ride alternative water sources that are further away than the cutoff distance past which maintenance spillovers do not occur.

neighbor investing in maintenance of their water source.[66]

The parameter governing the importance of the second 'cheapest' alternative water source for free riding relative to the 'cheapest' alternative water source, λ_2 in equation (5), is identified by the best response of communities with at least two working alternative water sources.[67] The cost of a community accessing an outside option if its pump is not functional, C_0 in equation (3), is identified by the best response of communities without any working alternative water sources in their cluster.[68] To see how the $\boldsymbol{\gamma}$ terms, which affect the cost of i accessing neighboring functional water sources, are identified, consider the best response function for communities with exactly one available functional alternative in their cluster: $m_i = 1$ iff $\beta_1 - \frac{\mathbf{X}_i^b \boldsymbol{\psi}}{1+\mathbf{N}_i(\boldsymbol{\delta})\mathbf{m}} + \exp(\gamma_0 + \gamma_1 d_{i1} + \mathbf{X}_1^c \boldsymbol{\gamma}_2) + \lambda_2 C_0 > \epsilon_i$.[69] Given the identification of the other parameters in this equation, we can identify the $\boldsymbol{\gamma}$ parameters. Finally, the $\boldsymbol{\sigma}$ terms are identified by variance in functionality and outcomes not explained by the model.

7 Results

The estimated structural parameters are presented in Table 3, along with their standard errors. The vast majority of parameters are estimated precisely. I discuss the key results from each of the groups of parameters in turn.

The estimates of the cost of maintenance parameters are all statistically significant, with the exception of ψ_1, the effect of pump age on the cost of maintenance, which is precisely estimated as equal to zero. This is consistent with the fact that the hazard rate of pump breakdown is close to constant for the first 20 years after installation, which might indicate that maintenance costs do not increase over this period (see Figure A4 in the Online Appendix). ψ_2 is negative and significant, indicating that

[66] As shown by Table A1 and Figure A3 in section A.1 of the Online Appendix, we have significant variation in the number of non-pumps, pumps of a different technology and pumps of the same technology within certain distances in the data. The histograms in Figure A24 in section A.3 show that there is also significant variation in the distance to the nearest working alternative water source.

[67] There are 7619 such communities in the data used to estimate the model. As noted in section 5, λ_1 is normalized to one as it is not separately identified to the $\boldsymbol{\gamma}$ parameters in $g(\cdot)$. See Section A.9 of the Online Appendix for more detail on identification of the λ terms.

[68] I assume that communities can only access alternative water sources in their own cluster, and there are 308 communities without any working alternative in their cluster. See Section A.9 of the Online Appendix for more detail.

[69] There are 587 such communities in the data used to estimate the model.

Table 3: Estimated structural parameters.

Cost of maintenance						
ψ_0	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5	ψ_6
1.02	-0.002	-0.43	-0.31	-0.15	-0.26	-0.41
(0.005)	(0.007)	(0.016)	(0.016)	(0.003)	(0.007)	(0.002)
Cost of access (free riding parameters)						
γ_0	γ_1	γ_2	γ_3	γ_4	λ_2	C_0
-3.98	0.24	2.66	-0.97	1.68	0.007	0.078
(0.001)	(0.065)	(0.131)	(0.061)	(0.030)	(0.018)	(0.000)
Maintenance discount (maintenance spillover parameters)						
δ_0	δ_1	δ_2	δ_3	δ_4		
-0.43	0.19	2.01	2.47	1.03		
(0.016)	(0.007)	(0.381)	(0.295)	(0.894)		
Outcomes: child survival rate						
β_0^s	β_1^s	β_2^s	β_3^s	β_4^s	β_5^s	
0.64	0.54	-0.45	0.14	-0.001	-0.028	
(0.025)	(0.002)	(0.019)	(0.025)	(0.006)	(0.025)	
Outcomes: girls' school attendance						
β_0^g	β_1^g	β_2^g	β_3^g	β_4^g	β_5^g	
0.13	0.103	0.065	0.65	0.013	-0.045	
(0.025)	(0.003)	(0.019)	(0.025)	(0.006)	(0.025)	
Outcomes: boys' school attendance						
β_0^b	β_1^b	β_2^b	β_3^b	β_4^b	β_5^b	
0.09	0.041	0.089	0.72	-0.001	-0.049	
(0.026)	(0.003)	(0.021)	(0.027)	(0.006)	(0.027)	

Notes: Standard errors in parentheses, calculated by numerically estimating the Hessian at the estimated parameter values. The estimated variances and covariances of the shock terms are reported in section A.10 of the Online Appendix.

it is 'cheaper' for a community to maintain a pump if it charges user fees, possibly because it is easier for them to overcome the collective action problem to carry out maintenance. The negative and significant estimates for $\psi_3, \psi_4, \psi_5, \psi_6$ indicate that it is cheaper to maintain a pump of one of the four most common technologies relative to a less common technology.

The estimates of the 'cost of access' parameters indicate which variables affect free riding between communities. γ_1 is significant and positive, which implies that it is more costly to access a pump if it is further away. Similarly, γ_2 is positive and

significant, indicating that it is more expensive to access an alternative water source that charges user fees. This effect is large: I estimate that a community would always prefer an unprotected water source (e.g. a lake or river) to a pump that charges user fees, but would be willing to travel up to 10km for free access to an alternative pump. λ_2 is insignificant and very close to zero, suggesting that communities only free ride on the 'cheapest' alternative water source, rather than the first and second cheapest.

The estimates of the δ terms determine the size of the maintenance discount a community receives from its neighbors' maintenance. δ_1 is significant and positive, implying that the strength of pump maintenance spillovers between two communities decreases as the distance between them increases. The significant and positive estimates for δ_2 and δ_3 indicate that the strength of spillovers between two communities are stronger when they each have pumps of the same technology. δ_4 is positive but insignificant, suggesting that the type of hole that a pump is installed on does not affect the strength of pump maintenance spillovers.

To aid interpretation of these parameters, Table 4 calculates the change in the cost of maintenance for a community when its first, second and third neighboring communities maintain their water sources of various types and technologies. I estimate that having neighbors with a different type of water source (i.e. a tap) provides only a small discount to the cost of pump maintenance. Having a pump of a different technology nearby provides a slightly larger discount, but having a pump of the same technology nearby has a much larger effect: pump maintenance costs fall by 26 percent if a single pump of the same technology is maintained 0.6km away. Having more than one pump nearby increases the size of this discount, though there is a diminishing marginal effect.

Table 5 shows the estimated marginal effect of having an additional water source nearby on the probability that a pump is functional, allowing me to compare the structural estimates to the reduced form estimates in section 4. I use the model to decompose the overall marginal effect into two terms: the effect from positive maintenance spillovers and from free riding. The maintenance spillovers from a nearby non-pump water source are small relative to the (negative) free riding effect, resulting in an overall negative effect on the probability that a pump will be functional. However, when there is an additional pump of the same technology nearby, the pos-

Table 4: Estimated pump maintenance discounts. The estimated discount on the cost of maintenance for community i when its first, second and third neighbors maintain their water sources of various types and technologies.

Cumulative discount from...	Non-pump water source	Pump, diff. technology	Pump, same technology
...first neighbor	0.4%	2.8%	25.8%
...second neighbor	0.8%	5.5%	41.0%
...third neighbor	1.2%	8.1%	51.0%

Notes: Discounts calculated for neighboring water sources 0.6km away, and using a value of 0.5 for whether two pumps are installed on the same type of hole, as the estimated coefficient on hole type was statistically insignificant. I use a distance of 0.6km to make this roughly comparable to the reduced form estimates in section 4, as this is approximately the average distance to neighboring communities within a 1.2km radius.

itive spillover effects dominate, and the pump is more likely to be functional. The estimated net effects from the model are broadly similar to those estimated in the reduced form.[70]

Table 5: Marginal effect of additional neighboring water source on probability that pump is functional (percentage points).

	Non-pump source	Pump, different technology	Pump, same technology
Spillover effect (model)	0.05	0.33	3.45
Free riding effect (model)	-0.89	-0.89	-0.89
Net effect (model)	-0.84	-0.56	2.56
Net effect (reduced form)	-0.38	-0.08	3.03

Notes: The marginal effects are calculated for a community and pump 0.6km away, with median characteristics for each variable in the model. The reduced form estimate of the net effect of additional water sources is taken from the specification that uses the number of *working* water sources of various types as explanatory variables (final panel in Table A6 in the Online Appendix).

Finally, the effect of pump maintenance on our three outcome variables is given by the β terms. I estimate a significant positive effect of water pump functionality on ward outcomes: a 10 percentage point increase in functionality would result in a 0.9 percentage point increase in the child survival rate, a 1.7 percentage point

[70]These marginal effects are partial equilibrium effects, as they hold fixed the actions of other communities. In practice, other communities will also respond to having an additional water source nearby, which will induce secondary network effects. I use the model to analyze the general equilibrium effects of two policies proposed by the Tanzanian government in section 7.2.

increase in girls' school attendance, and a 1.3 percentage point increase in boys' school attendance.[71,72] There is a positive correlation of child survival and school attendance with the adult literacy rate (β_3 terms), but no significant correlation with whether a ward is rural (β_4 terms) or the distance from a ward to a major city (β_5 terms).

7.1 Model fit

7.1.1 Within-sample fit

It is challenging to assess the fit of the model in the presence of multiple equilibria, because even if the model is well specified and the estimates of the structural parameters are correct, when we simulate outcomes the equilibria chosen in the simulation may not correspond to those being played in the data. Therefore, to assess how well the model fits the sample used to estimate it, I use the model estimates to simulate maintenance decisions and outcomes in 100 datasets, calculate the proportion of times each community maintains its pump or not, and compare this to the functionality observed in the data.

The model fits the key patterns of pump functionality in the data well. The pump functionality rate predicted by the model (71.6 percent) is similar to that in the data (70.8 percent), and the model classifies the functionality of 70.6 percent of observations correctly. Figure 3 shows that the distribution of cluster functionality rates in the data is very similar to the distribution predicted by the model, though the model slightly over-predicts the number of clusters in which all or no pumps are functional. I further demonstrate the good fit of the model in the Online Appendix: Figure A5 shows the functionality rate of pumps by the fragmentation of technology in their cluster (as measured by the Herfindahl-Hirschman Index), which is similar in the model and the data; Figure A6 shows that the functionality rate of pumps by the

[71] Note that the outcomes equation is estimated at the ward level, as given by equation (8), so we need to interpret the effect of the pump functionality rate in a ward on its outcomes as $\hat{\beta}_1 + \hat{\beta}_2$. Note that although $\frac{1}{n_w}\sum_{i=1}^{n_w} m_i$ and $\frac{1}{n_w}\sum_{i=1}^{n_w} \bar{m}_{-i}$ are highly positively correlated, they are not equal. The first term averages pump maintenance decisions over all communities in a ward, while the second takes an average of an average (of all pumps but i in a given cluster). These two terms are different if a ward contains a cluster with only one pump that is functional. In the data, these two values are different in approximately 35 percent of wards, allowing separate identification of β_1 and β_2.

[72] These estimates are interpreted as causal because I have explicitly modeled and estimated pump functionality using exogenous variation in whether nearby communities have a similar pump.

number of other pump and non-pump water sources in its cluster is also similar in the model and data.

7.1.2 Out-of-sample fit

As discussed in section 3.1, the data used to estimate the model was collected between 2011 and 2013 by GeoData Consultants Limited on behalf of the Tanzanian Ministry of Water and Irrigation. To assess out-of-sample fit, I use data from a water point mapping exercise carried out by three international NGOs between 2005 and 2008 in 486 wards in Tanzania, 303 (62%) of which are not included in the 2011-2013 sample I use to estimate the model.[73,74] I assess model fit using data on 9,119 water sources, 5,138 of which are pumps.[75]

The model fits the key patterns of the out-of-sample data well. The model predicts a functionality rate of 67.2 percent, compared to 68.5 percent in the data, and the model classifies the functionality status of 69.1% of observations correctly. Figure 4 shows that the distribution of cluster pump functionality rates predicted by the model is very similar to the distribution observed in the data. Again, I demonstrate the good out-of-sample fit in the model in more detail in the Online Appendix: the predicted functionality rate of pumps by the fragmentation of technology in its cluster (Figure A9) and by the number of pump and non-pump water sources in its cluster (Figure A10) is similar to that observed in the data.

7.2 Counterfactual policy evaluation

I use the model to estimate the effects of two policies proposed by the Tanzanian government in an attempt to improve rural water supply. The first policy is the standardization of pump installations to a single technology, which would increase

[73] 42 of 132 districts were mapped by WaterAid in partnership with Engineers Without Borders and SNV, a Dutch NGO, in a pilot water point mapping exercise.

[74] Note that although the 2011-2013 dataset is from a national water point mapping exercise, I excluded some districts from the data because a significant proportion of observations were missing key data, as described in section 6.1. These districts were largely the same ones as those covered by the pilot mapping exercise in 2005-2008, which explains why there is little geographic overlap between the sample used to estimate the model and the data used to test its out-of-sample fit. Note that these two samples are not entirely independent, as some of the observations used to estimate the model are in wards also covered by out-of-sample data, collected approximately five years earlier. I can also assess out-of-sample fit excluding these wards, and the results are similar.

[75] I define clusters of water sources as in section 6.1, and the distribution of cluster sizes (given in Figure A8) is similar to the distribution of clusters defined in the 2011-2013 data used to estimate the model (Figure 2).

Figure 3: Within-sample model fit: distribution of cluster pump functionality rate. Overlaid histograms show that the distribution of the cluster pump functionality rate in the data and predicted by the model are reasonably similar.

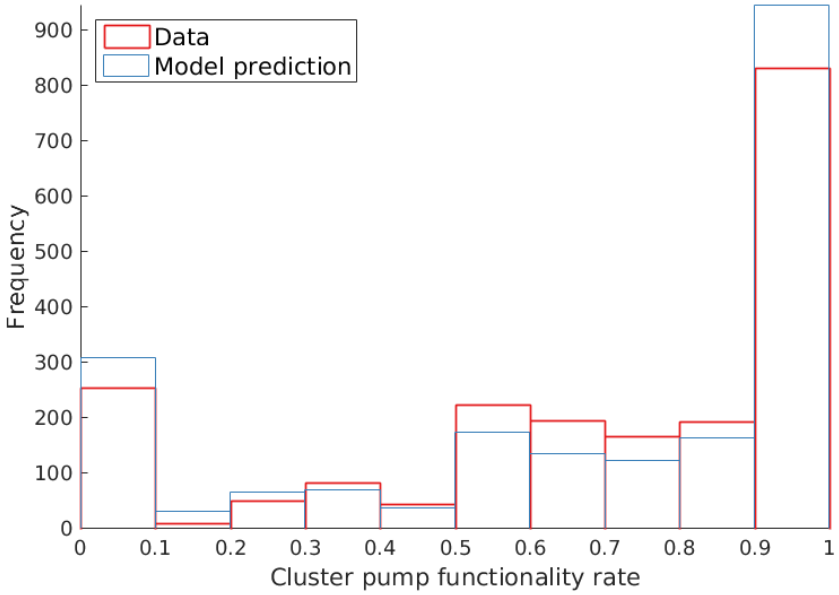
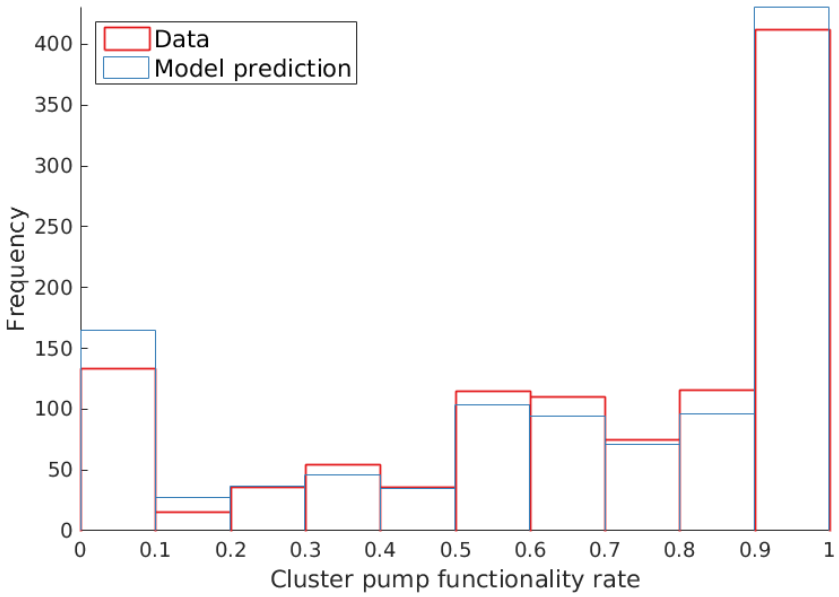


Figure 4: Out-of-sample model fit: distribution of cluster pump functionality rate. Overlaid histograms show the distribution of cluster pump functionality rates in the 2005-2008 data and predicted by the model.



Note: Histogram shown for an individual simulation (rather than averaging over multiple simulations). The distributions in other simulations are very similar.

maintenance cost-reduction spillovers between nearby communities but would not affect free riding in my model. The second policy requires all communities to charge user fees for their water sources, which would decrease free riding but have no effect on spillovers in my model. I estimate the effect of each policy on the pump functionality rate and child outcomes.

7.2.1 Technology standardization

As discussed in section 2, many water sector practitioners, including the majority of respondents to my survey, are in favor of more standardization of pump technologies to improve the sustainability of pump installations. Formal technology standardization has been attempted in fifteen sub-Saharan African countries with the support of UNICEF (MacArthur [2015]). It was proposed in Tanzania in the Tanzania National Water Policy [2002], but has not been implemented in practice: the proportion of pumps installed using the technologies chosen for standardization has actually decreased since 2002 (see Figure A1).

Table 6: Predicted effect of technology standardization. Estimated effect of standardization to each of the four most common technologies on pump functionality, child survival and school attendance rates, in percentage points.

		Technology standardized to:			
		Nira	Afridev	SWN 80	India Mk
Change in functionality	Technology effect	2.9	0.4	-1.1	-4.5
	Spillover effect	3.2	3.2	3.2	3.2
	Net effect	6.1	3.6	2.1	-1.4
Change in outcomes	Child survival	0.36	0.18	0.08	-0.17
	Girl attendance	0.61	0.31	0.14	-0.27
	Boy attendance	0.48	0.25	0.11	-0.21

Notes: The baseline rate of functionality predicted by the model without standardization is 71.6 percent. The baseline rates of outcomes are 81.6 percent for child survival, 73.9 percent for girls' school attendance and 71.1 percent for boys' school attendance.

Table 6 shows the change in pump functionality, child survival and school attendance rates predicted by the model as a result of standardizing the technology of installed pumps to each of the four most common technologies. The model predicts that if all pumps were standardized to the technology that it estimates is cheapest to maintain, the Nira pump, the functionality rate would increase by 6.1 percentage points,

from 71.6 percent to 77.7 percent. There are two channels through which this effect works: first, by switching every pump to the technology that is easiest to maintain (the 'technology effect'); and second, through increased maintenance cost-reduction spillovers. I estimate that the increase in spillovers accounts for 3.2 percentage points of the increase in functionality, just over half of the total effect.[76] Standardization to a sub-optimal technology could still increase the functionality rate, because of the increase in positive spillovers in pump maintenance. I estimate that standardization to the Afridev or SWN 80 technologies would increase the functionality rate by 3.6 and 2.1 percentage points respectively, but standardization to the worst performing technology in the sample, India Mark II, would decrease the functionality rate by 1.4 percentage points, despite an increase in spillovers.[77] The model estimates that increased functionality from technology standardization would have a modest positive effect on school attendance and child survival rates, and that the effect on school attendance is greater for girls than for boys. This is consistent with previous evidence which shows that girls' school attendance is more sensitive to water availability than that of boys (UNDP [2006]).[78]

7.2.2 Universal user fees

Guidelines in the Tanzania National Water Policy [2002] stipulate that communities should charge user fees, but as shown in Table 1 in section 3, only 35 percent of pumps and 49 percent of non-pump water sources charge users for water. I use the model to evaluate the effects of increasing the proportion of pumps charging fees to 100 percent.

User fees can affect functionality through two channels in my model, by reducing free riding and by changing communities' cost of maintenance.[79] As shown by Table 7, I

[76]The Online Appendix shows that this increase would be largest in clusters with more fragmented technologies (Figure A11), but is similar among clusters of different sizes (Figure A12).

[77]In the data sample used to estimate the model, the India Mark II pump has a functionality rate of 67.1 percent, compared to 74.1 percent for the Nira, 75.1 percent for the Afridev and 71.9 percent for the SWN 80.

[78]In the Online Appendix I show that outcomes would improve in the vast majority of wards, and would improve by a greater amount in wards with lower initial rates of child survival and school attendance, reducing geographic inequality in these outcomes (Figure A13).

[79]The model only estimates the first order effects of user fees on pump functionality and human capital outcomes. There are many possible secondary effects not captured by the model, including on households' other expenditure, distributional impacts within communities, possible negative effects on poor households, or long run effects on relationships between communities. The model also treats

estimate that universal user fees would increase the functionality rate of pumps by about 11 percentage points. Most of this increase (8.9 percentage points) is driven by a decreased cost of maintenance, which I interpret as having more resources available for pump maintenance to help overcome the collective action problem. I estimate that the reduction in free riding accounts for a 1.8 percentage point increase in pump functionality rates.[80] Again, I estimate that this increase in functionality would have a modest, positive effect on child survival and school attendance rates, with school attendance increasing more for girls.[81]

Table 7: Predicted effect of universal user fees. Estimated effect of all water sources charging fees on pump functionality, child survival and school attendance rates, in percentage points.

		Universal user fees
Change in functionality	Cost of maintenance effect	8.9
	Free riding effect	1.8
	Net effect	10.7
Change in outcomes	Child survival	0.5
	Girl attendance	1.7
	Boy attendance	1.2

Notes: The baseline rate of functionality predicted by the model without standardization is 71.6 percent. The baseline rates of outcomes are 81.6 percent for child survival, 73.9 percent for girls' school attendance and 71.1 percent for boys' school attendance.

the charging of user fees as exogenous from the point of view of the community. I do not model communities' choice of user fees in order to keep the model tractable and because respondents to my survey indicate that installing organizations play a significant role in determining whether user fees are charged (Figure A34).

[80]Figures A14 and A15 in the Online Appendix show that universal user fees would increase pump functionality rates in clusters of all levels of technology fragmentation, and of all sizes, and would attenuate differences in functionality rates by technology fragmentation and size.

[81]Figure A16 in the Online Appendix shows that estimated outcomes would improve in nearly all wards, with the largest improvements in child survival and school attendance rates in wards with lower initial rates.

