Should Resource Efficient Technologies be Subsidized? Evidence from the Diffusion of Drip Irrigation in Gujarat *

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PRELIMINARY DRAFT - NOT FOR CIRCULATION

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Abstract

The adoption of modern agricultural technologies in developing countries has become a major policy agenda in recent years. In this paper, we study the spatial and temporal diffusion of subsidized micro-irrigation technologies (MIS), including drip and sprinkler irrigation, across 18,000 villages in the Indian state of Gujarat. MIS are proven to increase yields and reduce crop water requirements by substantial amounts, but unlike improved seeds or fertilizers, represent quantum leaps for farmers in terms of their difference from existent cultivation practices, high costs, and yield increases. To boost adoption, the Indian government is offering 50% of the cost in subsidies, and in the recent decade, more than 400,000 farmers in Gujarat, one of India's most water scarce states, have utilized this subsidy to purchase MIS. Using detailed data on adopters, we examine the merit of the three-pronged rationale for public subsidies: 1. Does the technology spread from early adopters to others, i.e. is the subsidy justified by informational externalities? 2. Would farmers have adopted MIS without the subsidy? 3. Does MIS adoption result in reductions in water (a common property, but unregulated resource) and energy use? Our findings are as follows. 1. We find robust causal evidence suggesting that the spatial diffusion of MIS between neighboring villages is responsible for a substantial part of the rapid increase in MIS adoption in Gujarat in recent years (450,000 purchases since 2006). We also show that the pattern of diffusion is consistent with a mechanism in which first adopters in a village learn about the likelihood that MIS will be profitable from the experience of past adopters in nearby villages: diffusion occurs only across farmers applying the same type of MIS to the same type of crop. 2. We find that variation in subsidy levels is associated with much higher rates of adoption, indicating the important role of the subsidy. 3. Preliminary results offer indications short-term increases in energy use after MIS adoption, and some indications of substantial long-term reductions, consistent with a model of learning. Our results provide new evidence on the merit of well-administered subsidy program for novel technologies that provide public goods.

JEL classification: O33, O38, Q55

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1 Introduction

Technological progress is a key aspect of economic growth. The adoption of improved agricultural technologies, in particular, has recently received renewed interest by policy makers because of persistent yield gaps in developing countries, as well as the growing need to adapt developing countries' agriculture to increasing environmental stress. Understanding the factors that drive and delay adoption of agricultural technologies has now become an important research agenda in development economics (Jack, 2011; Foster and Rosenzweig, 2010). When these technologies also provide a public good, e.g. when they have the potential to reduce the consumption of resources like water or energy, adoption is further challenged by additional obstacles and market failures Greenstone and Jack (2013), but far fewer studies have investigated the adoption of such technologies.

The subsidization of resource conserving technologies is widely practiced in developed and developing countries alike, particularly in the case of energy Allcott and Greenstone (2012); Davis et al. (2013). Subsidies can be justified, from a social point of view, on the basis of three types of market failures. First, learning externalities may justify the subsidization of early adopters, at least. A growing literature in development economics has demonstrated the importance of social learning in technology adoption: whether and from whom farmers learn about new cultivation practices (Foster and Rosenzweig, 1995; Munshi, 2004; Conley and Udry, 2010; Bandiera and Rasul, 2006). [1] Second, subsidies can help address credit constraints, especially when adoption requires high up-front fixed costs. Third, subsidies can be justified if the adoption of these technologies

[1] Foster and Rosenzweig (1995) and Munshi (2004) investigate how Indian farmers learn to use hybrid varieties and chemical fertilizers during the Green Revolution. Conley and Udry (2010) show that new pineapple