8 Conclusion

This paper estimates the costs of fragmented provision of water in rural Tanzania by structurally estimating a spatial network model to analyze decentralized pump maintenance decisions of communities. I model pump maintenance decisions in a static network game of complete information, in which communities simultaneously make a binary decision whether to maintain their pumps or not. To distinguish social interactions from spatially correlated unobservables, I use exogenous variation in the similarity of neighboring water sources as a shifter in the strength of maintenance spillovers that are possible between them. To estimate this game in the presence of multiple equilibria, I partition the data into geographic clusters using a clustering algorithm and calculate the likelihood of the observed action profile in each cluster using an equilibrium selection rule. I find evidence that a lack of coordination between organizations installing water sources, combined with decentralized 'community based management' of water pumps, is costly: it decreases the functionality rate of pumps and lowers rates of child survival and school attendance.

This paper is among the first to empirically estimate the effects of strategic interactions in the provision of local public goods in a network setting. There are a number of exciting avenues for future research in this area. First, the framework developed in this paper might be extended to a dynamic setting. In my empirical context, this would allow us to analyze whether the timing of installation and maintenance of pumps is important: for example, if communities reduce maintenance in anticipation of new installations, there may be costs of 'aid dependency' in addition to the costs of a lack of 'aid coordination' shown in this paper. The framework developed in this paper may also be applied to other settings. Although the provision of public goods by non-state actors makes this analysis particularly relevant in developing countries, strategic interactions may also be important in the provision of public goods in developed countries, such as local investments in law and order, transport infrastructure, public schools and the reduction of pollution. In each case, identifying social interactions and estimating network models remains challenging, but this paper demonstrates methods of overcoming these challenges that may be successfully adapted and applied in other contexts.

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A Online Appendix

A.1 Additional figures and tables

Figure A1: Annual proportion of pumps of each technology installed. The proportion of Nira and SWN 80 pumps installed in Tanzania has declined since the Tanzania National Water Policy [2002] attempted to standardize to these two technologies in 2002.

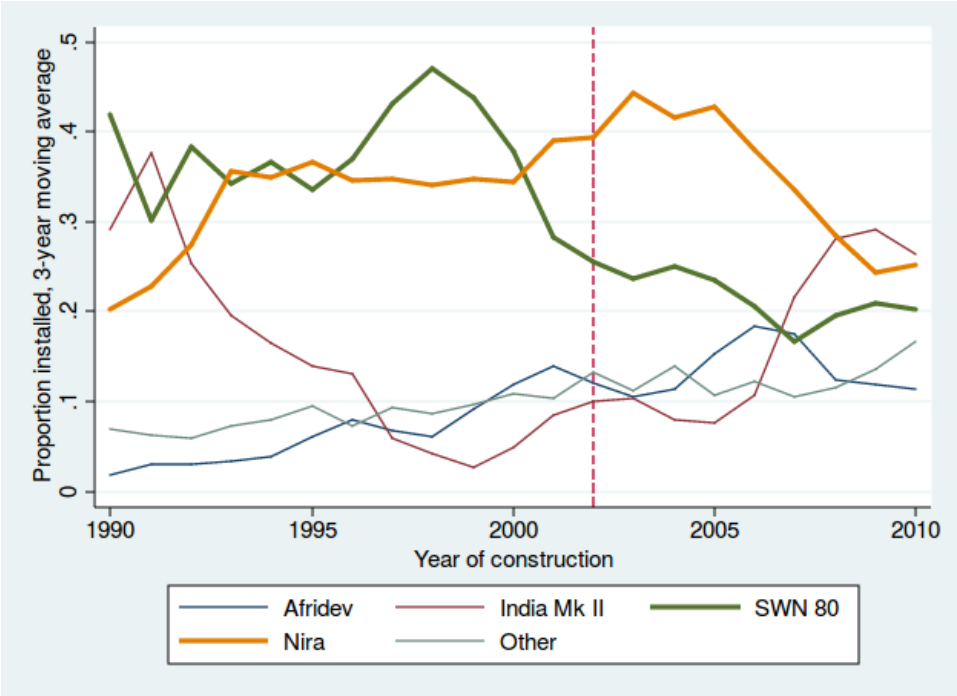
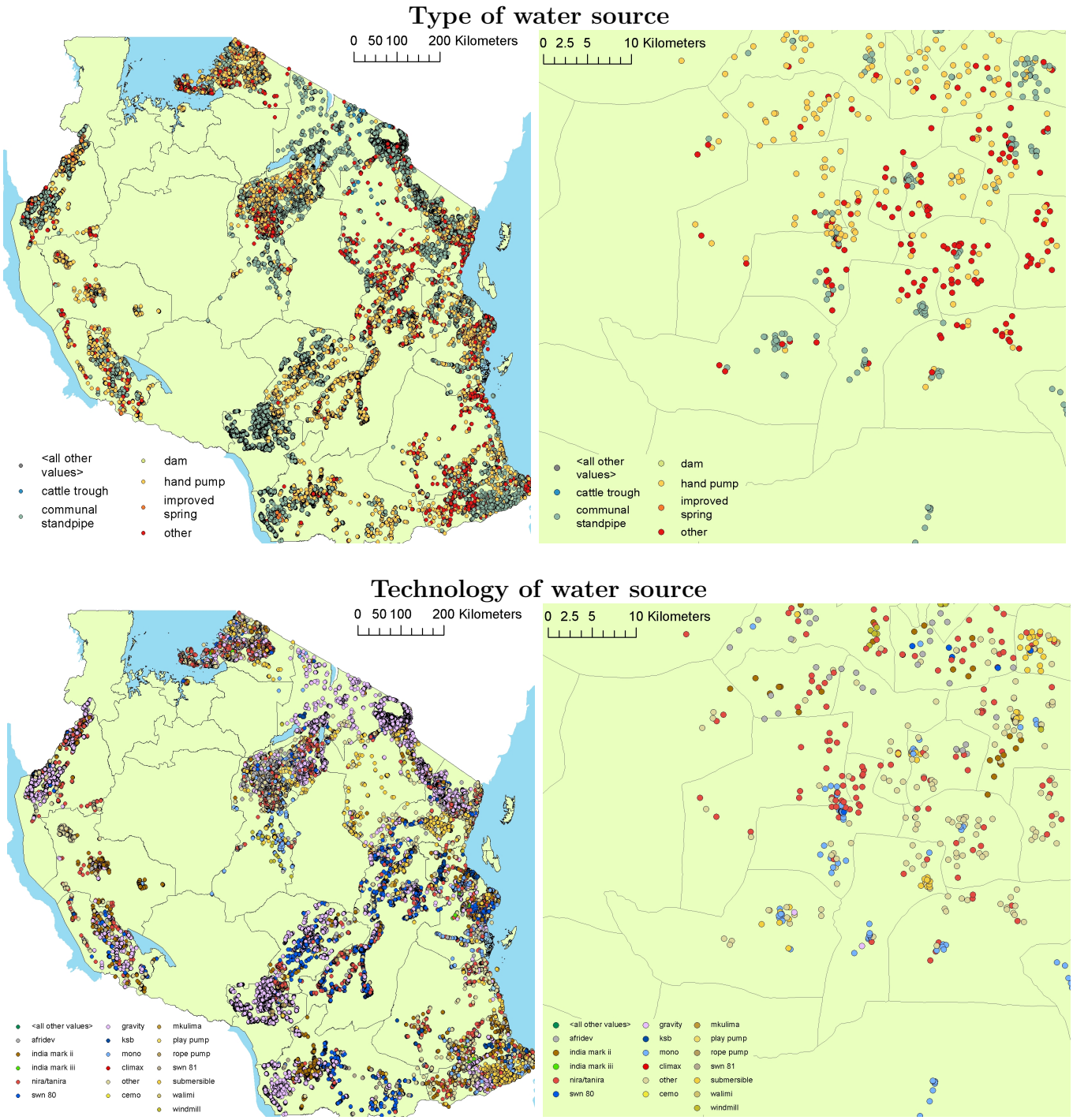


Table A1: Summary statistics for centrality measures, different cutoff distances. Median, mean and standard deviation for the number of water sources within 1.2km, 0.7km and 1.7km.

	1.2km cutoff			0.7km cutoff			1.7km cutoff		
	Med.	Mean	S.D.	Med.	Mean	S.D.	Med.	Mean	S.D.
Number of non-pumps	0	2.83	6.84	0	1.50	4.08	1	4.08	9.05
Number of pumps, diff tech	0	1.64	3.96	0	0.83	1.98	1	2.51	6.47
Number of pumps, same tech	1	2.44	3.81	0	1.32	2.33	2	3.44	5.22
Number of pumps	2	4.08	6.05	1	2.16	3.25	3	5.95	9.42
Number of water sources	4	6.91	10.61	2	3.65	5.86	6	10.03	15.5

Figure A2: Location, type and technology of water sources in Tanzania. Water point mapping data, Tanzania (2013).



Notes: The left hand side image shows the water sources in the main source of data and their functionality status. The right hand side image zooms in on a specific region, Morogoro. Regions with missing data are excluded. Map with functionality of water source is shown in Figure 1 in section 3.1.

Figure A3: Histograms of the number of water sources within 1.2km, 0.7km or 1.7km. Histograms for non-pumps, pumps of a different technology and pumps of the same technology. Each distribution is positively skewed and has approximately half of observations without a water source of that type within 1.2km.

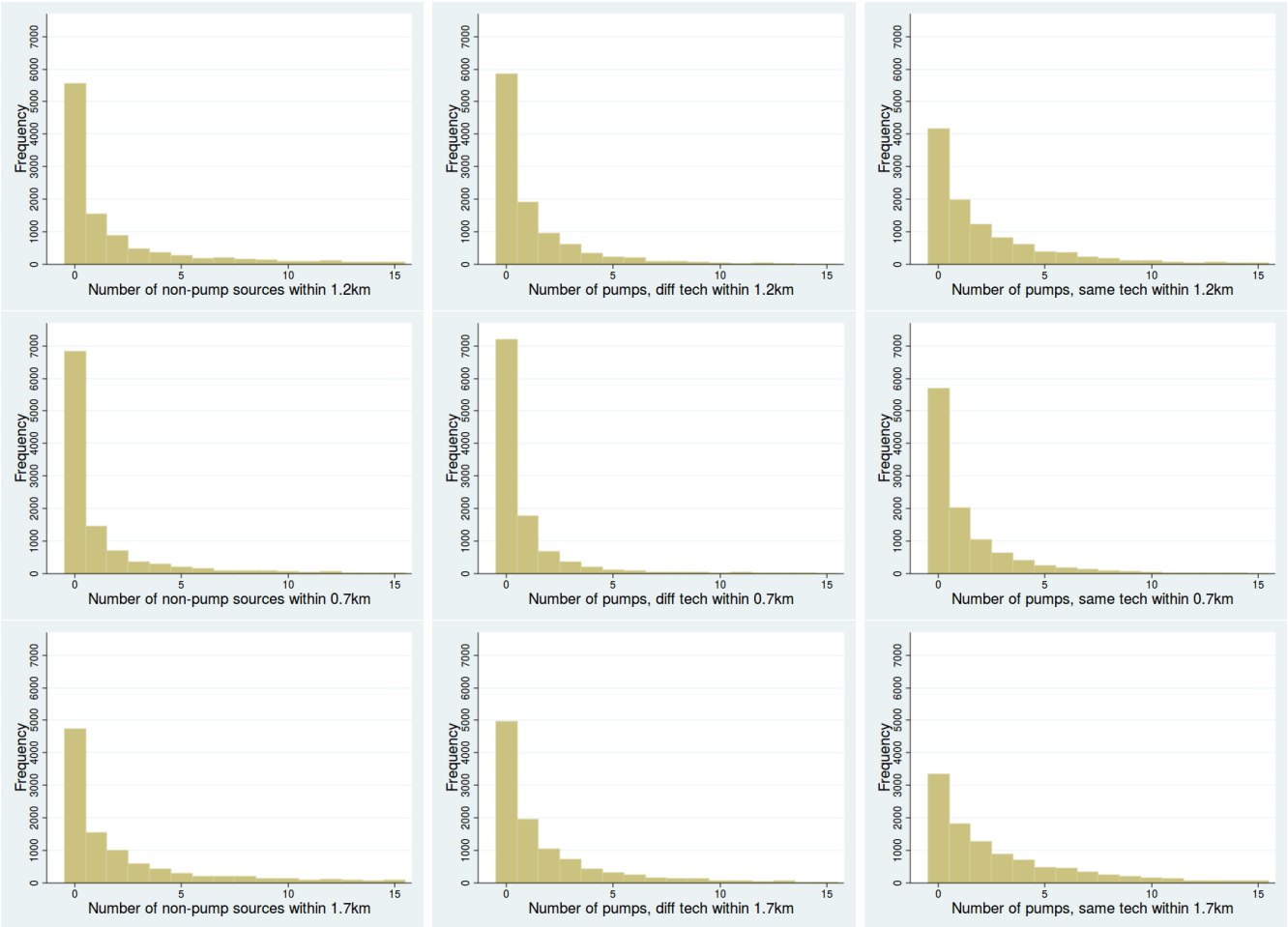


Figure A4: Hazard rate of pump breakdown. The Kaplan-Mier estimator shows that the hazard rate of pump breakdown is almost constant for the first 20 years (95 percent confidence interval given by pink dotted line). The survivor function shows that nearly all pumps are broken after 35 years.

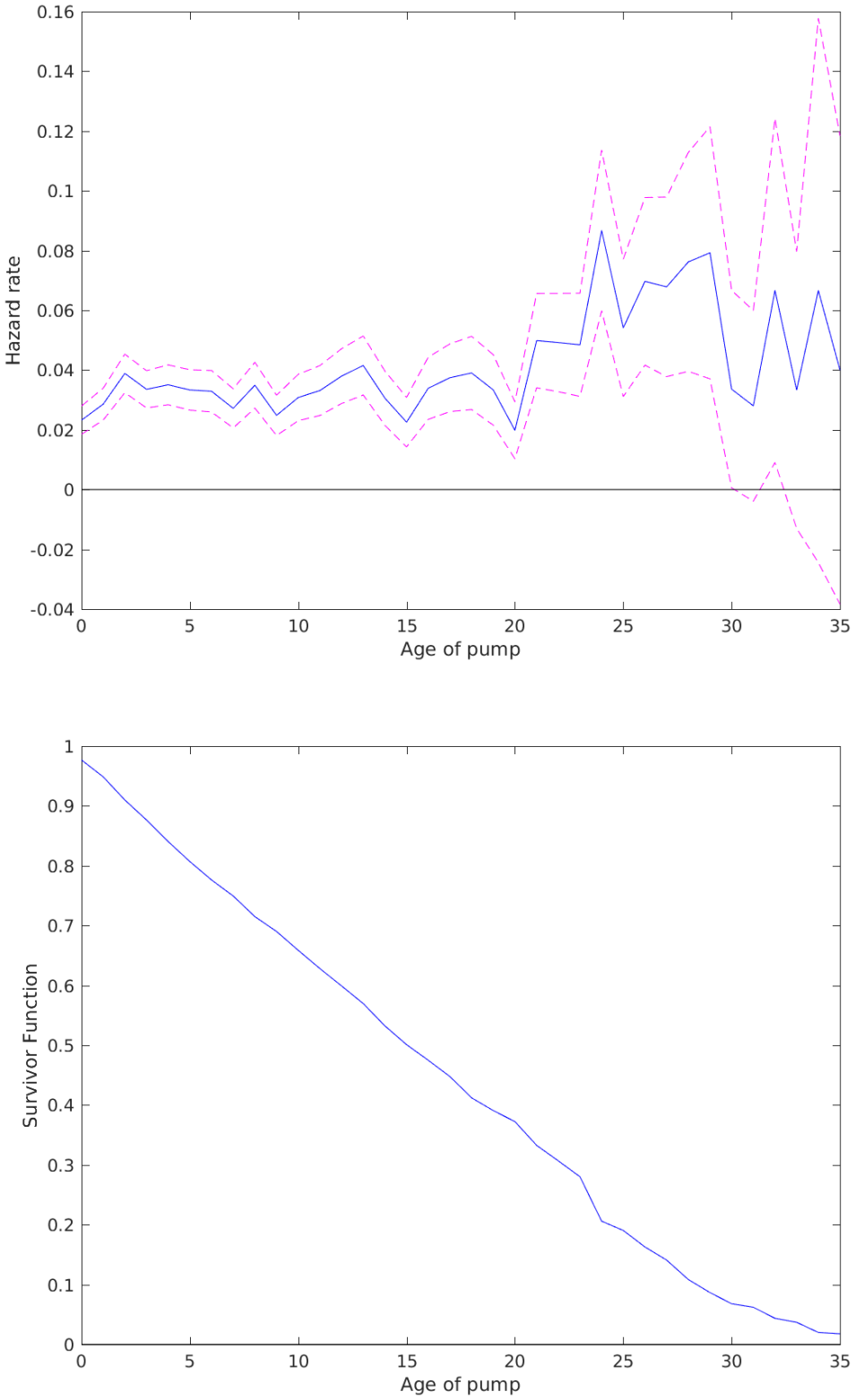
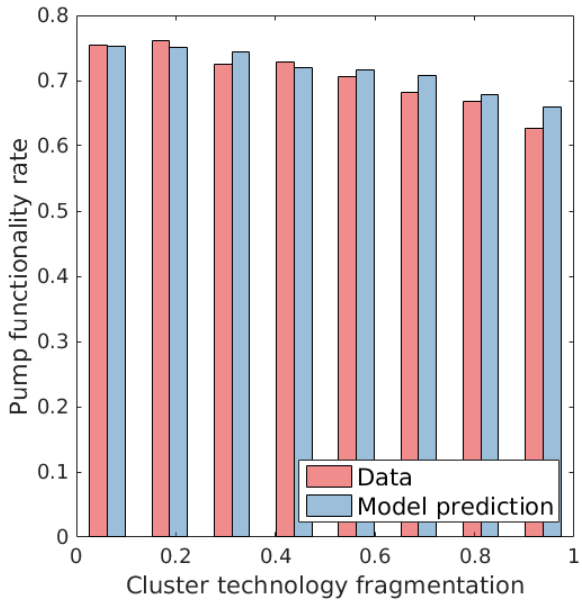


Figure A5: Within-sample model fit: pump functionality rate by cluster technology fragmentation. There is a clear pattern in the data that pumps are less likely to be functional if they are in clusters with higher fragmentation of technology. The model predicts both this pattern and the level of functionality rates very well.



Notes: I calculate fragmentation using the Herfindahl-Hirschman Index (HHI): technology fragmentation in cluster k is given by $frag_k = 1 - \sum_j s_{jk}^2$, where s_{jk} is the share of technology j in cluster k.

Figure A6: Within-sample model fit: pump functionality rate by cluster size. There is a clear pattern in the data that pumps are more likely to be functional if they are in a cluster with a greater number of other pumps and the model captures this fact well, predicting the functionality rate of different cluster sizes very accurately. The data also shows that in general pumps are less likely to be functional if they are in a cluster with more non-pump water sources, though this relationship is not quite monotonic. The model predicts this broad pattern reasonably, though it does not do as well at predicting the pump functionality rate for clusters with five or more non-pump water sources, over-predicting the functionality rate in each case.

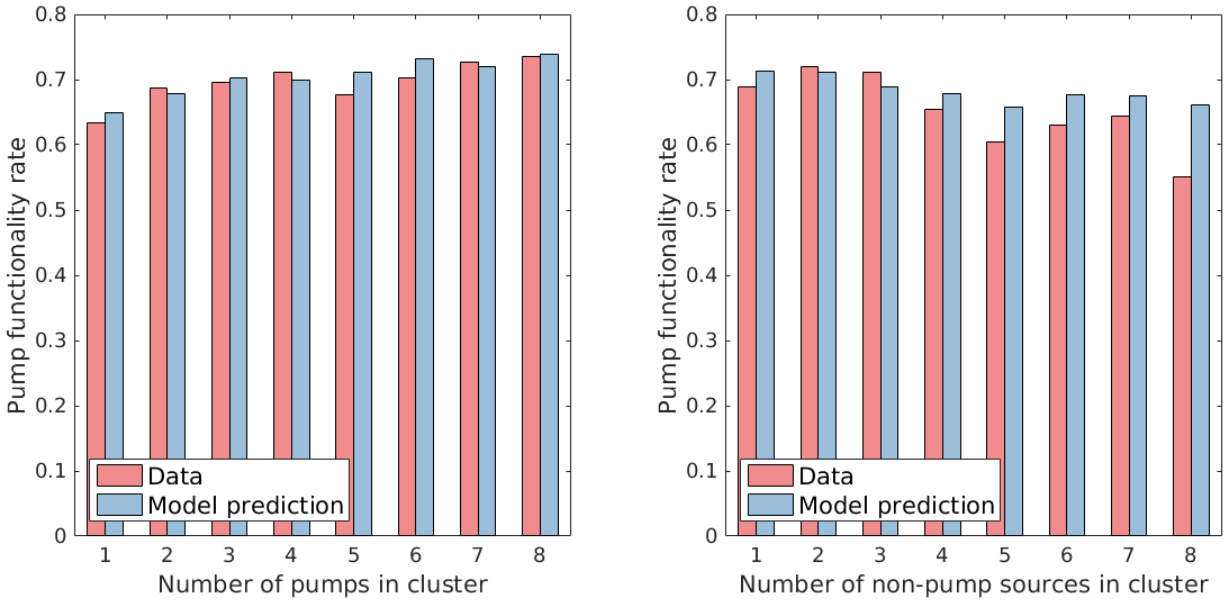


Figure A7: Within-sample model fit: outcomes. Although the model is mainly focused on explaining pump functionality, not outcomes, we can plot the outcomes in the data and the outcomes predicted by the model in each ward, for each of the three outcomes. If the model predictions were perfect, these points would be on the 45 degree line. The model does not predict patterns of child survival rates very well, with a lot of variance in the data left unexplained by the model, presumably because there are many other factors that explain child survival beyond water availability that are not included in the model. However, the model does a good job of explaining the patterns of school attendance in the data, explaining 46 percent of the variance in girls' school attendance and 52 percent of boys' school attendance.

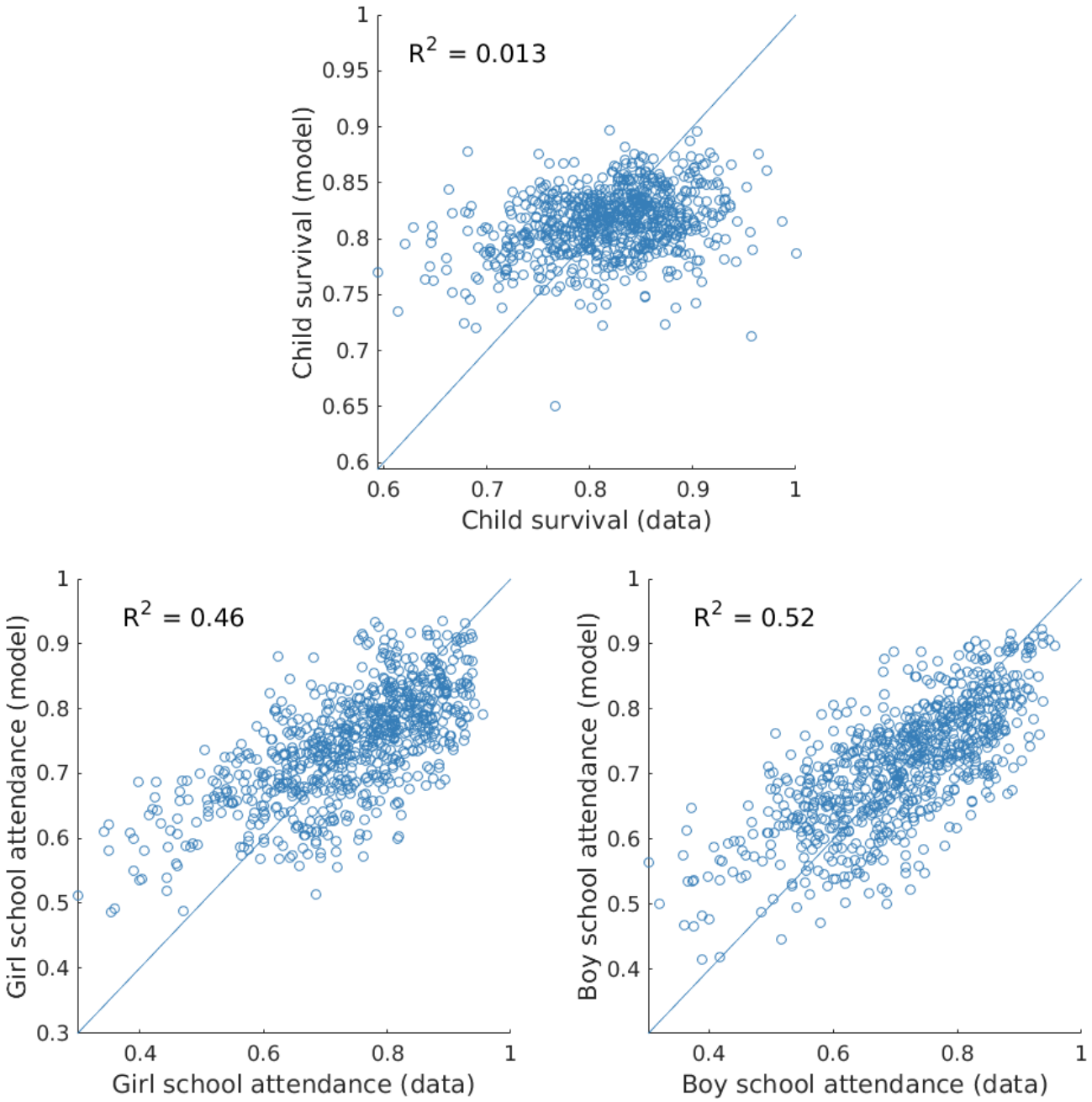


Figure A8: Definition of clusters in 2005-2008 data. Distribution of cluster sizes, by number of pumps and number of all water sources in each cluster in the 2005-2008 data used for out-of-sample fit.

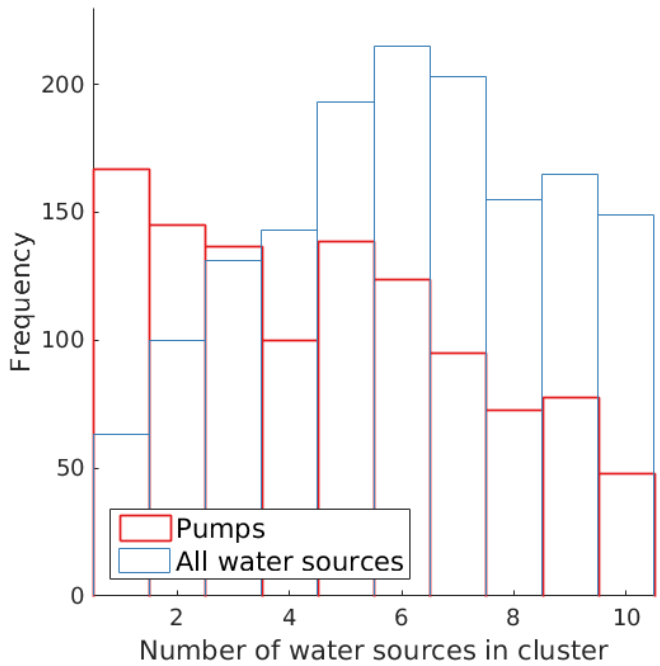


Figure A9: Out-of-sample model fit: pump functionality rate by cluster technology fragmentation. As in the data used to estimate the model, pumps are less likely to be functional if they are in clusters with higher fragmentation of technology and the model predicts both this pattern and the level of functionality rates very well.

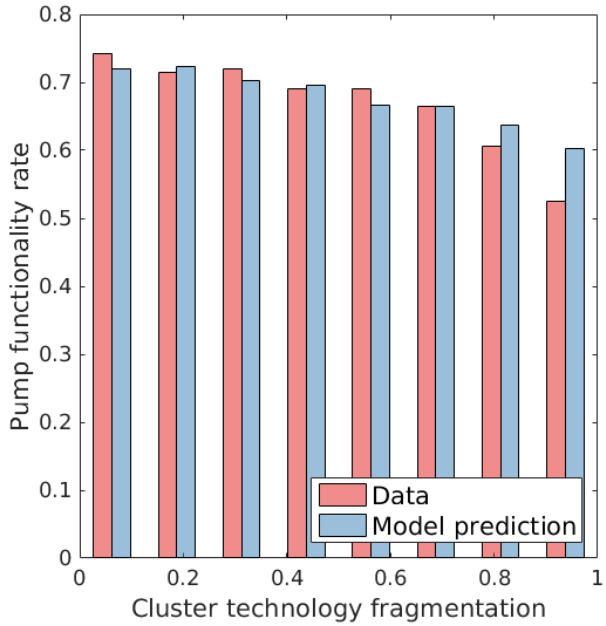


Figure A10: Out-of-sample model fit: pump functionality rate by cluster size. The model fits the level and slope of the pump functionality rate in the 2005-2008 data well, for both the number of pumps and non-pumps in a cluster.

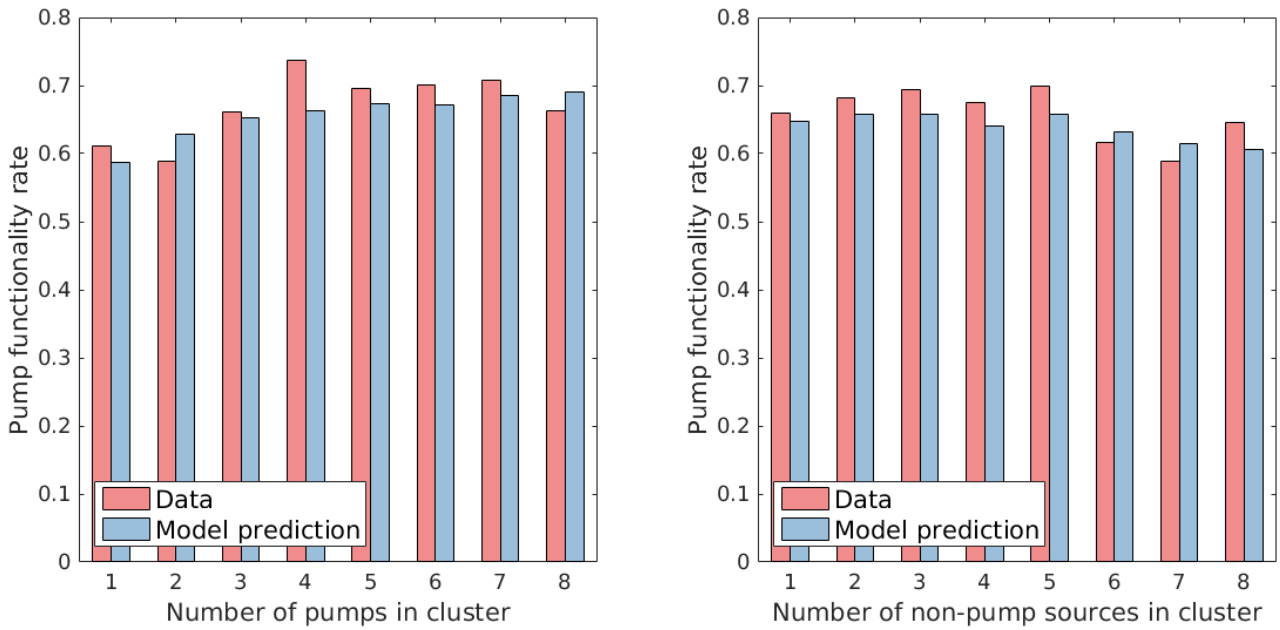


Figure A11: Standardization of technology counterfactual: pump functionality rate by cluster technology fragmentation. Predicted functionality rates shown for standardization to the best performing technology, the Nira pump. Standardization of technology results in larger increases in pump functionality rates for clusters with a high initial fragmentation of technology.

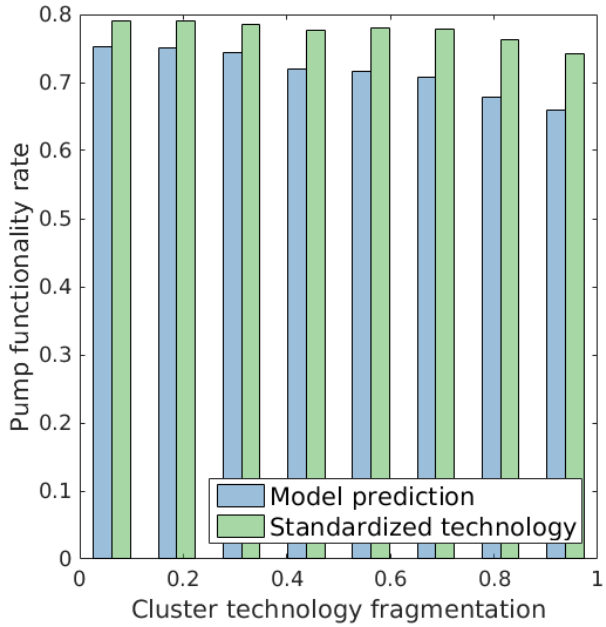


Figure A12: Standardization of technology counterfactual: pump functionality rate by cluster size. Predicted functionality rates shown for standardization to the best performing technology, the Nira pump. Pump functionality rates increase across clusters of all sizes, though pumps are still more likely to be functional if they are in a cluster with more pumps and fewer non-pumps.

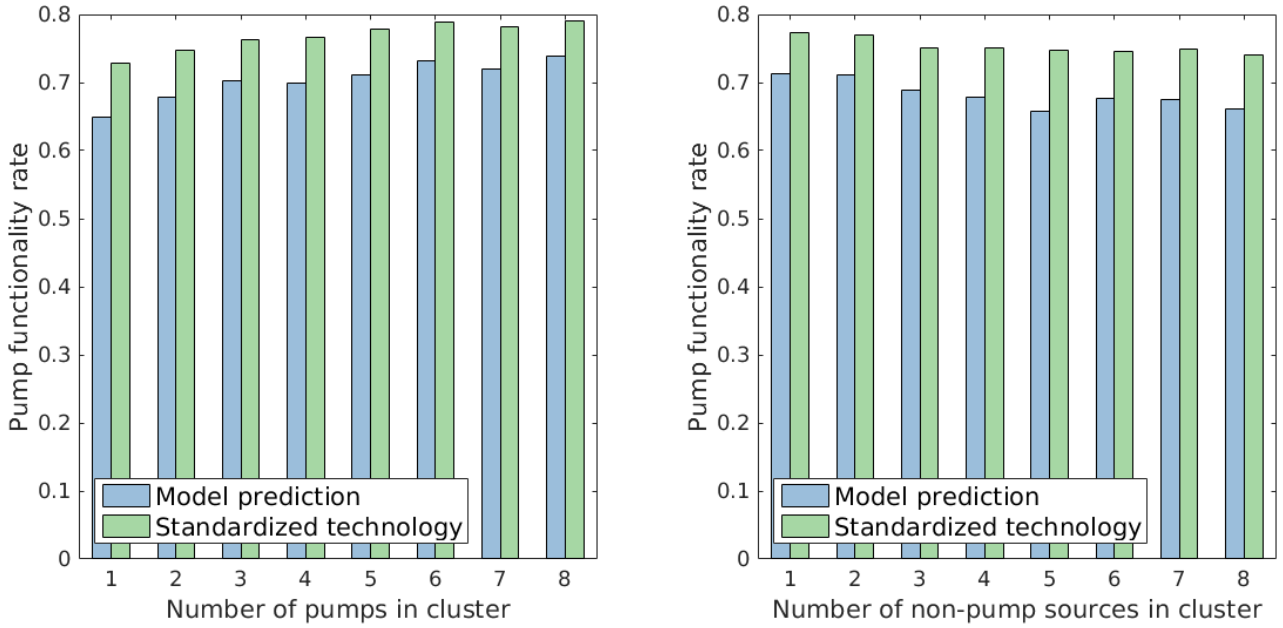
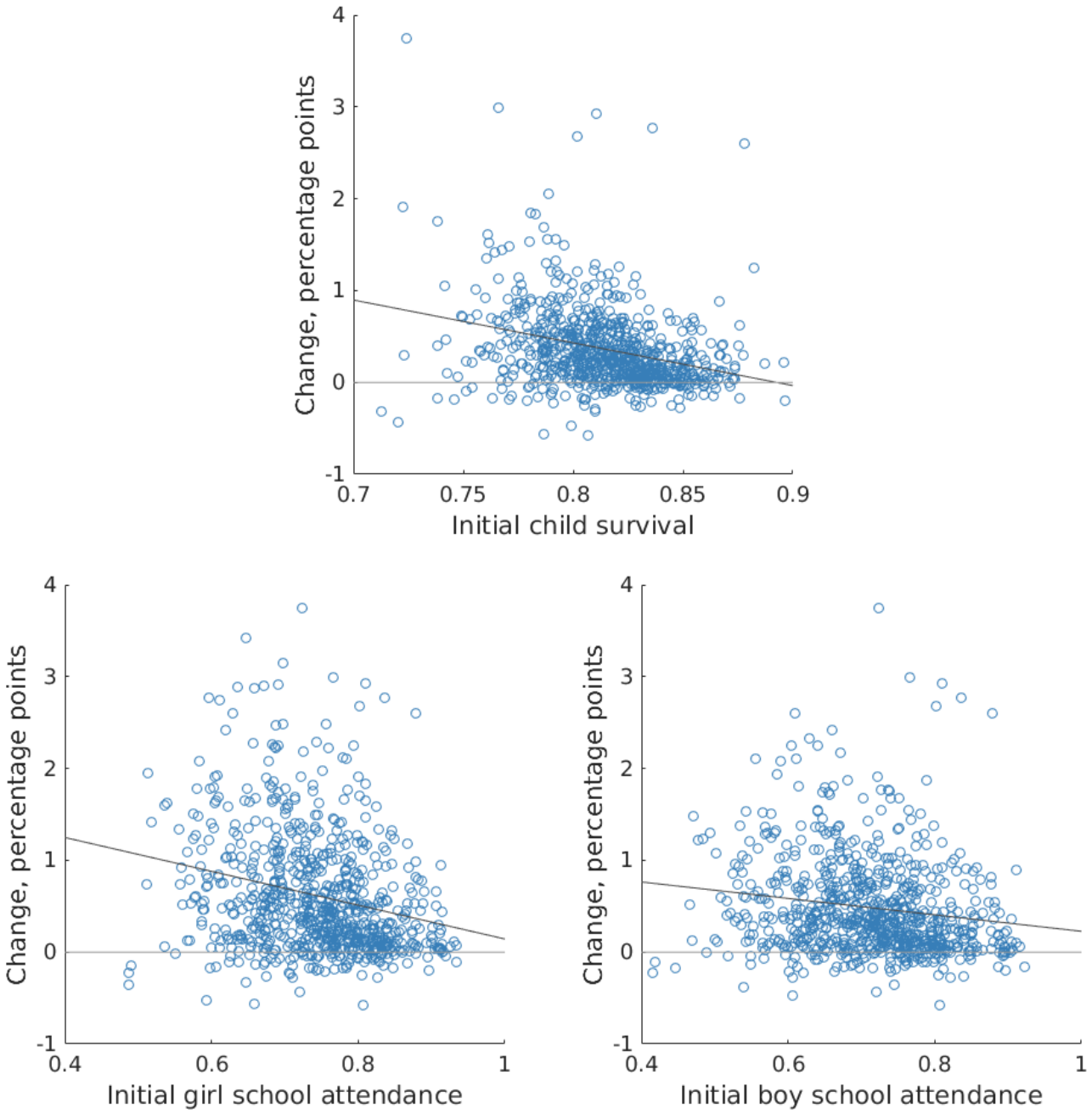


Figure A13: Standardization of technology counterfactual: change in outcomes. The initial outcomes of each ward are given on the horizontal axis, with the percentage change in the outcomes as a result of standardization of technology given on the vertical axis. The model predicts that standardization of technology increases the rates of child survival and school attendance in the vast majority of wards. The increases are larger for wards with a lower initial level of these outcomes.



Notes: Change in outcomes shown for counterfactual in which pumps are standardized to the best performing technology, the Nira pump.

Figure A14: Universal user fees counterfactual: pump functionality rate by cluster technology fragmentation. Charging universal user fees significantly increases the average functionality rate for clusters with different levels of fragmentation. It attenuates the negative effect of technology fragmentation, though the functionality rate is still slightly lower in clusters with higher technology fragmentation.

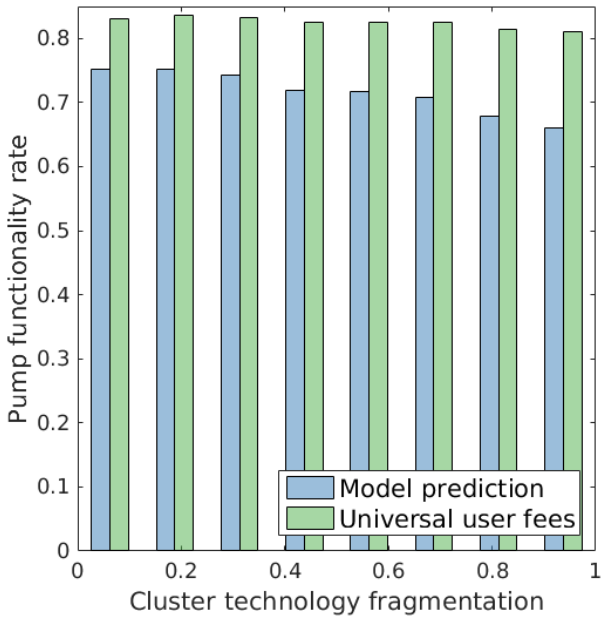
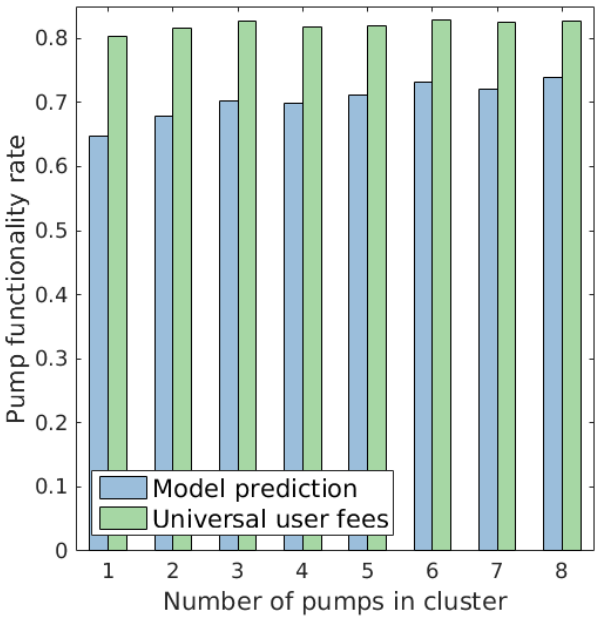


Figure A15: Universal user fees counterfactual: pump functionality rate by cluster size. Universal user fees significantly increase the average functionality rate for clusters of all sizes. They attenuate the effects of different numbers of water sources in a cluster, though the functionality rate is still slightly higher in clusters with more pumps and fewer non-pump water sources.



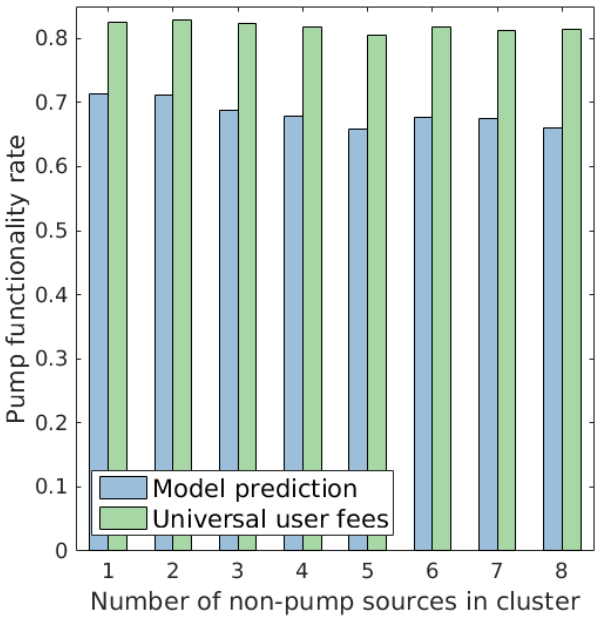


Figure A16: Universal user fees counterfactual: change in outcomes. The initial outcomes of each ward are given on the horizontal axis, with the percentage change in the outcomes as a result of universal user fees given on the vertical axis. The model predicts that universal user fees increase the rates of child survival and school attendance in the vast majority of wards. The increases are larger for wards with a lower initial level of these outcomes.

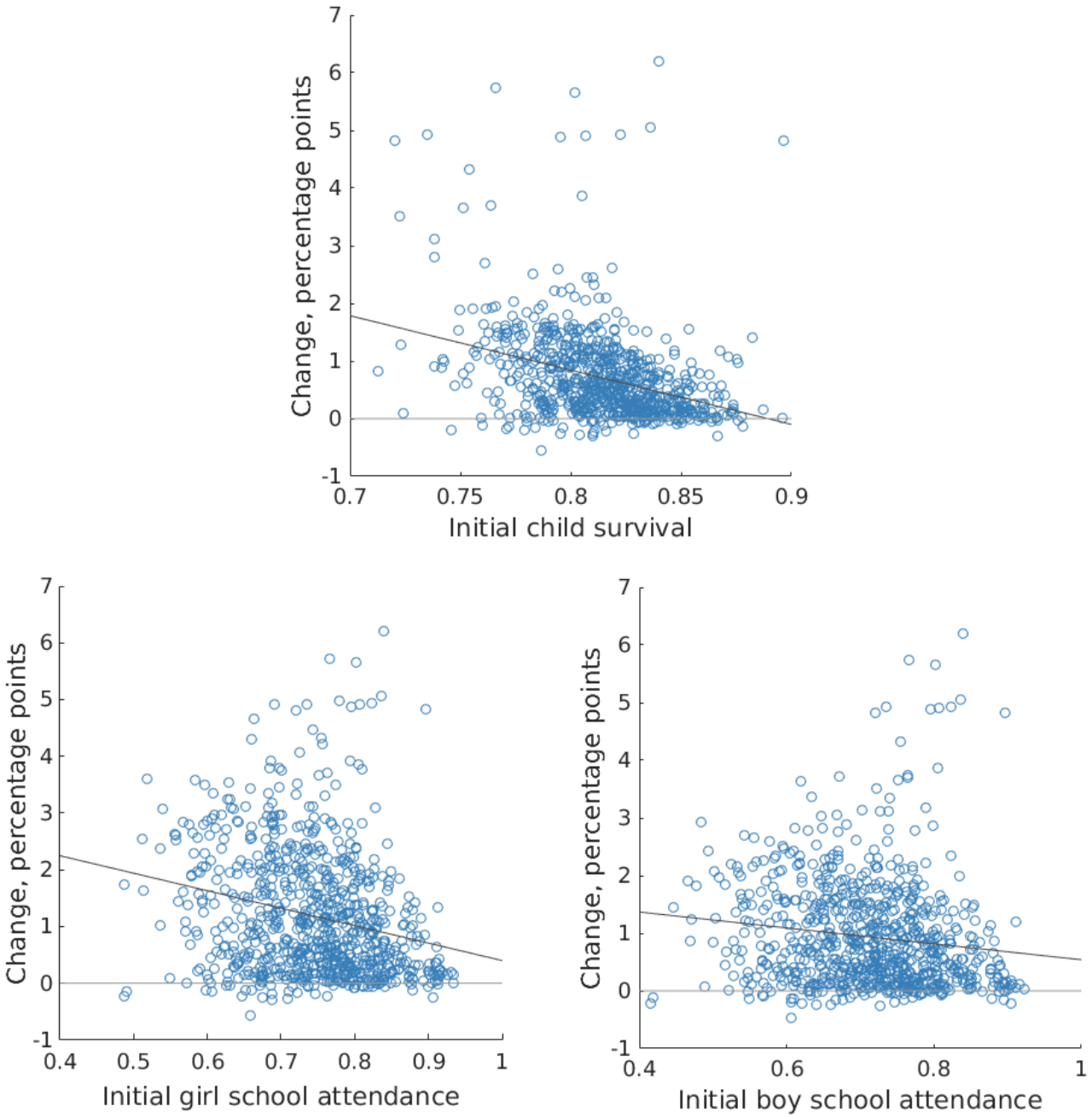
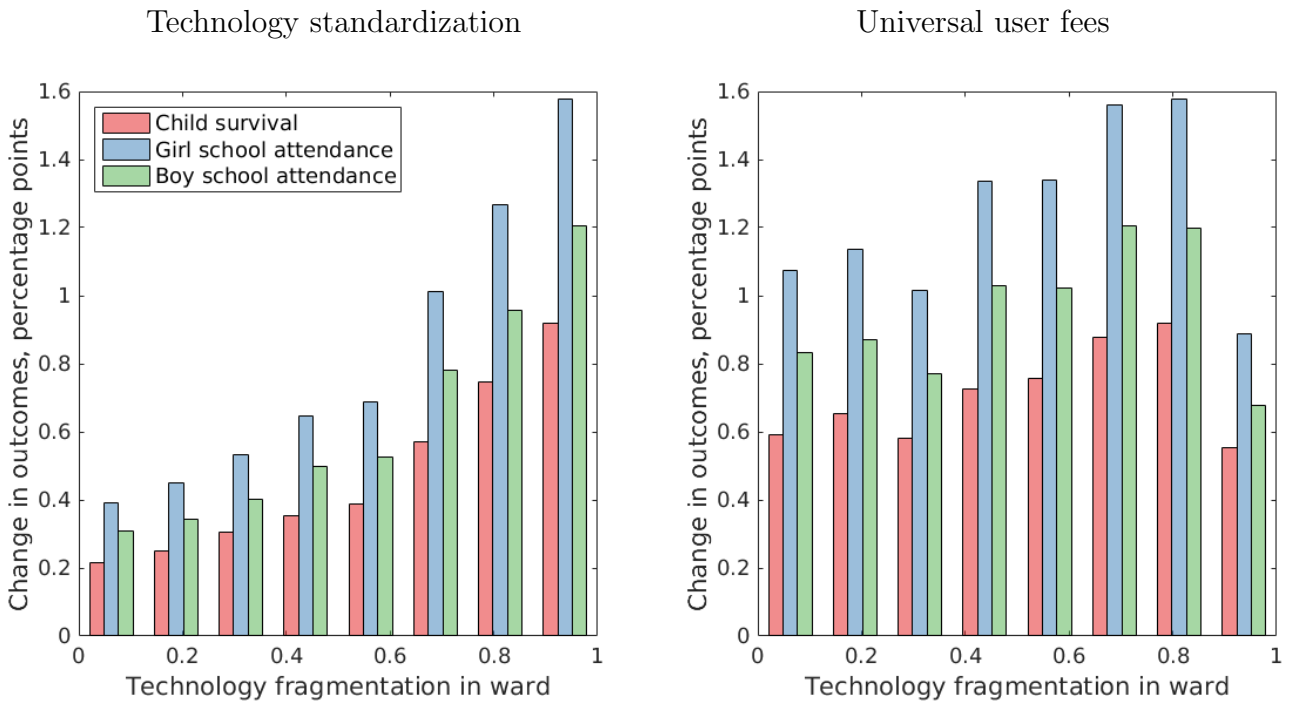


Figure A17: Counterfactual policies: outcomes by ward fragmentation. Both counterfactual policies predict increased pump functionality and a resulting increase in outcomes across wards with various levels of initial technology fragmentation. However, standardization of technology would lead to significantly larger gains in outcomes for wards with a higher initial fragmentation of technology, while universal user fees would have a similar effect on outcomes in wards with different levels of initial fragmentation.



Notes: The counterfactual in which pumps are standardized is shown for standardization to the best performing technology, the Nira pump.

A.2 Pump technology details

Figure A18: Afridev pump. Picture, technical details and design.

Description
The AFRIDEV Pump is a conventional lever action handpump. The configuration includes an "open top" cylinder: the piston can be removed from the cylinder without dismantling the rising main. The footvalve is retractable with a fishing tool.

Technical data

Cylinder diameter:	50.0 mm
Maximum Stroke:	225 mm
*) Approx. discharge,(75 watt input)	
at 10 m head:	1.4 m³/hour
at 15 m head:	1.1 m³/hour
at 20 m head:	0.9 m³/hour
at 30 m head:	0.7 m³/hour
Pumping lift	10 - 45 m
Population served:	- 300 people
Households:	30 households
Water consumption:	15 - 20 l/per capita
Type of well:	borehole or dugwell

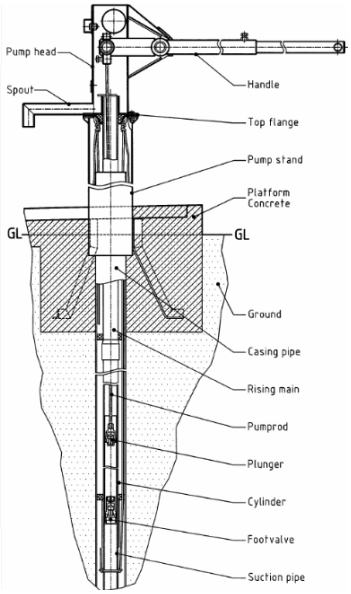
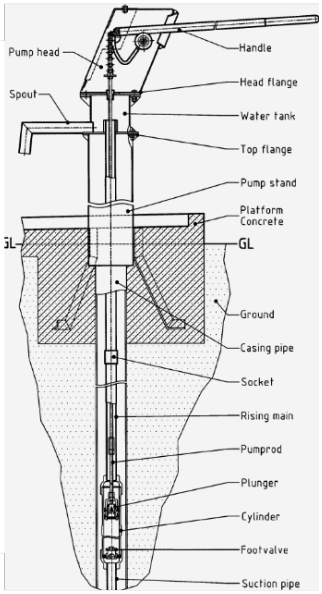


Figure A19: India Mark II pump. Picture, technical details and design.

Description
The INDIA Mark II Pump is a conventional lever action handpump and is subject to Indian Standard IS 9301. The down hole components exist of a brass lined cast iron cylinder and the brass plunger has a double nitrile rubber cup seal. The rising main is of Ø32 mm GI pipe and the pumprods are of galvanized steel with threaded connectors.

Technical data

Cylinder diameter:	63.5 mm
Maximum Stroke:	125 mm
*) Approx. discharge,(75 watt input)	
at 10 m head:	1.8 m³/hour
at 15 m head:	1.3 m³/hour
at 20 m head:	1.0 m³/hour
at 25 m head:	0.9 m³/hour
at 30 m head:	0.8 m³/hour
Pumping lift	10 - 50 m
Population served:	- 300 people
Households:	30 households
Water consumption:	15 - 20 l/per capita
Type of well:	borehole or dugwell



Notes: Information from Rural Water Supply Network (RWSN) [2005].

Figure A20: Nira/Tanira pump. Picture, technical details and design.

Description
The NIRA AF-85 Direct Action Handpump is based on a buoyant pump rod that is directly articulated by the user, discharging water at the up- & down stroke. The NIRA AF-85 Pump is completely corrosion resistant.

Technical data

Cylinder diameter:	50 mm
Maximum Stroke:	410 mm
*) Approx. discharge,(75 watt input)	
at 5 m head:	3 m³/hour
at 10 m head:	1.8 m³/hour
at 15 m head:	1.2 m³/hour
Pumping lift:	1 - 15 m
Population served:	- 300 people
Households:	30 households
Water consumption:	15 - 20 l/per capita
Type of well:	borehole or dugwell

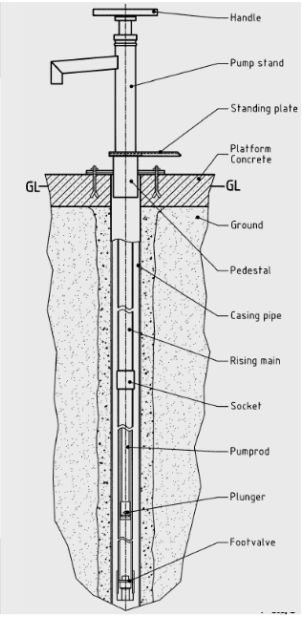
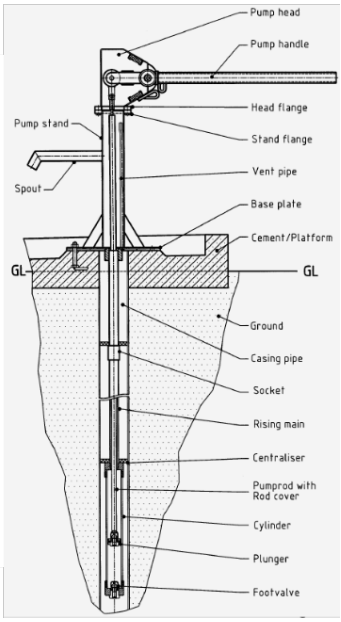


Figure A21: SWN 80 pump. Picture, technical details and design.

Description
The WALIMI Pump is a conventional lever action handpump. The riser pipes are made of PVC-HI and are connected by threads. The bearings for the lever action are made of specially treated hardwood. Cylinders are available in 2" and 3" diameter.

Technical data

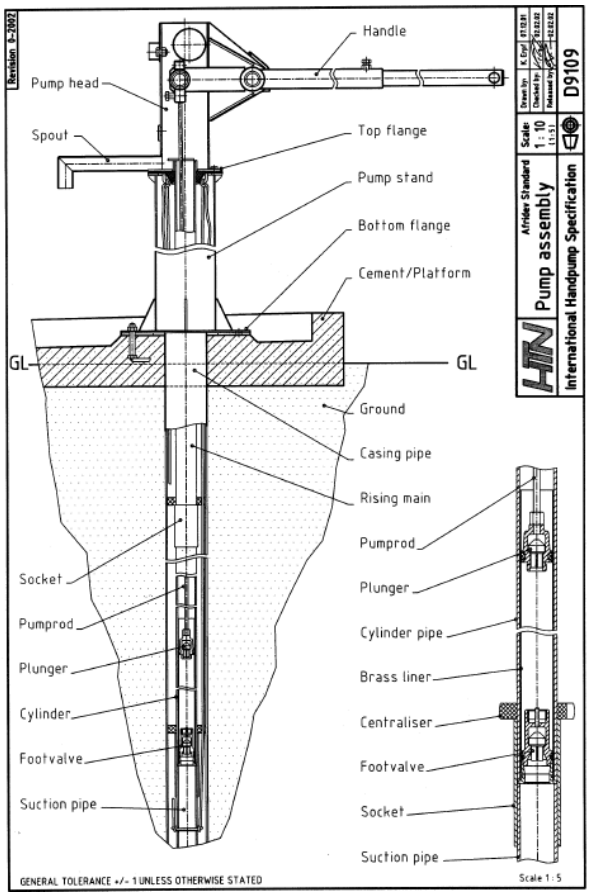
Cylinder diameter:	50.0 mm
Maximum Stroke:	170 mm
*) Approx. discharge,(75 watt input)	
at 5 m head:	2.0 m³/hour
at 10 m head:	1.3 m³/hour
at 15 m head:	1.0 m³/hour
Pumping lift	2 - 40 m
Population served:	- 300 people
Households:	30 households
Water consumption:	15 - 20 l/per capita
Type of well:	borehole or dugwell



Notes: Information from Rural Water Supply Network (RWSN) [2005].

Figure A22: Afridev pump components and approximate cost.

$ 0.27	U-seal
$ 0.15	O-ring
$ 0.47	Bobbin x 2
$ 2.43	Bearing x 2
$ 6.00	Rod centralizers
$ 198.00	Pump rods
$ 90.00	Pipes
$ 85.50	Cylinders
$ 5.84	Hanger pin
$ 8.64	Fulcrum pin
$ 3.90	Foot Valve
$ 7.50	Rope
$ 139.50	Stand, Head & Handle



Notes: Information from Rural Water Supply Network (RWSN) [2007].

Table A2: Reasons for pump breakdown. Primary reason given for breakdown of water pumps in 2005-2008 Tanzania data.

Breakdown type	Freq.	Percent
Dried	143	26.3%
Major housing issue	25	4.6%
Major rising main issue	121	22.3%
Minor housing issue	42	7.7%
Minor rising main issue	105	19.3%
No longer used	79	14.6%
Water contaminated	28	5.2%

Notes: Information taken from the 2010 Tanzanian water point mapping dataset (main analysis uses 2013 data). Breakdown classified as 'minor' if malfunctioning components cost less than $10 to replace according to Figure A22.

A.3 Reduced form: robustness tests

The main reduced form specifications in section 4 show two key results: that pumps are less likely to work if there are more non-pump water sources within 1.2km, but more likely to work if there are more pumps of the same technology within 1.2km. In this section, I report the full results of specifications that test the robustness of these findings. In each specification, I use the same control variables as those used in specifications (1) to (5) of the main specifications in Table 2. The estimated marginal effects for the control variables are qualitatively similar to those in Table 2, so I only report the key marginal effects of interest.

Table A3 shows probit regressions with pump functionality as the dependent variable and various other measures of the number of water sources within 1.2km as explanatory variables. The overall number of water sources within 1.2km is not a statistically significant predictor of pump functionality, suggesting that the positive correlation with pumps of the same technology cancels out the negative correlation with non-pumps. The number of pumps (of any technology) within 1.2km is positively correlated with pump functionality, and the estimated marginal effects for the number of non-pumps and pumps of the same technology are very similar to those in the main specifications.

I estimate the same specifications with different 'cutoff' distances of 0.7km and 1.7km, instead of 1.2km, and present the key results in Tables A4 and A5. The estimated marginal effects all have the same sign and significance as the main specifications, and have a very similar magnitude. I also restrict the number of water sources within 1.2km to just the number of working water sources within 1.2km, and present the results in Table A6. Again, the key results are very similar to the main specifications in Table 2. The only significant difference is that the marginal effect of the number of working pumps of the same technology within 1.2km is about three times larger than in the main specifications, suggesting that these positive correlations are largely driven by working pumps.

In addition to testing whether the number of water sources within a certain radius predicts pump functionality, I test whether the distance to the nearest alternative water source is correlated with functionality. Figure A23 shows non-parametric regressions of pump functionality on the distance to the nearest non-pump, pump of a different technology and pump of the same technology. They show a clear negative relationship between pump functionality and the distance to the nearest pump of the same technology, but no relationship for non-pumps and pumps of a different technology. Figure A24 shows similar relationships when we only consider the distance to working water sources as do probit estimates in Tables A7 and A8. These results show that pumps that are close to other pumps of the same technology are more likely to be functional, but that the distance to pumps of a different technology and to non-pump water sources does not predict functionality.

Finally, I also test whether 'fragmentation' of water source types and pump technologies predicts pump functionality rates at the ward and village level.[82] I calculate fragmentation using the Herfindahl-Hirschman Index (HHI): fragmentation in ward or village k is given by $frag_k = 1 - \sum_j s_{jk}^2$, where s_{jk} is the share of type or technology j in ward or village k. Therefore a village which only has one type and technology of water source would have a fragmentation value of zero, but a village with a wide variety of types and technologies would have a fragmentation value closer to one. Figures A25 and A26 show the distribution of the number of water sources in each ward and village, and the distribution of type and technology fragmentation in wards and villages.

Table A9 shows regressions of ward functionality rates on fragmentation of type and technology, as well as other ward characteristics. There is strong evidence that wards with more fragmentation of pump technologies have lower functionality rates, suggesting that water sources are more likely to be functional when there are a greater number of similar water sources nearby. Similarly, Table A10 shows that villages with a greater variety of pump technologies have a lower pump functionality rate. Interestingly, villages with more variety in water source types have a higher pump functionality rate, once we control for pump technology fragmentation. It is not clear what is driving this result, but the main pattern from the previous specifications remains, that pumps are less likely to be functional when they are in villages with fewer pumps of the same technology.

[82] The administrative divisions in Tanzania are broken down as follows: 26 regions, containing a total of 132 districts, with further sub-divisions into wards, villages and sub-villages.

Table A3: Alternative specifications, 1.2km cutoff. Each panel shows the key estimated marginal effects of separate probit regressions with pump functionality as the dependent variable. A pump is more likely to be functional if there are more pumps nearby (panels 2 and 4). This positive correlation is driven by pumps of the same technology (panels 3 and 5). The overall number of water sources has no significant predictive power over pump functionality (panel 1).

	(1)	(2)	(3)	(4)	(5)
Number of water sources within 1.2km	0.147**	0.113*	0.0116	0.0352	-0.0150
	(0.0713)	(0.0678)	(0.0661)	(0.0613)	(0.0713)
Number of pumps within 1.2km	0.506***	0.484***	0.329***	0.363***	0.340**
	(0.186)	(0.135)	(0.115)	(0.131)	(0.157)
Number of pumps, same tech within 1.2km	1.56***	1.02***	0.912***	1.04***	1.01***
	(0.284)	(0.205)	(0.201)	(0.215)	(0.222)
Number of non-pump sources within 1.2km	-0.212	-0.245**	-0.314***	-0.296***	-0.321***
	(0.134)	(0.111)	(0.111)	(0.113)	(0.119)
Number of links to pumps, 1.2km cutoff	0.591***	0.583***	0.445***	0.470***	0.472***
	(0.196)	(0.146)	(0.127)	(0.143)	(0.171)
Number of non-pump sources within 1.2km	-0.190*	-0.245**	-0.291***	-0.346***	-0.331***
	(0.114)	(0.106)	(0.107)	(0.104)	(0.112)
Number of pumps, diff tech within 1.2km	-0.437*	0.0822	0.0957	0.0222	-0.156
	(0.232)	(0.185)	(0.194)	(0.191)	(0.243)
Number of pumps, same tech within 1.2km	1.74***	1.12***	1.06***	1.13***	1.17***
	(0.293)	(0.224)	(0.215)	(0.202)	(0.221)
Observations	10,667	10,667	10,667	10,667	10,667

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2 the key marginal effects of which are in the final panel of this table).

A.3.1 Centrality robustness specifications

Table A4: Alternative specifications, 0.7km cutoff. The correlations are very similar when we use a cutoff of 0.7km instead of 1.2km. Each panel shows the key estimated marginal effects in probit regressions with pump functionality as the dependent variable. The fifth panel shows the estimates that are analogous to the main specifications (including non-pumps, pumps of a different technology and pumps of the same technology as the key regressors).

	(1)	(2)	(3)	(4)	(5)
Number of water sources within 0.7km	0.229*	0.141	-0.0204	0.0296	-0.0400
	(0.135)	(0.123)	(0.117)	(0.114)	(0.120)
Number of pumps within 0.7km	0.885***	0.734***	0.504**	0.599**	0.478*
	(0.255)	(0.230)	(0.224)	(0.235)	(0.270)
Number of pumps, same tech within 0.7km	2.18***	1.25***	1.13***	1.36***	1.24***
	(0.421)	(0.324)	(0.318)	(0.331)	(0.340)
Number of non-pump sources within 0.7km	-0.284	-0.288*	-0.394**	-0.369**	-0.380**
	(0.199)	(0.167)	(0.168)	(0.168)	(0.173)
Number of pumps within 0.7km	0.981***	0.829***	0.617***	0.702***	0.593**
	(0.256)	(0.239)	(0.233)	(0.244)	(0.280)
Number of non-pump sources within 0.7km	-0.266	-0.290*	-0.393**	-0.364**	-0.372**
	(0.180)	(0.162)	(0.162)	(0.161)	(0.165)
Number of pumps, diff tech within 0.7km	-0.687*	0.200	-0.165	-0.253	-0.459
	(0.414)	(0.404)	(0.414)	(0.396)	(0.444)
Number of pumps, same tech within 0.7km	2.36***	1.33***	1.27***	1.49***	1.36***
	(0.441)	(0.338)	(0.320)	(0.331)	(0.338)
Observations	10,667	10,667	10,667	10,667	10,667

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Table A5: Alternative specifications, 1.7km cutoff. The correlations are very similar when we use a cutoff of 1.7km instead of 1.2km. Each panel shows the key estimated marginal effects in probit regressions with pump functionality as the dependent variable. The fifth panel shows the estimates that are analogous to the main specifications (including non-pumps, pumps of a different technology and pumps of the same technology as the key regressors).

	(1)	(2)	(3)	(4)	(5)
Number of water sources within 1.7km	0.125**	0.128***	0.0563	0.0705*	0.0460
	(0.0541)	(0.0461)	(0.0412)	(0.0401)	(0.0509)
Number of pumps within 1.7km	0.333**	0.371***	0.253***	0.266**	0.291***
	(0.161)	(0.121)	(0.0902)	(0.104)	(0.110)
Number of pumps, same tech within 1.7km	1.26***	0.916***	0.782***	0.866***	0.897***
	(0.285)	(0.186)	(0.179)	(0.196)	(0.185)
Number of non-pump sources within 1.7km	-0.146	-0.179**	-0.216**	-0.195**	-0.220**
	(0.112)	(0.0893)	(0.0895)	(0.0925)	(0.0992)
Number of pumps within 1.7km	0.391**	0.443***	0.334***	0.339***	0.386***
	(0.173)	(0.130)	(0.101)	(0.115)	(0.123)
Number of non-pump sources within 1.7km	-0.150*	-0.186**	-0.212**	-0.187**	-0.206**
	(0.0903)	(0.0833)	(0.0857)	(0.0880)	(0.0941)
Number of pumps, diff tech within 1.7km	-0.310**	0.0452	-0.0351	-0.0920	-0.0581
	(0.151)	(0.0984)	(0.109)	(0.109)	(0.152)
Number of pumps, same tech within 1.7km	1.44***	1.01***	0.902***	0.992***	0.991***
	(0.276)	(0.204)	(0.194)	(0.205)	(0.196)
Observations	10,667	10,667	10,667	10,667	10,667

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Table A6: Alternative specifications, working water sources, 1.2km cutoff. The correlations in functionality are very similar if we just look at the number of working water sources within 1.2km, instead of the total number of water sources. The positive correlations are driven by the number of working pumps of the same technology, with a negative correlation between pump functionality and the number of working non-pump water sources within 1.2km. Each panel shows the key estimated marginal effects in probit regressions with pump functionality as the dependent variable. The fifth panel shows the estimates that are analogous to the main specifications (including non-pumps, pumps of a different technology and pumps of the same technology as the key regressors).

	(1)	(2)	(3)	(4)	(5)
Number of working water sources, 1.2km	0.600***	0.506***	0.353***	0.386***	0.382***
	(0.137)	(0.103)	(0.101)	(0.108)	(0.122)
Number of working pumps, 1.2km	1.65***	1.47***	1.22***	1.26***	1.47***
	(0.532)	(0.354)	(0.327)	(0.350)	(0.290)
Number of working pumps, same tech, 1.2km	3.56***	2.81***	2.67***	2.80***	2.92***
	(0.489)	(0.381)	(0.339)	(0.352)	(0.330)
Number of working non-pump sources, 1.2km	-0.298**	-0.288**	-0.359**	-0.329**	-0.376**
	(0.151)	(0.132)	(0.142)	(0.145)	(0.148)
Number of working pumps, 1.2km	1.75***	1.56***	1.31***	1.33***	1.58***
	(0.587)	(0.389)	(0.350)	(0.369)	(0.304)
Number of working non-pump sources, 1.2km	-0.343***	-0.347***	-0.376***	-0.342***	-0.381***
	(0.110)	(0.122)	(0.128)	(0.131)	(0.131)
Number of working pumps, diff tech, 1.2km	-0.359	0.107	-0.186	-0.276	-0.0868
	(0.297)	(0.309)	(0.257)	(0.277)	(0.339)
Number of working pumps, same tech, 1.2km	3.76***	2.93***	2.82***	2.94***	3.03***
	(0.466)	(0.406)	(0.343)	(0.345)	(0.337)
Observations	10,667	10,667	10,667	10,667	10,667

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

A.3.2 Distance specifications

Table A7: Probit distance specifications, all water sources. There is a negative relationship between pump functionality and distance to the nearest alternative pump of the same technology. This is significant whether we estimate this separately or jointly with distance to non-pumps and pumps of a different technology. The distance to non-pumps or pumps of a different technology does not predict pump functionality.

	(1)	(2)	(3)	(4)	(5)
Dist. nearest non-pump, km	0.0571	0.0919	0.110	0.0685	0.142
	(0.205)	(0.223)	(0.209)	(0.213)	(0.221)
Dist. nearest pump, diff tech, km	0.218	0.0967	0.236	0.248	0.311*
	(0.162)	(0.174)	(0.175)	(0.176)	(0.177)
Dist. nearest pump, same tech, km	-0.734***	-0.436***	-0.349**	-0.374**	-0.329**
	(0.143)	(0.150)	(0.147)	(0.150)	(0.153)
Dist. nearest non-pump, km	-0.00321	0.0951	0.0830	0.0353	0.0955
	(0.211)	(0.227)	(0.212)	(0.213)	(0.220)
Dist. nearest pump, diff tech, km	0.260	0.107	0.243	0.260	0.308*
	(0.166)	(0.176)	(0.178)	(0.177)	(0.178)
Dist. nearest pump, same tech, km	-0.756***	-0.447***	-0.367**	-0.388**	-0.342**
	(0.146)	(0.151)	(0.148)	(0.151)	(0.154)
Observations	10,667	10,667	10,667	10,667	10,667

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Figure A23: Non-parametric distance specifications, all water sources. Non-parametric regression of pump functionality on distance to the nearest non-pump water source, pump of a different technology and pump of the same technology, plotted above histograms of distances observed in the data. There is no linear relationship between pump functionality and the distance to the nearest non-pump or pump of a different technology, but a negative relationship with distance to the nearest pump of the same technology.

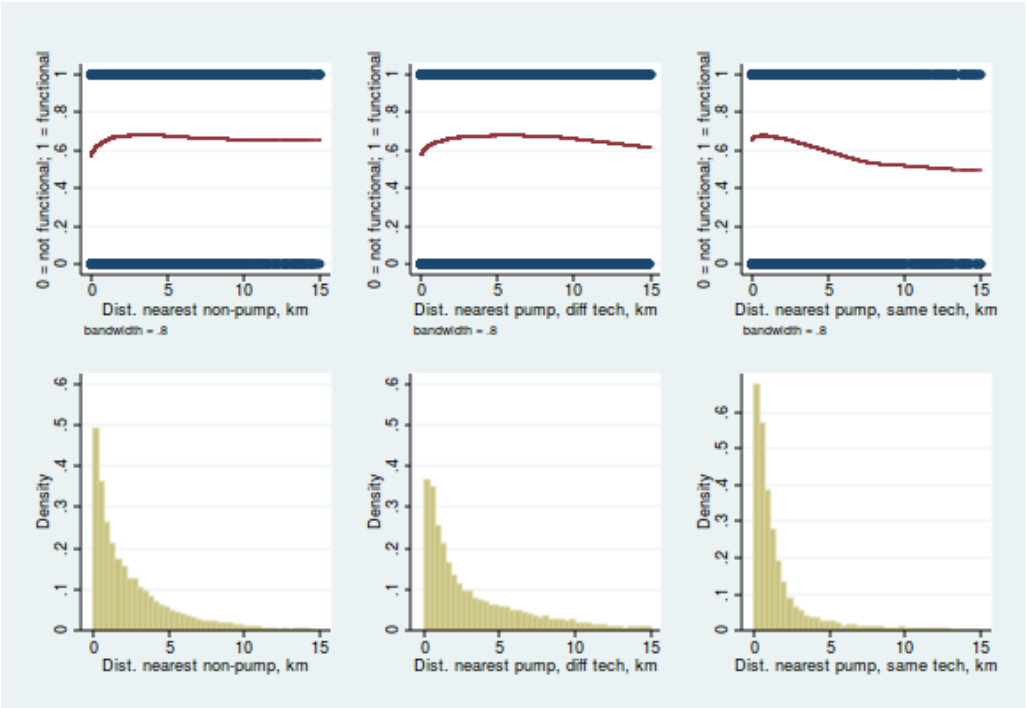


Figure A24: Non-parametric distance specifications, working water sources. Non-parametric regression of pump functionality on distance to the nearest working water sources show a similar negative relationship between pump functionality and distance to the nearest working pump of the same technology.

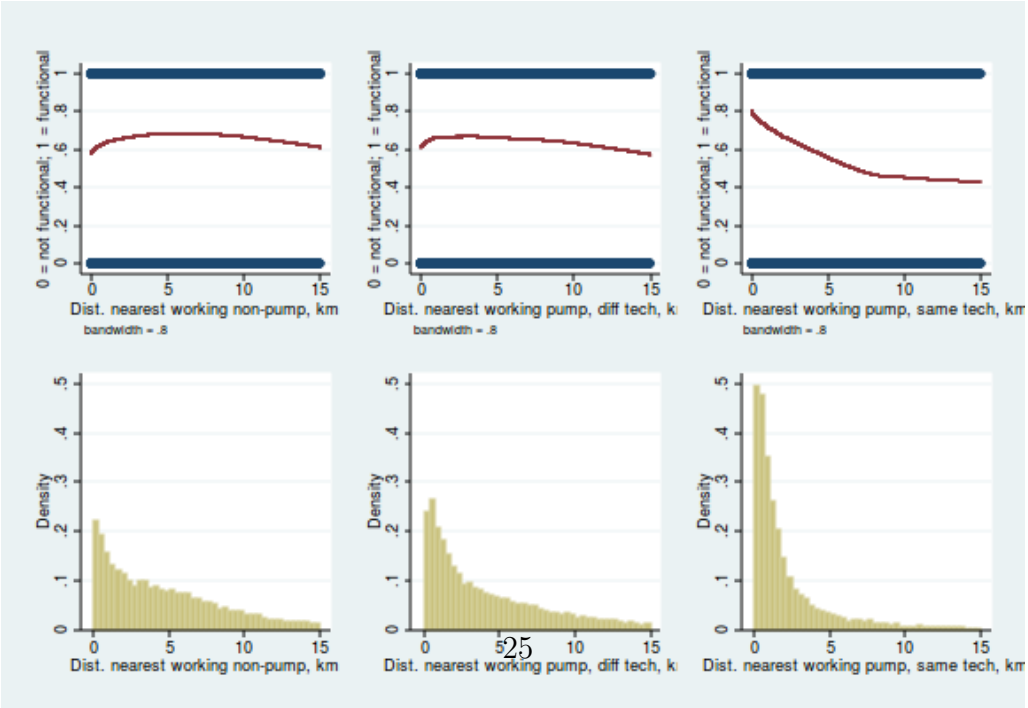


Table A8: Probit distance specifications, working water sources. Regressions of pump functionality on the distance to the nearest *working* water sources show a significant and negative relationship between pump functionality and the distance to the nearest pump of the same technology. Again, there is no significant relationship between pump functionality and distance to non-pumps or pumps of a different technology.

	(1)	(2)	(3)	(4)	(5)
Dist. nearest working non-pump, km	-0.331*	-0.167	-0.0676	-0.121	-0.117
	(0.177)	(0.147)	(0.148)	(0.144)	(0.155)
Dist. nearest working pump, diff tech, km	-0.0356	0.00542	0.121	0.156	0.201
	(0.167)	(0.135)	(0.136)	(0.138)	(0.139)
Dist. nearest working pump, same tech, km	-1.67***	-1.24***	-1.11***	-1.11***	-1.09***
	(0.109)	(0.117)	(0.116)	(0.119)	(0.122)
Dist. nearest working non-pump, km	-0.258	-0.0819	0.00140	-0.0517	-0.0643
	(0.160)	(0.143)	(0.142)	(0.139)	(0.148)
Dist. nearest working pump, diff tech, km	0.117	0.0558	0.144	0.163	0.183
	(0.131)	(0.128)	(0.130)	(0.132)	(0.134)
Dist. nearest working pump, same tech, km	-1.66***	-1.23***	-1.12***	-1.11***	-1.09***
	(0.107)	(0.118)	(0.116)	(0.119)	(0.122)
Observations	10,667	10,667	10,667	10,667	10,667

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

A.3.3 Cluster-level analysis

This section presents analysis at the ward and village level, by aggregating individual pump data. The main relationship of interest is whether the 'fragmentation' of water source types and technologies is a significant predictor of functionality rates at the village or ward level. I calculate fragmentation using the Herfindahl-Hirschman Index (HHI): fragmentation in cluster k is given by $frag_k = 1 - \sum_j s_{jk}^2$, where s_{jk} is the share of type/technology j in cluster k. The specifications presented here show the relationship between fragmentation and functionality rates of all water sources at the ward level, and the functionality rates of pumps only at the village level.

Figure A25: Number and fragmentation of water sources in wards. The left plot shows the distribution of the number of water sources in a ward, the middle plot shows shows the distribution of type fragmentation, and the right plot shows the distribution of technology fragmentation at the ward level.

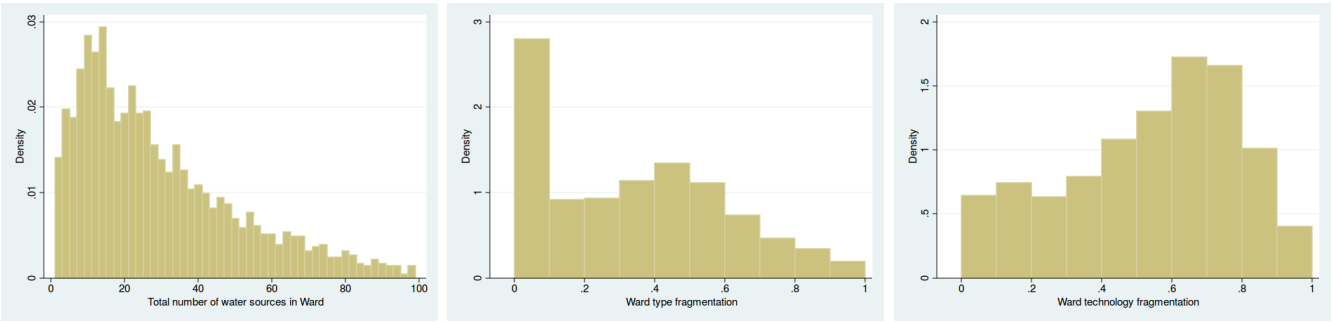


Figure A26: Number and fragmentation of water sources in villages. The left plot shows the distribution of the number of pumps in a village, for villages with at least one pump, the middle plot shows the distribution of type fragmentation, and the right plot shows the distribution of technology fragmentation at the village level.

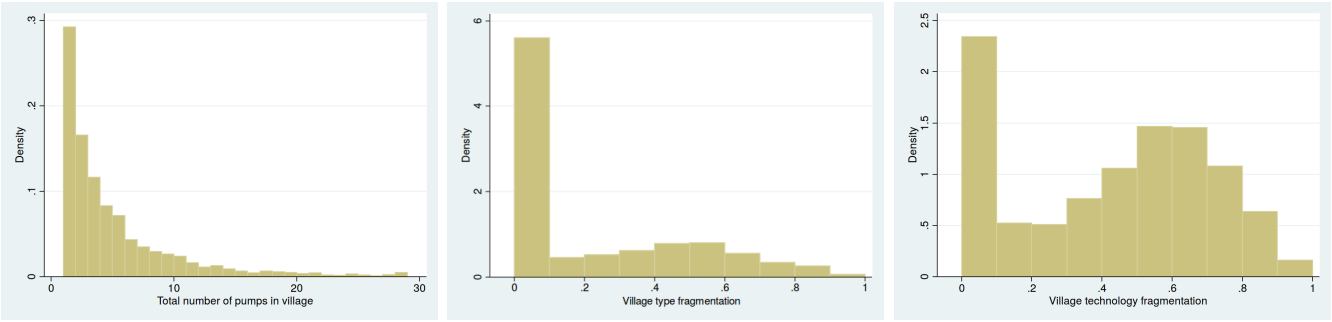


Table A9: Ward-level regressions. Linear regressions of water source functionality rates on fragmentation of type and technology at the ward level. The functionality rate is higher when there is less fragmentation of technology. Functionality rates are also higher when there is a higher proportion of women in the Ward, a finding consistent with other literature showing women are more likely to invest in public goods.

	(1)	(2)	(3)	(4)	(5)	(6)
Ward type fragmentation	-0.352***	-0.0998**			-0.274***	0.0300
	(0.0255)	(0.0456)			(0.0376)	(0.0566)
Ward technology fragmentation			-0.269***	-0.150***	-0.0931***	-0.165***
			(0.0232)	(0.0329)	(0.0334)	(0.0410)
Total no. water sources in Ward	0.00134***	0.000227	0.00126***	0.000226	0.00129***	0.000232
	(0.000155)	(0.000208)	(0.000147)	(0.000207)	(0.000153)	(0.000208)
Average age at record		-0.00605***		-0.00644***		-0.00646***
		(0.000906)		(0.000900)		(0.000897)
Proportion that pay for use		0.178***		0.173***		0.173***
		(0.0230)		(0.0229)		(0.0229)
Ward area, (km squared)		4.99e-06		4.31e-06		4.43e-06
		(6.03e-06)		(5.76e-06)		(5.80e-06)
Ward total population		-6.00e-06		-6.34e-06		-6.16e-06
		(5.30e-06)		(5.09e-06)		(5.09e-06)
Ratio of females to males		0.279***		0.238**		0.232**
		(0.0927)		(0.0925)		(0.0920)
Ward population density		-1.33e-07		-1.17e-07		-1.18e-07
		(2.60e-07)		(2.56e-07)		(2.51e-07)
Ward nationality fractionalization		-0.114		-0.105		-0.102
		(0.154)		(0.152)		(0.152)
Constant	0.634***	0.181	0.629***	0.341	0.647***	0.324
	(0.0152)	(0.521)	(0.0161)	(0.524)	(0.0164)	(0.530)
Observations	1,376	1,376	1,376	1,376	1,376	1,376
R^2	0.160	0.529	0.131	0.536	0.165	0.536
District fixed effects	No	Yes	No	Yes	No	Yes
Proportion data in each month	No	Yes	No	Yes	No	Yes
Proportion of types in Ward	No	Yes	No	Yes	No	Yes
Ward census variables	No	Yes	No	Yes	No	Yes

Notes: Robust standard errors, *** p<0.01, ** p<0.05, * p<0.1. Estimated coefficients reported. Pay for use includes per bucket, month or year. Ward census variables include dependency ratio, population per water source, number of pumps in ward, number of water sources in ward.

Table A10: Village-level regressions. Linear regressions of pump functionality rate on fragmentation of type and technology at the village level. The pump functionality rate is higher when there is less fragmentation of technology, and more pumps in a village (both in absolute number and as a proportion of overall water sources). Holding these variables fixed, the pump functionality rate is higher when there is more type fragmentation.

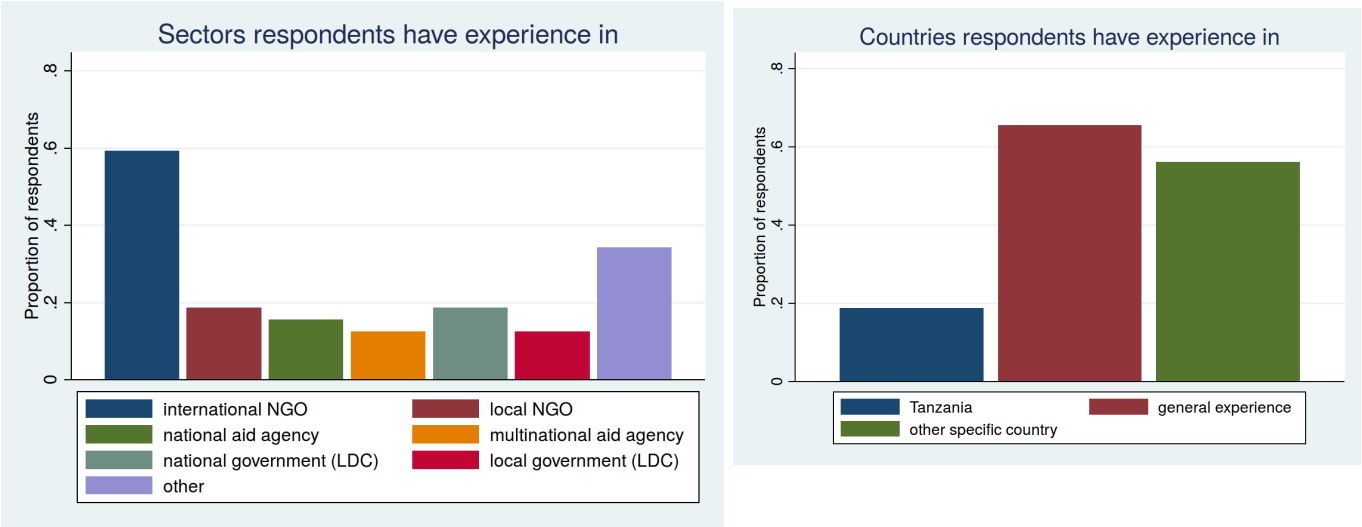
	(1)	(2)	(3)	(4)	(5)	(6)
Village type fragmentation	0.0487	0.0806			0.255***	0.230***
	(0.0454)	(0.0682)			(0.0569)	(0.0759)
Village technology fragmentation			-0.113***	-0.111***	-0.234***	-0.174***
			(0.0312)	(0.0354)	(0.0383)	(0.0392)
Total number of pumps in village	0.00546***	0.00627***	0.0102***	0.0102***	0.00866***	0.00802***
	(0.00195)	(0.00209)	(0.00192)	(0.00197)	(0.00196)	(0.00206)
Village pump proportion	0.0727	4.183**	-0.0287	2.005***	0.0918*	4.126**
	(0.0491)	(1.865)	(0.0373)	(0.594)	(0.0495)	(1.984)
Total no. water sources in Ward	2.11e-05	-0.00116	-0.00150	-0.00218**	-0.000124	-0.00126
	(0.00105)	(0.00102)	(0.00101)	(0.000994)	(0.00106)	(0.00103)
Average age at record		-0.000399		-0.000607		-0.000314
		(0.00115)		(0.00114)		(0.00114)
Proportion that pay for use		0.163***		0.158***		0.160***
		(0.0225)		(0.0224)		(0.0224)
Ward area, (km squared)		-1.04e-05		-1.06e-05		-9.21e-06
		(7.92e-06)		(7.68e-06)		(7.66e-06)
Ward total population		-9.43e-07		-5.79e-07		4.95e-07
		(9.14e-06)		(9.08e-06)		(9.02e-06)
Ratio of females to males		-0.126		-0.131		-0.129
		(0.158)		(0.158)		(0.158)
Ward population density		6.26e-07		6.77e-07		6.86e-07
		(9.81e-07)		(9.26e-07)		(9.58e-07)
Ward nationality fractionalization		-0.147		-0.130		-0.121
		(0.215)		(0.214)		(0.215)
Constant	0.506***	-3.175*	0.624***	-1.008	0.515***	-3.097
	(0.0456)	(1.886)	(0.0353)	(0.681)	(0.0457)	(2.003)
Observations	2,635	2,635	2,635	2,635	2,635	2,635
R^2	0.008	0.139	0.013	0.141	0.020	0.145
District fixed effects	No	Yes	No	Yes	No	Yes
Proportion data in each month	No	Yes	No	Yes	No	Yes
Proportion of types in village	No	Yes	No	Yes	No	Yes
Ward census variables	No	Yes	No	Yes	No	Yes

Notes: Robust standard errors, *** p<0.01, ** p<0.05, * p<0.1. Estimated coefficients reported. Pay for use includes per bucket, month or year. Ward census variables include dependency ratio, population per water source, number of pumps in ward, number of water sources in ward.

A.4 Survey of water practitioners

To help understand what is driving the patterns of installation and functionality of different types of water sources observed in the data, I conducted a survey of water sector experts. This survey was carried out using Survey Gizmo, an online surveying tool. It was sent to a wide variety of stakeholders with significant experience working in the provision of water in rural areas of low income countries. It was distributed through multiple channels: directly to personal contacts in the water sector, via email lists (in collaboration with non-governmental and monitoring organizations working in the sector), and to participants of online discussion groups about rural water supply. After the initial responses were collected, I also wrote a blog summarizing my research which was published on the websites of three prominent organizations to encourage further responses.[83] The survey responses are summarized in the following Figures. In all Figures (apart from Figure A27), I report a summary from all respondents, and from only those with experience specific to Tanzania.

Figure A27: Sector and country experience of respondents. The majority of respondents have worked for an international NGO at some point, though there is a wide variety of experience from other sectors, including positions for developing country organizations and governments. Only a minority of respondents have experience specific to Tanzania.



[83]The blog was published by the International Water and Sanitation Centre (IRC), Rural Water Supply Network (RWSN), and the Water Point Data Exchange (WPDx).

Figure A28: Location of installation. The most important factor determining where a water source is installed is the existing access to an improved water source.

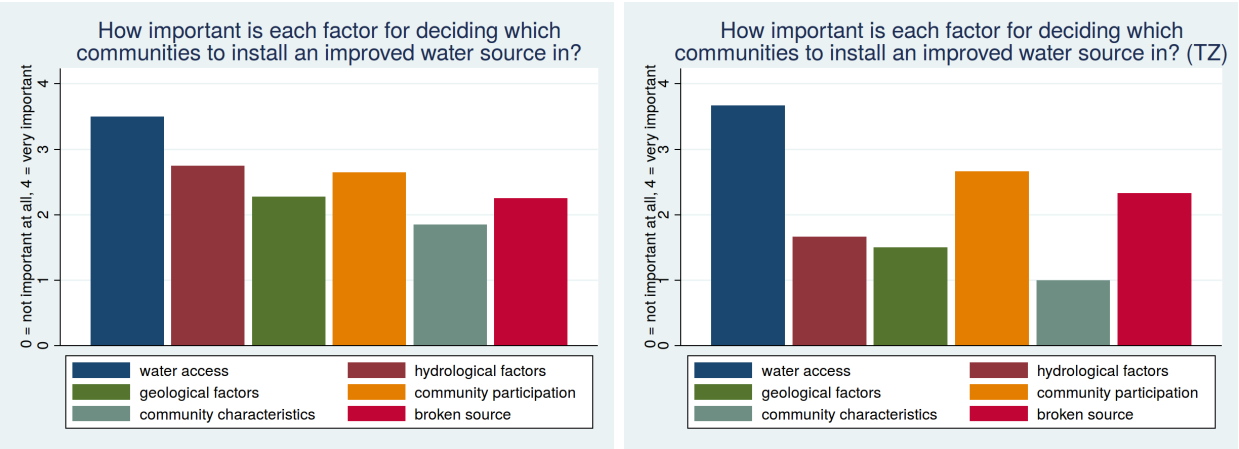


Figure A29: Type and technology of installation. The most important factor for deciding the type or technology of an installation is the preferences of the installing organization, particularly in Tanzania where all respondents ranked this as the single most important factor. Community characteristics and community preferences are not ranked as important factors, particularly in Tanzania, where all respondents said that community preferences were not important at all in determining the type of water source installed.

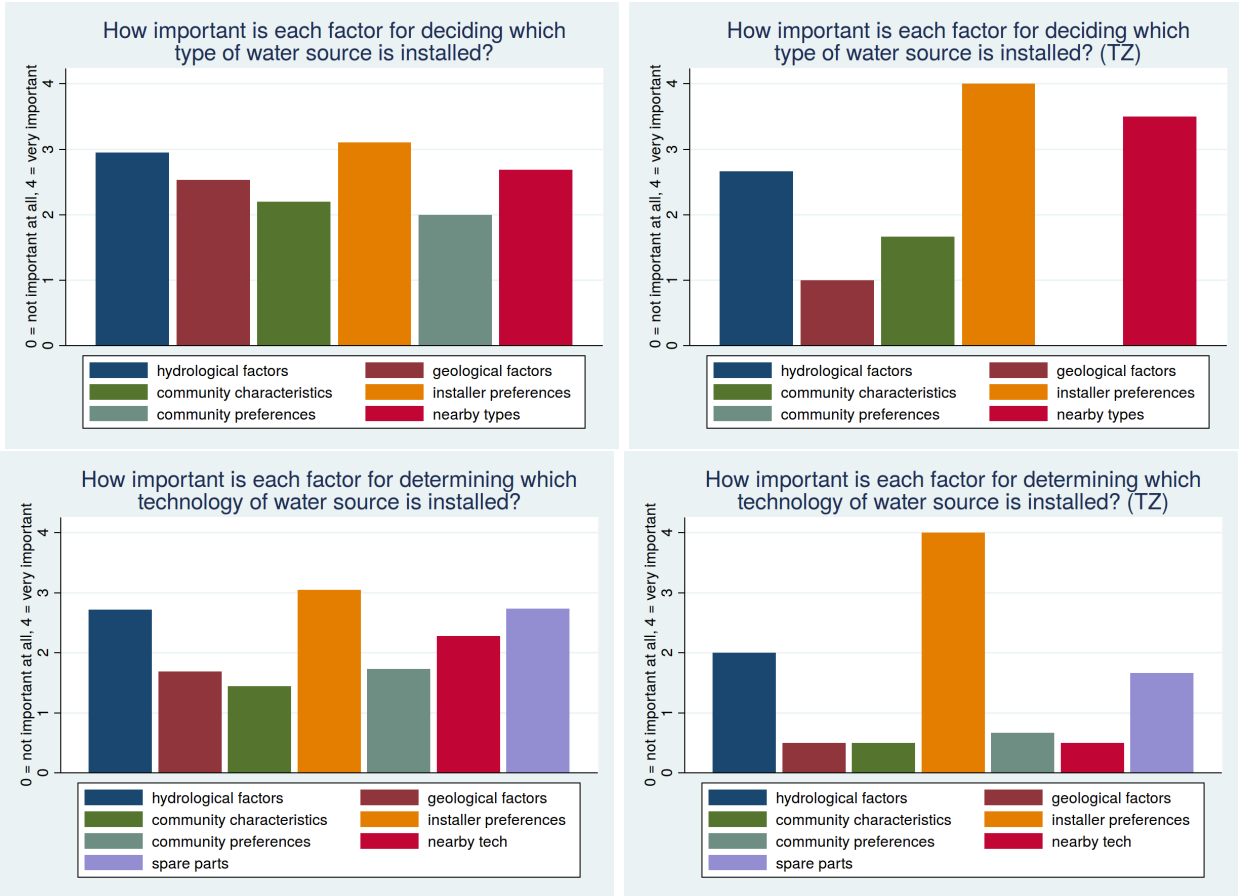


Figure A30: Coordination of installing organizations. Respondents indicated that there is very little coordination between installing organizations in choice of location for a water source or the type or technology that is installed.

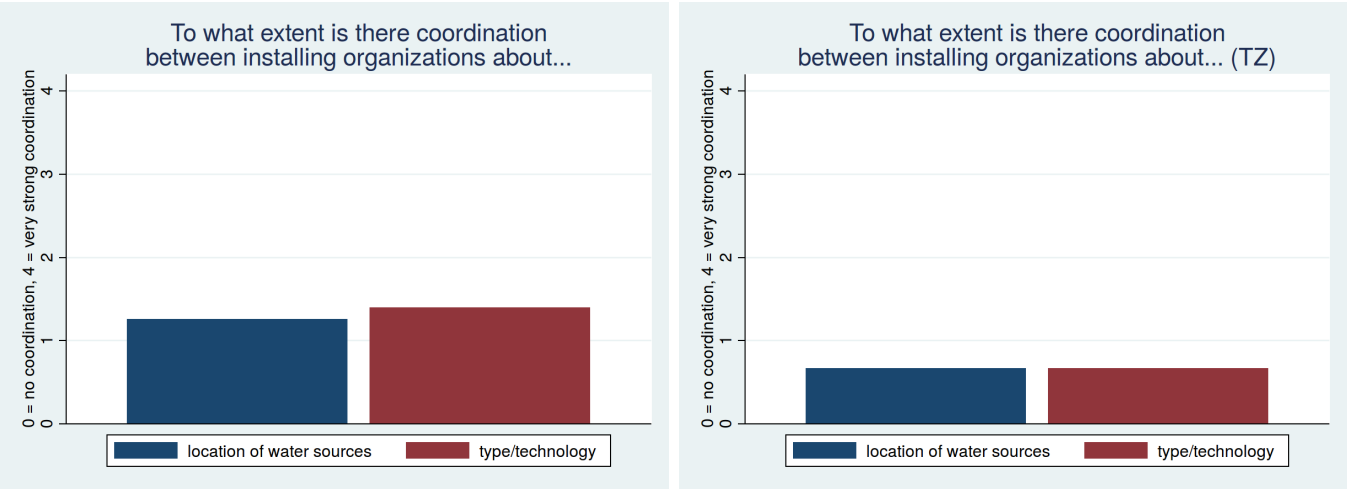


Figure A31: Community preferences. Respondents think that beneficiaries have stronger preferences over the type of water source they get (i.e. a pump or a tap) relative to their preferences for one technology of pump over another.

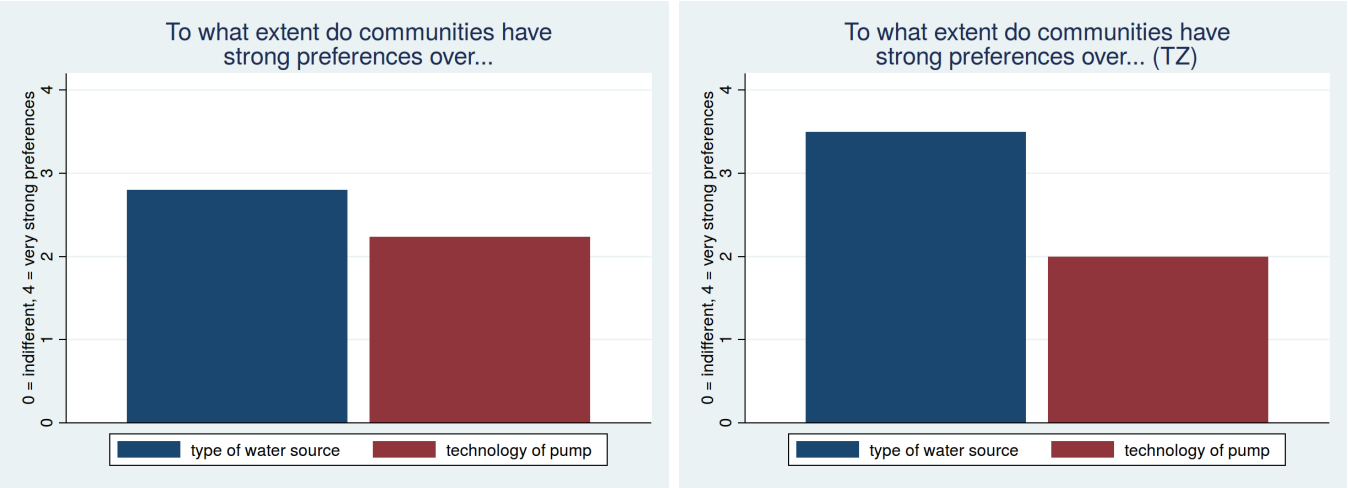


Figure A32: Factors explaining pump breakdown. It is clear that most respondents think that there are a number of important factors explaining pump functionality, the most important of which are community resources, installation quality and a lack of post-construction institutional support. To control for the second and third factors, we must include installer fixed effects in the analysis. In Tanzania, physical shocks were ranked as the least important factor explaining functionality.

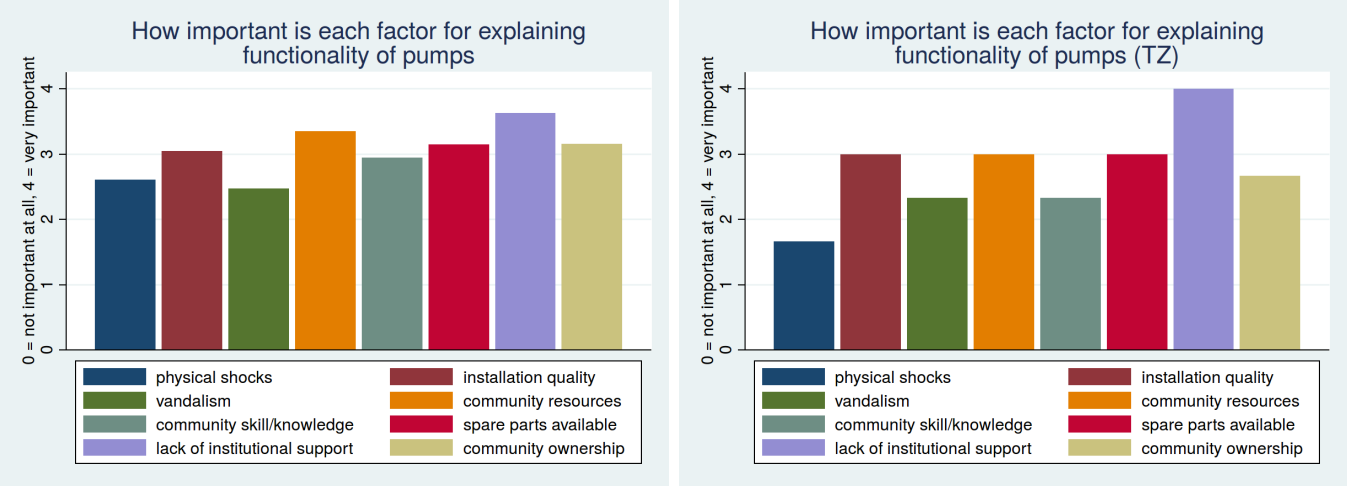


Figure A33: Effects of pump technology standardization. Respondents strongly agreed that increased standardization would increase the availability of spare parts and pump mechanics, and agreed that it would increase cooperation and cost-sharing. They also agreed that there may be potential benefits of having a variety of different types and technologies of water sources.

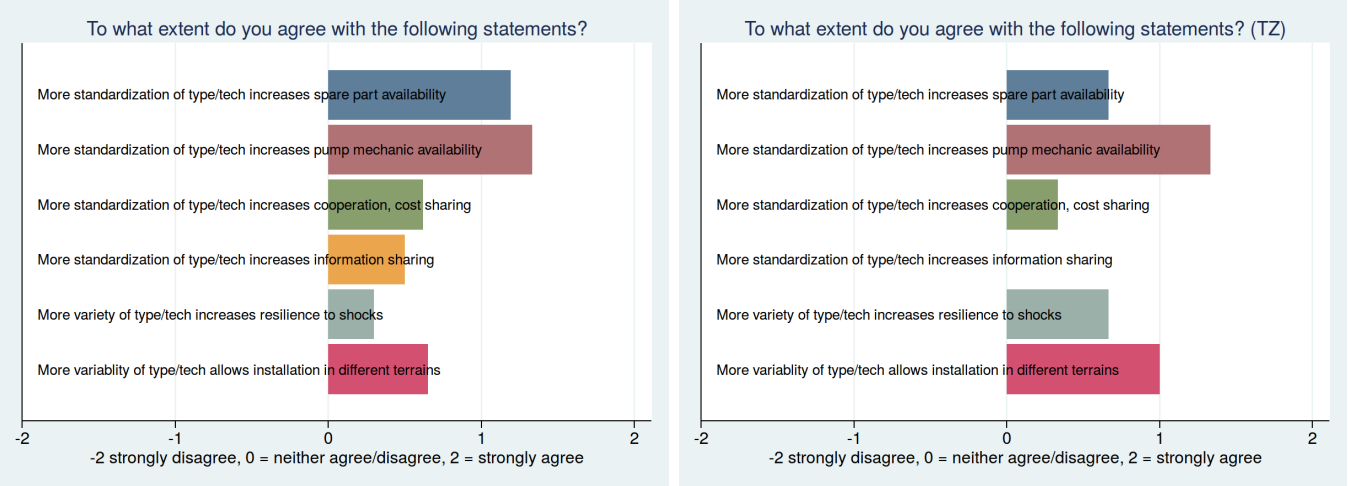


Figure A34: Appointment of WPC and choice of user fees. Water point committee members seem to be chosen by the community in Tanzania, and in a mixture of ways in other countries. Installing organizations seem to exert significant influence over how user fees are determined, though respondents think that communities have more influence over this in Tanzania relative to other countries.

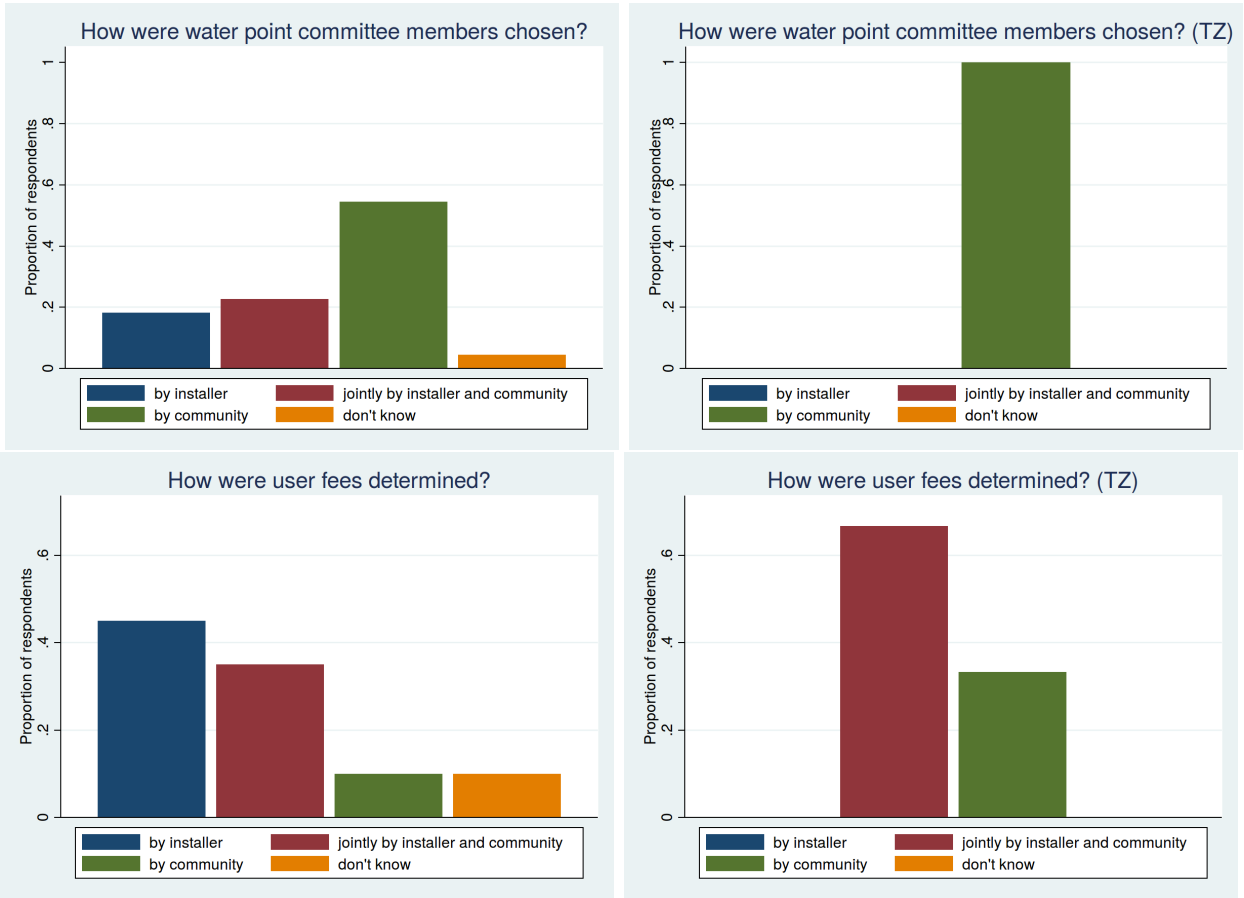
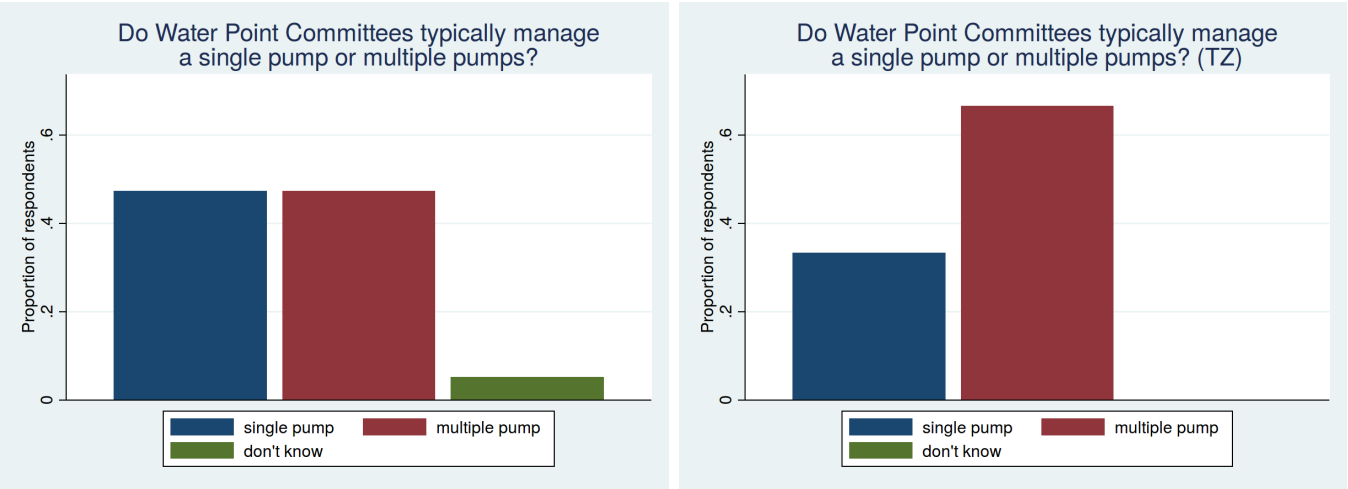


Figure A35: Water point committee management responsibilities. There seems to be a mix of respondents who think that water point committees (WPCs) typically manage a single pump, and those who reported WPCs managing multiple pumps



A.5 Tests of correlated effects

Table A11: Summary of tests of technology-specific correlated effects. I test seven possible explanations for the spatial correlations explaining pump functionality demonstrated in section 4. This table gives a brief overview of each explanation and how I test it.

Potential source of correlation	Survey evidence	Reduced form evidence
Selection of tech on community characteristics	- Installer preferences most important factor in choice of technology (Figure A29) - Community characteristics and preferences among least important factors (Figure A29).	- Selection regressions of technology on community characteristics from Tanzania National Panel Survey [2008-09] (Tables A12 and A13)
Installer/funder fixed effects	- Installation quality fairly important in explaining functionality (Figure A32)	- Include installer and funder fixed effects (Table 2) - Restrict to installations by largest orgs (Table A15) - Interact same installer with same tech (Table A16)
Selection of tech on physical conditions	- Installer preferences most important factor in choice of technology (Figure A29) - Hydrological factors fairly important, geological factors less so (Figure A29)	- Technology selection on groundwater (Table A17) - Include groundwater variables and interaction with technology (Table A18) - Interaction of hole type with technology (Table A19)
Technology-specific physical shocks	- Physical shocks least important factor explaining functionality (Figure A32)	- Control for hole type and groundwater variables (Table 2) - Include interaction of groundwater variables and technology (Table A18)
Spatial correlation in management	- Community ownership fairly important factor explaining functionality (Figure A32)	- Ward/village-level analysis (Section A.3.3) - Pump name as proxy for same ownership: exclude if same name (Table A20), and treat as single observation (Table A21)
Technology-specific effects of community shocks	- Community resources fairly important factor explaining functionality (Figure A32)	- Interact technology with district (Table A22)
Spatial correlation in timing of installation	NA	- Control for year of installation and interaction with technology (Table A23)
Technology-specific water demand shocks	- Only 0.12% households use handpumps for agriculture (Tanzania National Panel Survey [2008-09])	- Control for number of users (Table 2)

Are different technologies installed in different types of communities?

Tables A12, A13 and A14 present regressions of the proportion of water points that are pumps (column 1), and the proportion of pumps that are of each technology (columns 2 to 6), on community characteristics in the National Panel Survey (NPS, 2007-08). They test whether 36 variables from the NPS are significant predictors of water source type or technology, at the enumeration area (EA) level from the surveys. The sub-sample of observations that can be matched to an enumeration area restricts the sample size, so the explanatory variables are split across eight regressions (shown by each panel). The null hypothesis of all variables in a group being insignificant predictors of type or technology is rejected at the 90 percent confidence level in 11 of 42 regressions. If we look only at the technology selection regressions (i.e. exclude the pump selection regression), 26 of 180 coefficients (14 percent) are significant at the 90 percent confidence level, again only slightly higher than we would expect if technology was randomly allocated.

Table A12: Type and technology selection regressions. The majority of explanatory variables are not significant predictors of pump technology, and the number of statistically significant predictors is roughly what we would expect if technology was randomly assigned.

	(1) Pump	(2) Afridev	(3) India	(4) SWN	(5) Nira	(6) Rope
Pre-primary school available	-0.0202	0.0707	0.0816	0.0629	-0.186**	-0.0155
	(0.0545)	(0.0534)	(0.0728)	(0.0612)	(0.0885)	(0.0201)
Government primary school available	0.158*	-0.0389	-0.156	0.0561	0.0739	0.00356
	(0.0850)	(0.159)	(0.188)	(0.120)	(0.192)	(0.00511)
Private primary school available	-0.134*	-0.0504	0.0162	0.0509	0.00673	0.00619
	(0.0729)	(0.0703)	(0.157)	(0.111)	(0.162)	(0.0126)
Government secondary school available	-0.00906	-0.0503	0.0743	0.00813	-0.0195	0.0277
	(0.0563)	(0.0529)	(0.0783)	(0.0748)	(0.0899)	(0.0207)
Private secondary school available	0.00309	-0.111**	0.0610	0.0354	-0.128	-0.00999
	(0.0952)	(0.0462)	(0.169)	(0.152)	(0.147)	(0.0154)
R^2	0.023	0.036	0.030	0.014	0.052	0.042
F stat	1.418	2.703	0.644	0.333	1.390	0.664
F p-value	0.219	0.0244	0.667	0.892	0.234	0.651
Government health center available	-0.0253	-0.0230	0.0860	-0.0682	0.0387	0.0169
	(0.0506)	(0.0526)	(0.0708)	(0.0602)	(0.0849)	(0.0139)
Government hospital available	-0.159**	-0.0367	0.287*	-0.245***	-0.0794	-0.00689
	(0.0709)	(0.0901)	(0.169)	(0.0575)	(0.146)	(0.00526)
Private health center available	0.103	-0.0395	0.00944	0.146	-0.113	-0.00129
	(0.0765)	(0.0694)	(0.0917)	(0.0950)	(0.116)	(0.00750)
Private hospital available	0.0308	-0.113**	-0.204***	-0.0624	0.444**	-0.00860
	(0.125)	(0.0453)	(0.0586)	(0.167)	(0.174)	(0.00672)
R^2	0.020	0.014	0.060	0.058	0.050	0.016
F stat	1.482	4.706	8.122	4.983	2.446	0.577
F p-value	0.209	0.00155	9.30e-06	0.00101	0.0508	0.680
Daily market available	0.0953	-0.0741	0.0925	-0.0770	0.0853	0.00578
	(0.0644)	(0.0488)	(0.0796)	(0.0610)	(0.102)	(0.0129)
Weekly market available	0.0554	0.0249	0.0496	-0.0312	0.0270	0.0187
	(0.0589)	(0.0660)	(0.0844)	(0.0676)	(0.100)	(0.0245)
Milling machine available	0.0974	-0.0796	0.0468	0.0210	-0.0728	0.0153
	(0.0591)	(0.0792)	(0.0898)	(0.0792)	(0.115)	(0.0104)
Bank available	0.0613	-0.0611	0.208	-0.0185	-0.104	-0.000689
	(0.105)	(0.0625)	(0.130)	(0.120)	(0.119)	(0.00568)
SACCO available	-0.0836	-0.00434	0.0737	0.0403	-0.0803	-0.0158
	(0.0551)	(0.0587)	(0.0815)	(0.0759)	(0.0916)	(0.0107)
R^2	0.034	0.034	0.063	0.017	0.029	0.029
F stat	1.666	1.435	1.427	0.476	0.723	0.495
F p-value	0.144	0.218	0.221	0.794	0.607	0.779
Observations	208	112	112	112	112	112

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A13: Type and technology selection regressions. The majority of explanatory variables are not significant predictors of pump technology, and the number of statistically significant predictors is roughly what we would expect if technology was randomly assigned.

	(1) Pump	(2) Afridev	(3) India	(4) SWN	(5) Nira	(6) Rope
Birth registration available	0.0914	-0.112**	0.0305	0.0870	0.0151	-0.0114
	(0.0601)	(0.0507)	(0.0856)	(0.0764)	(0.0970)	(0.00828)
Police station/post available	0.00584	0.0445	0.216	-0.206***	-0.0300	-0.00296
	(0.0886)	(0.0964)	(0.137)	(0.0697)	(0.148)	(0.00342)
Court available	-0.0191	-0.0869*	0.0774	0.0762	0.0563	-0.00643
	(0.0835)	(0.0494)	(0.129)	(0.103)	(0.137)	(0.00506)
Post office available	-0.0749	-0.121**	-0.158	-0.101**	0.281*	-0.00544
	(0.104)	(0.0574)	(0.125)	(0.0452)	(0.163)	(0.00464)
R^2	0.012	0.064	0.055	0.069	0.036	0.009
F stat	0.760	4.266	1.202	5.575	1.087	0.480
F p-value	0.553	0.00305	0.314	0.000409	0.367	0.750
Number of public goods projects	0.0342*	0.0215	-0.0190	-0.0139	0.0474	-0.00288
	(0.0206)	(0.0221)	(0.0205)	(0.0170)	(0.0357)	(0.00237)
Received public funding for public goods	-0.0881	0.0447	0.199**	0.162**	-0.384***	0.0176
	(0.0852)	(0.0636)	(0.0883)	(0.0692)	(0.130)	(0.0124)
Received NGO funding for public goods	0.0147	-0.0688	0.0440	0.0965	-0.134	-0.00698
	(0.0807)	(0.0808)	(0.106)	(0.105)	(0.139)	(0.00560)
Received other funding for public goods	-0.0258	-0.0475	0.0197	0.0147	0.00185	0.00254
	(0.0567)	(0.0577)	(0.0843)	(0.0712)	(0.0977)	(0.0104)
R^2	0.019	0.028	0.026	0.030	0.080	0.009
F stat	0.896	1.189	1.524	1.939	2.706	0.698
F p-value	0.467	0.320	0.200	0.109	0.0341	0.595
Observations	208	112	112	112	112	112

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A14: Type and technology selection regressions. The majority of explanatory variables are not significant predictors of pump technology, and the number of statistically significant predictors is roughly what we would expect if technology was randomly assigned.

	(1) Pump	(2) Afridev	(3) India	(4) SWN	(5) Nira	(6) Rope
Farmer's co-operative group in village?	0.0662	0.0296	-0.154**	-0.0397	0.170**	0.00716
	(0.0517)	(0.0552)	(0.0715)	(0.0618)	(0.0821)	(0.0147)
SACCO in village?	-0.0189	-0.00908	0.0962	0.0570	-0.127	-0.0126
	(0.0565)	(0.0642)	(0.0829)	(0.0689)	(0.0895)	(0.0127)
Number of village assemblies in last year	0.00850	0.00375	0.0264**	-0.0101	-0.0123	0.000883
	(0.0108)	(0.00983)	(0.0128)	(0.00786)	(0.0162)	(0.00146)
Ward tribunal available?	-0.0320	-0.0386	0.0682	0.0311	-0.0718	0.0131
	(0.0719)	(0.0964)	(0.0956)	(0.0740)	(0.119)	(0.00933)
Christianity most common religion	0.0583	-0.00203	-0.0171	0.0503	-0.0506	0.0169
	(0.0532)	(0.0605)	(0.0720)	(0.0628)	(0.0871)	(0.0132)
Inheritance procedure gender-neutral	0.00709	-0.0295	-0.0662	-0.145	0.133	0.0151
	(0.0624)	(0.0751)	(0.0947)	(0.0960)	(0.106)	(0.0115)
R^2	0.017	0.008	0.078	0.058	0.069	0.029
F stat	0.526	0.198	1.805	1.299	1.585	0.450
F p-value	0.788	0.977	0.105	0.264	0.159	0.844
Years leader in position	-0.00725	-0.00104	0.00356	-0.0110*	0.00385	0.000389
	(0.00549)	(0.00661)	(0.00852)	(0.00642)	(0.0106)	(0.000529)
Leader member of CCM party?	0.0124	-0.0439	0.0118	0.156***	-0.115	0.0118
	(0.0813)	(0.113)	(0.122)	(0.0386)	(0.160)	(0.00886)
Education level of leader	-0.00817	-0.140**	0.103	0.0562	0.0186	0.00382
	(0.0455)	(0.0572)	(0.0717)	(0.0687)	(0.0693)	(0.00671)
Female community leader	-0.219***	-0.0990	-0.280***	-0.0772	0.256	0.00196
	(0.0707)	(0.0625)	(0.0825)	(0.106)	(0.209)	(0.0164)
Age of leader	-0.00378	-0.00602*	0.00126	0.00745**	-0.00125	0.000236
	(0.00255)	(0.00311)	(0.00418)	(0.00305)	(0.00420)	(0.000791)
Leader is Christian	0.0365	0.0669	0.00718	0.0736	-0.165*	0.0167
	(0.0522)	(0.0523)	(0.0740)	(0.0619)	(0.0858)	(0.0131)
R^2	0.041	0.101	0.038	0.088	0.051	0.018
F stat	2.285	1.649	4.568	3.884	1.036	0.534
F p-value	0.0372	0.141	0.000371	0.00153	0.406	0.782
Observations	208	112	112	112	112	112

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Do installer or funder fixed effects explain the correlations between pump functionality and the number of pumps of the same technology nearby?

Table A15: Main specifications, large installers only. Restricting the sample to only those pumps installed by organizations who installed more than 1 percent of pumps, and including fixed effects for each of these installers, does not change the key marginal effects. If the key correlations were being driven by installer fixed effects (of either larger, included organizations, or smaller excluded organizations), we would expect the key coefficients to change in this regression.

	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.105	-0.255*	-0.372***	-0.324**	-0.367***
	(0.153)	(0.132)	(0.131)	(0.133)	(0.131)
Number of pumps, diff tech within 1.2km	-0.895**	0.0382	0.151	0.0263	-0.213
	(0.378)	(0.273)	(0.281)	(0.280)	(0.300)
Number of pumps, same tech within 1.2km	1.61***	0.923***	0.859***	1.01***	0.834***
	(0.306)	(0.228)	(0.241)	(0.246)	(0.259)
Observations	6,396	6,396	6,396	6,396	6,396
R^2	0.018	0.149	0.191	0.210	0.213

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Table A16: Main specifications, same installer interaction. Including whether pumps were installed by the same organization as an interaction term with the number of pumps of the same technology does not have a significant effect in the preferred specifications. This suggests that it is variation in whether there are nearby pumps of the same technology that explains pump functionality rates, not variation in whether nearby pumps of the same technology were installed by the same organization.

	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.536*	-0.686**	-0.838***	-0.771***	-0.820***
	(0.314)	(0.284)	(0.283)	(0.286)	(0.299)
Number of pumps, diff tech within 1.2km	-1.41**	-0.0160	-0.319	-0.504	-0.592
	(0.649)	(0.500)	(0.549)	(0.535)	(0.694)
Number of pumps, same tech within 1.2km	7.17***	5.64***	4.17***	4.31***	4.21***
	(1.82)	(1.40)	(1.09)	(1.08)	(1.07)
No. pumps, same tech, same installer, 1.2km	-3.43*	-3.65**	-1.90	-1.57	-1.62
	(1.98)	(1.53)	(1.32)	(1.36)	(1.34)
Observations	10,667	10,667	10,667	10,667	10,667

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Are different technologies more appropriate for different physical conditions, leading to a correlation between functionality and the number of similar pumps nearby?

If some technologies of pump are more likely to be functional in certain physical conditions than others, and if installing organizations use this information, then pumps are both more likely to be functional and more likely to be close to other pumps of the same technology when physical conditions are favorable for that technology. I test this explanation using three measures of groundwater derived from data on geological, rainfall and hydrological conditions.

The dataset comes from the British Geological Survey (BGS), and the methods used to construct it are described in more detail in MacDonald, Bonsor, Dochartaigh, and Taylor [2012]. It includes three measures at 5km resolution: groundwater storage (calculated using the saturated thickness and effective porosity of rock, in units of mm), groundwater productivity (liters per second measured at an existing borehole), and depth to water (meters). The dataset gives groundwater estimates for the whole of Africa, and is based on hydrogeological and geological reports, maps and data, as well as 283 separate studies within 152 publications, and has undergone peer review by 12 regional experts.

Table A17 estimates probit regressions of water source type (specification (1)) and pump technology (specifications (2) to (6)) on the key groundwater variables. There is reasonably strong evidence of

selection of water source type (handpump or not) on groundwater variables, with handpumps more likely to be installed when the depth of groundwater is less than 25m, and less likely to be installed when the groundwater productivity is less than 1 liter per second. These results make intuitive sense. Given that a handpump is installed, the evidence that there is selection of the technology on groundwater variables is much weaker: only 5 of the 40 estimated coefficients are significant at the 95 percent level.

Although the results in Table A17 do not give strong evidence for selection of pump technology on groundwater variables, they do suggest that India Mark II pumps are less likely in areas with low groundwater storage or productivity, and that SWN pumps are more likely in areas with a grater depth to groundwater. To see if this is explaining the regressions in the main specifications, I include these groundwater variables, and their interaction with pump technologies, in the main specifications. The results in Table A18 show that including these interaction terms hardly changes the main estimated marginal effects. This suggests that the selection of pump technology in areas with favorable physical conditions is unlikely to explain the key observed correlations.

Table A17: Water source type and technology selection on groundwater variables. There is strong evidence for selection of water source type (pump or not) on groundwater variables (specification (1)), but only weak evidence that there is selection of pump technologies on groundwater variables (specifications (2) to (6)).

VARIABLES	(1) Pump	(2) Afridev	(3) India	(4) SWN	(5) Nira	(6) Rope
Groundwater depth 0-7m	0.0892***	-1.74e-05	-0.0331	-0.103**	0.0900*	0.0283*
	(0.0187)	(0.0289)	(0.0444)	(0.0521)	(0.0520)	(0.0145)
Groundwater depth 7-25m	0.0738***	0.0147	-0.0105	-0.129***	0.0924	0.0606
	(0.0236)	(0.0315)	(0.0407)	(0.0423)	(0.0612)	(0.0506)
Groundwater productivity 5-20 l/s	0.0446*	-0.0172	-0.0229	0.00719	-0.0155	0.00297
	(0.0239)	(0.0199)	(0.0298)	(0.0380)	(0.0369)	(0.0120)
Groundwater productivity 1-5 l/s	0.0475	-0.0141	-0.0524	-0.0661	0.0975*	0.0466
	(0.0413)	(0.0268)	(0.0376)	(0.0473)	(0.0548)	(0.0468)
Groundwater productivity 0.5-1 l/s	-0.0473**	-0.00598	-0.0986***	0.0626	0.0533	0.0194
	(0.0220)	(0.0244)	(0.0306)	(0.0564)	(0.0475)	(0.0350)
Groundwater storage, <1000mm	0.00838	-0.00600	-0.0303	0.0344	-0.0117	-0.0109
	(0.0216)	(0.0216)	(0.0262)	(0.0403)	(0.0340)	(0.0224)
Groundwater storage, 1000-10,000mm	-0.0146	-0.0318*	-0.000827	0.0204	-0.000571	0.0171
	(0.0194)	(0.0173)	(0.0266)	(0.0353)	(0.0336)	(0.0281)
Groundwater storage, 0mm	0.117	-0.00250	-0.112***	-0.0160	0.229**	
	(0.0719)	(0.0342)	(0.0103)	(0.145)	(0.116)	
Observations	66,992	7,680	9,736	8,574	10,348	2,911
Pseudo R^2	0.279	0.323	0.387	0.411	0.208	0.415
Chi-squared test stat	49.58	13.16	33.58	19.99	16.90	13.71
Chi-squared p-value	4.92e-08	0.107	4.85e-05	0.0104	0.0311	0.0566

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Regressions include district, installer and funder fixed effects. Number of observations varies because some districts do not have any pumps of a particular technology and are therefore excluded from the probit.

Table A18: Main specifications, technology and groundwater interactions. Including groundwater variables and their interaction with pump technology does not change the key estimated marginal effects, as given in Table 2.

	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.241**	-0.296***	-0.327***	-0.292***	-0.327***
	(0.0963)	(0.0986)	(0.104)	(0.105)	(0.112)
Number of pumps, diff tech within 1.2km	-0.0266	0.111	-0.0745	-0.174	-0.177
	(0.145)	(0.190)	(0.203)	(0.199)	(0.251)
Number of pumps, same tech within 1.2km	1.48***	1.08***	1.08***	1.22***	1.20***
	(0.232)	(0.222)	(0.221)	(0.235)	(0.247)
Observations	10,617	10,617	10,617	10,617	10,617

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Do physical shocks specific to the type of hole a pump is installed on explain the correlations? A similar explanation to the selection of technology on physical conditions is that certain technologies may be more likely to be installed on certain types of holes. If physical shocks are specific to hole types then this might explain the observed technology-specific correlations. As shown in Table 1, there are two main types of hole that account for more than 93 percent of pumps in the data: machine drilled boreholes, and hand dug shallow wells. Machine drilled boreholes tend to be deeper, so if the water table falls below a certain level, this may affect pumps installed on shallow wells, but not those installed on boreholes.[84] However, I test this hypothesis and find that while there is correlation between the functionality of pumps of the same technology and type of hole, there is no correlation between functionality of pumps with the same type of hole but a different technology (Table A19). These results suggest that it is pump technology rather than hole type that explains the observed correlations.

[84]The water table is the level below which the ground is saturated with water: essentially this is the depth to groundwater.

Table A19: Main specifications, hole type and technology interactions. Adding the hole type to the centrality regressions shows that the positive correlation seems to be entirely driven by pumps of the same technology installed on the same type of hole, and there is evidence of a negative correlation between pump functionality and the number of pumps of the same technology installed on a different type of hole. There are two plausible explanations for this: that positive spillovers are dependent on the hole type, or that there are shocks that are specific to the hole type. However, if the second explanation was true, we would expect a positive coefficient on the number of pumps of a different technology installed on the same type of hole, but this coefficient is in fact negative (and insignificant). Together, these results suggest that I should include the hole type in the measure of how similar two sources are (i.e. include hole type in the definition of two pumps being of the same technology), and therefore the possible strength of spillovers between them.

	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.184	-0.234**	-0.289***	-0.265**	-0.286***
	(0.113)	(0.104)	(0.104)	(0.106)	(0.110)
Number of pumps, diff tech within 1.2km	-0.413	0.999*	0.806	0.657	0.542
	(0.460)	(0.567)	(0.599)	(0.595)	(0.610)
No. pumps, diff tech, same hole, 1.2km	-0.0268	-1.03*	-0.989	-0.911	-0.835
	(0.466)	(0.614)	(0.626)	(0.629)	(0.628)
Number of pumps, same tech within 1.2km	-0.796	-2.17	-3.86**	-3.62**	-3.77**
	(1.76)	(1.33)	(1.52)	(1.60)	(1.62)
No. pumps, same tech, same hole, 1.2km	2.56	3.32**	4.97***	4.86***	4.96***
	(1.77)	(1.35)	(1.54)	(1.62)	(1.64)
Observations	10,667	10,667	10,667	10,667	10,667

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Does overlap of members of the water point committees explain the correlations?
The main analysis uses individual water sources as the unit of analysis, and the model uses each water point to define a 'community' that makes maintenance decisions in a network game. I make this assumption because decisions about pump maintenance are made by a water point committee appointed by the community for each water source. A valid concern is that a single committee may manage more than one water source, or that there may be overlap of members of the committees, which might explain the correlations in pump functionality. Indeed survey responsents were split about whether they thought water point committees typically manage a single pump or multiple pumps (see Figure A35).

Although the data does not contain information about all of the members of the water point committee (WPC), water sources are typically named after the leader of the WPC in the dataset. I use this information to test for evidence that overlapping management explains the correlations using two specifications. Of the 10,667 water pumps used in the main specifications, 1201 (11.3 percent) are listed as having the same water point name as another water source in their village, but only 608 of these (5.7 percent) have the same name as a pump of the same technology in their village.

I use this information to run two robustness tests. First, I estimate the main centrality specifications (from Table 2) but excluding all observations that share the same water point name with another water point in their village. The results are shown in Table A20. Second, I estimate the main centrality specifications but treating pumps with the same name and of the same technology as a single observation, averaging pump characteristics between them. The dependent variable will be the proportion of pumps that are functional in these newly defined 'communities', and so I use a linear regression, with the results given in Table A21.

Table A20: Main specifications, excluding observations with same name. Excluding observations that have the same water point name and are in the same village does not significantly change the main estimated marginal effects.

	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.141	-0.229*	-0.275**	-0.260**	-0.285**
	(0.127)	(0.121)	(0.121)	(0.124)	(0.129)
Number of pumps, diff tech within 1.2km	-0.550**	-0.0259	-0.233	-0.297	-0.364
	(0.252)	(0.201)	(0.194)	(0.192)	(0.247)
Number of pumps, same tech within 1.2km	1.84***	1.20***	0.979***	1.10***	1.05***
	(0.332)	(0.254)	(0.229)	(0.229)	(0.243)
Observations	9,464	9,464	9,464	9,464	9,464
Pseudo R^2	0.012	0.114	0.149	0.162	0.163

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Table A21: Main specifications, merging observations with same name. Treating pumps in the same village with the same name and technology as a single observation does not significantly change the main estimated marginal effects.

	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.204*	-0.221**	-0.244**	-0.224**	-0.244**
	(0.112)	(0.0937)	(0.0948)	(0.0934)	(0.0981)
Number of pumps, diff tech within 1.2km	-0.474**	0.0369	-0.0829	-0.142	-0.179
	(0.228)	(0.164)	(0.166)	(0.160)	(0.210)
Number of pumps, same tech within 1.2km	1.72***	1.05***	0.856***	0.948***	0.916***
	(0.273)	(0.203)	(0.182)	(0.182)	(0.194)
Number of pumps with same name and tech	-1.26	-0.691	-0.358	-0.591	-0.735
	(1.03)	(1.10)	(1.13)	(1.19)	(1.20)
Observations	10,302	10,302	10,302	10,302	10,302
R^2	0.015	0.138	0.175	0.190	0.191

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Do technology-specific physical shocks, or shocks to the community that affect functionality of one technology more than another, explain the observed correlations? If there were local shocks to specific technologies, we would expect the key correlations to lose significance once we control for the interaction of technology with district fixed effects. However, including these interaction terms does not change our estimates of the key marginal effects.

Table A22: Main specifications, district and technology interactions. Including interactions between district fixed effects and technology dummies does not change the key marginal effects.

	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.226**	-0.247***	-0.289***	-0.268***	-0.271***
	(0.0915)	(0.0933)	(0.0934)	(0.0923)	(0.0951)
Number of pumps, diff tech within 1.2km	0.185	0.149	0.0743	0.0294	0.0115
	(0.173)	(0.153)	(0.141)	(0.141)	(0.186)
Number of pumps, same tech within 1.2km	1.13***	0.861***	0.853***	0.947***	0.903***
	(0.192)	(0.182)	(0.189)	(0.203)	(0.212)
Observations	10,667	10,667	10,667	10,667	10,667
R^2	0.157	0.188	0.218	0.232	0.233

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

Do year of installation and technology-specific fixed effects (and their interaction) explain these correlations? It is possible that pumps are installed in 'cohorts' and have a fixed expected lifetime. If an organization installed a number of pumps of the same technology in the same year, they may break down at a similar time, inducing technology-specific spatial correlations. However, including dummies for the year of installation, technology dummies and their interactions does not change the key marginal effects.

Table A23: Main specifications, year and technology interactions. Including dummies for the year of installation, technology dummies and their interactions does not change the key marginal effects.

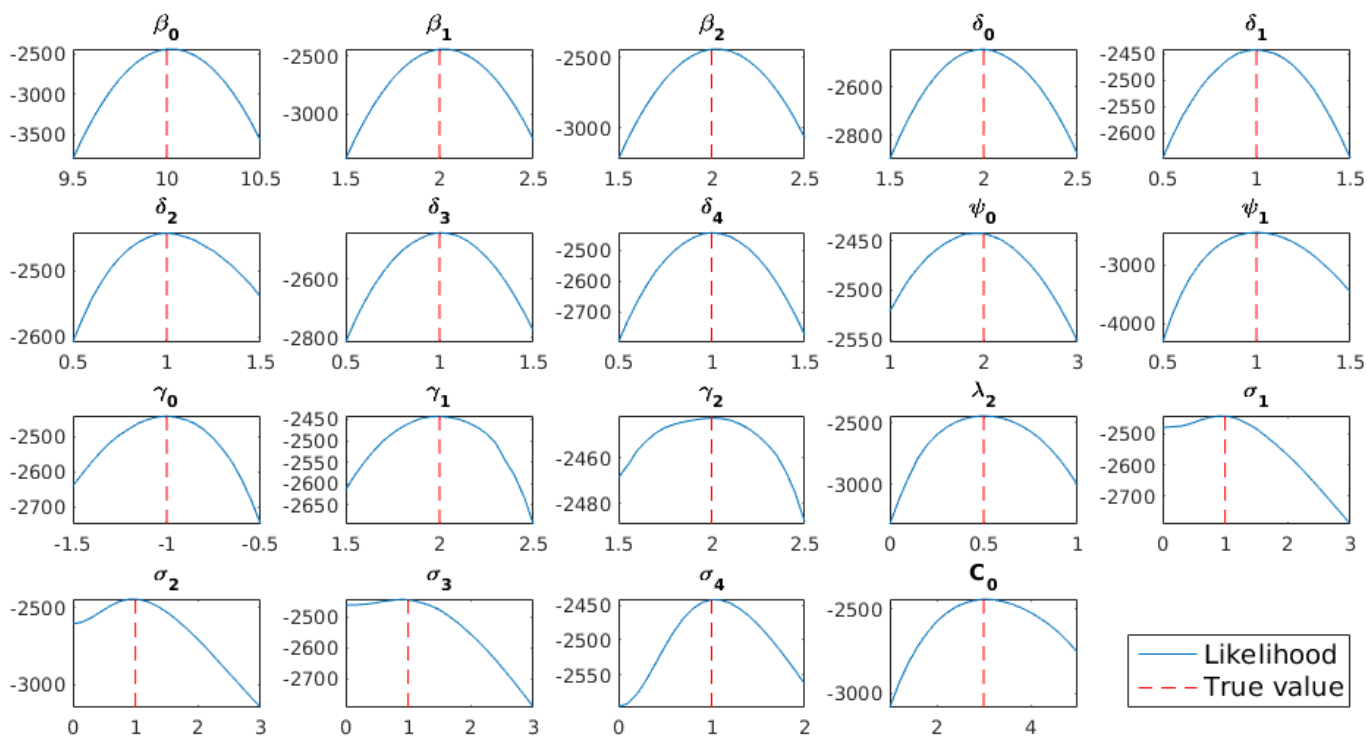
	(1)	(2)	(3)	(4)	(5)
Number of non-pump sources within 1.2km	-0.262**	-0.226**	-0.296***	-0.271***	-0.284***
	(0.106)	(0.0932)	(0.0930)	(0.0895)	(0.0958)
Number of pumps, diff tech within 1.2km	0.0825	0.0455	0.0354	-0.0133	-0.142
	(0.115)	(0.157)	(0.156)	(0.152)	(0.195)
Number of pumps, same tech within 1.2km	1.20***	0.908***	0.877***	0.961***	0.868***
	(0.207)	(0.193)	(0.174)	(0.172)	(0.191)
Observations	10,667	10,667	10,667	10,667	10,667
R^2	0.122	0.188	0.204	0.219	0.220

Notes: Standard errors clustered at the ward level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Marginal effects reported in percentage points. The control variables used in each specification correspond to those used in the main specification (reported in Table 2).

A.6 Simulations to test performance of estimation procedure

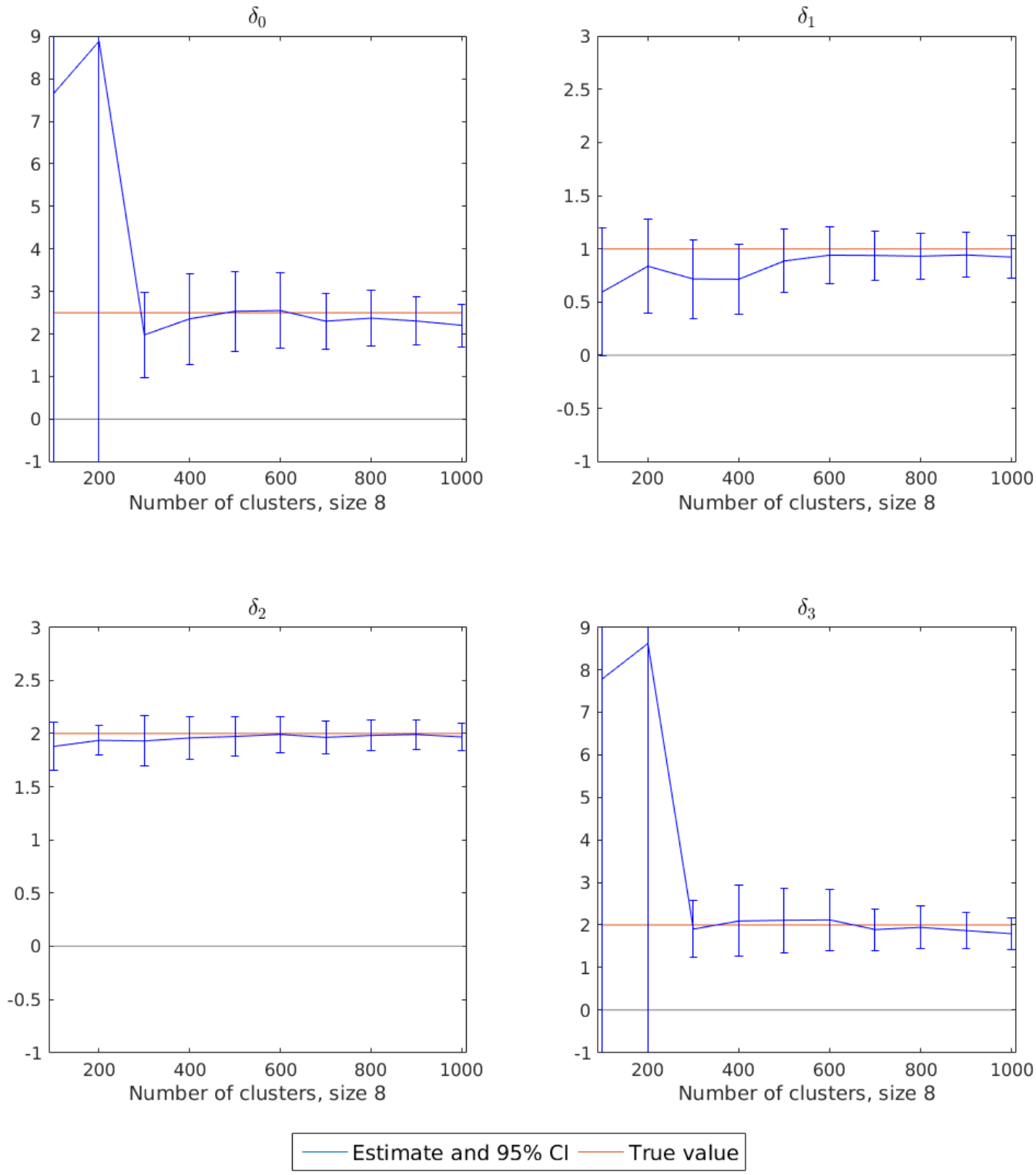
This section shows the performance of the estimation procedure for simulated data. Figure A36 shows that the simulated likelihood function is well behaved, and attains a maximum around the true parameter values. Figure A37 shows the performance of estimates of the $\boldsymbol{\delta}$ parameters as we increase the number of observations in the simulation (equivalent figures for other model parameters are available upon request). To carry out this Monte Carlo exercise, I generated a dataset of 1000 clusters of size 8, with random characteristics of water sources (including location, type and technology), then estimated the model on the first 100 clusters, then the first 200 clusters and so on. This, and similar exercises, indicated that I need more than 2400 observations with reasonable variation in the key model parameters for the estimates to converge to the true parameters.

Figure A36: Shape of simulated likelihood function. The likelihood function achieves a maximum very close to the true parameters in simulations, and is well behaved.



Notes: Simulated data was constructed to closely match the sample used to estimate the model (see section 6.1). There are 789 wards, each containing 2-7 clusters (randomly selected), with each cluster containing 1-10 observations (randomly selected), giving a total of 19,399 observations. 42 percent of observations are pumps.

Figure A37: Performance of estimation procedure as we increase the sample size (selected parameters). The estimated parameters are close to the true parameters used to simulate the data when there are more than 300-400 clusters (2400-3200 observations). The estimation procedure is not able to separately identify δ_0 and δ_3 when there are fewer clusters.



A.7 Derivation of likelihood

This section fills out the missing steps from section 6, to derive the expressions for $f_{\xi_w}(\bar{v}_w|\epsilon_w)$, $\sigma^2_{\xi_w}$, $\sigma^2_{\epsilon_w}$ and ρ_w in terms of our structural parameters.

First note that we can use an orthogonal decomposition of ξ_w to give $\frac{\xi_w}{\sigma_{\xi_w}} = \rho_w \frac{\epsilon_w}{\sigma_{\epsilon_w}} + \omega$ such that $\omega \sim N(0, 1-\rho_w^2)$. We can use this decomposition to rearrange the density in terms of ω, and then standardize this as follows:

$$
\begin{aligned}
f_{\xi_w}(\bar{v}_w|\epsilon_w) &= f_{\xi_w}(\underbrace{y_w - \beta_0 - \beta_1 \frac{1}{n_w}\sum_{i=1}^{n_w} m_i - \beta_2 \frac{1}{n_w}\sum_{i=1}^{n_w} m_{-i} - \mathbf{X}_w^a \beta}_{\bar{v}_w} \,|\epsilon_w) && (10)\\
&= f\left(\xi_w = \bar{v}_w|\epsilon_w\right) && (11)\\
&= f\left(\rho_w \frac{\sigma_{\xi_w}}{\sigma_{\epsilon_w}}\epsilon_w + \sigma_{\xi_w}\omega = \bar{v}_w\right) && (12)\\
&= f\left(\omega = \frac{\bar{v}_w - \rho_w \frac{\sigma_{\xi_w}}{\sigma_{\epsilon_w}}\epsilon_w}{\sigma_{\xi_w}}\right) && (13)\\
&= \frac{1}{\sigma_{\xi_w}\sqrt{1-\rho_w^2}}\phi\left(\frac{\bar{v}_w - \rho_w \frac{\sigma_{\xi_w}}{\sigma_{\epsilon_w}}\epsilon_w}{\sigma_{\xi_w}\sqrt{1-\rho_w^2}}\right) && (14)
\end{aligned}
$$

To derive $\sigma^2_{\xi_w}$, $\sigma^2_{\epsilon_w}$ and ρ_w, recall that $\epsilon_i = \eta_{1c} + \eta_{2i} + \eta_{3i}$ and $\xi_i = b\eta_{2i} + \eta_{4i}$, where $\eta_{1c}, \eta_{2i}, \eta_{3i}, \eta_{4i}$ are independent normal random variables with variances $\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2$. Therefore, we get $\sigma^2_{\xi_w}$, $\sigma^2_{\epsilon_w}$ and ρ_w in terms of our structural parameters:

$$
\begin{aligned}
\epsilon_w &= \frac{1}{n_{cw}}\sum_{c=1}^{n_{cw}} \eta_{1c} + \frac{1}{n_w}\sum_{i=1}^{n_w}(\eta_{2i} + \eta_{3i}) && \Rightarrow\ \sigma^2_{\epsilon_w} = \frac{\sigma_1^2}{n_{cw}} + \frac{\sigma_2^2 + \sigma_3^2}{n_w} && (15)\\
\xi_w &= \frac{1}{n_w}\sum_{i=1}^{n_w}(b\eta_{2i} + \eta_{4i}) && \Rightarrow\ \sigma^2_{\xi_w} = \frac{b^2\sigma_2^2 + \sigma_4^2}{n_w} && (16)\\
\sigma_{\epsilon_w,\xi_w} &= \mathbb{E}\left[b\left(\frac{1}{n_w}\sum_{i=1}^{n_w}(\eta_{2i})\right)^2\right] = \frac{b\sigma_2^2}{n_w} && \Rightarrow\ \rho_w = \frac{b\sigma_2^2/n_w}{\sigma_{\epsilon_w}\sigma_{\xi_w}} && (17)
\end{aligned}
$$

A.8 Model functional forms

I use three outcomes variables from the Tanzania Population and Housing Census [2012]: the child survival rate, girls' school attendance rate and boys' school attendance rate. I stack the following outcomes equation, and estimate them in the model, controlling for the adult literacy rate (taken from the population census), whether a ward is listed as rural or urban, and the distance to the nearest of Tanzania's 11 largest cities. The specific functional form of the outcomes equations (from equation (8) in the model) is therefore:

$$
\begin{aligned}
surv_w =& \beta_0^s + \beta_1^s \frac{1}{n_w}\sum_{i=1}^{n_w} m_i + \beta_2^s \frac{1}{n_w}\sum_{i=1}^{n_w} m_{-i} + \beta_3^s adultlit_w + \beta_4^s ruraldum_w + \beta_5^s distcity_w + \xi_w^s \\
attg_w =& \beta_0^g + \beta_1^g \frac{1}{n_w}\sum_{i=1}^{n_w} m_i + \beta_2^g \frac{1}{n_w}\sum_{i=1}^{n_w} m_{-i} + \beta_3^g adultlit_w + \beta_4^g ruraldum_w + \beta_5^g distcity_w + \xi_w^g \\
attb_w =& \beta_0^b + \beta_1^b \frac{1}{n_w}\sum_{i=1}^{n_w} m_i + \beta_2^b \frac{1}{n_w}\sum_{i=1}^{n_w} m_{-i} + \beta_3^b adultlit_w + \beta_4^b ruraldum_w + \beta_5^b distcity_w + \xi_w^b
\end{aligned}
$$

The baseline cost of pump maintenance, given in equation (2), is a linear function of community and pump characteristics: the age of a pump (age_i), whether users must pay to use it (pay_i), and dummies for the four most common technologies (Afridev, India Mk II, SWN 80 and Nira):

$$\mathbf{X}_i^b \psi = \psi_0 + \psi_1 age_i + \psi_2 pay_i + \psi_3 TE1_i + \psi_4 TE2_i + \psi_5 TE3_i + \psi_6 TE4_i$$

The cost of a community i accessing water from community j in the case that i's pump is non-functional (see equation (3)) depends on the distance they have to travel, whether they have to pay to use the alternative water source, and whether it is a pump or a tap:

$$g^{ij}(d_{ij}, m_j, \mathbf{X}_j^c) = min\{C_0, (1-m_j)C_0 + m_j \exp(\gamma_0 + \gamma_1 d_{ij} + \gamma_2 pay_j + \gamma_3 pumpdum_j + \gamma_4 tapdum_j)\}$$

A.9 Identification of model parameters

This section provides a more detailed explanation of the identification of model parameters discussed in less detail in section 6.2.

In the estimation I set $\mathcal{R} = \{1, 2\}$ to test the effect of the cheapest and second cheapest alternative working water source on community i's maintenance decision. λ_1 is not separately identified to the $\boldsymbol{\gamma}$ parameters affecting the cost of accessing an alternative water source, so I normalize it to one. I estimate λ_2, which is identified by the best response equation of communities with at least two working alternative water sources. There are 7619 such communities in the data used to estimate the model, Intuitively, λ_2 is identified by the effect of the second cheapest alternative water source on the maintenance decision of community i, relative to the effect of the cheapest alternative.

The cost of a community accessing an outside option if its pump is not functional, C_0, is identified by the best response of communities without any working alternative water sources in their cluster.[85] Note that these communities must necessarily also have $\mathbf{N}_i(\boldsymbol{\delta})\mathbf{m} = 0$ and so their best response is given by: $m_i = 1$ iff $\beta_1 - \mathbf{X}_i^b\boldsymbol{\psi} + (1 + \lambda_2)C_0 > \epsilon_i$. Given that β_1, ψ, λ_2 are separately identified, we can therefore also identify C_0.

To see how the $\boldsymbol{\gamma}$ terms, which affect the cost of i accessing neighboring functional water sources, are identified, consider the best response function for communities with exactly one available functional alternative in their cluster: $m_i = 1$ iff $\beta_1 - \frac{\mathbf{X}_i^b\boldsymbol{\psi}}{1+\mathbf{N}_i(\boldsymbol{\delta})\mathbf{m}} + \exp(\gamma_0 + \gamma_1 d_{i1} + \mathbf{X}_1^c\boldsymbol{\gamma}_2) + \lambda_2 C_0 > \epsilon_i$. There are 587 such communities in the data used to estimate the model. Given the identification of the other parameters in this equation, we can identify the $\boldsymbol{\gamma}$ parameters.

Finally, the $\boldsymbol{\sigma}$ terms are identified by: the variance in functionality not explained by the model, and the extent to which this is correlated within clusters; and the variance in outcomes not explained by the model, and how this is correlated with unexplained variance in functionality.

[85] I assume that communities can only access alternative water sources in their own cluster, and there are 308 communities without any working alternative in their cluster. Without any restriction on which alternative water sources a community may access, every community would have an alternative water source available at some distance. Modeling and estimating an outside option is a good reflection of reality, as communities are likely to prefer using an unprotected water source, such as a stream or pond, to traveling many kilometers to collect water.

A.10 Estimated variance and covariance of shock terms

Table A24: Estimated variance and covariance of the shock terms. See section A.7 for the definition of the σ terms and how they relate to the variance of the cost of maintenance shock, ϵ_{ic}, the outcomes shocks, ξ_i^s, ξ_i^g and ξ_i^b.

σ_1	σ_2	σ_3	σ_4^s	σ_4^g	σ_4^b
0.50	0.38	0.34	0.041	0.002	0.15
(0.040)	(0.0001)	(0.003)	(0.022)	(0.019)	(0.027)

Notes: Standard errors in parentheses, calculated by numerically estimating the Hessian at the estimated parameter values.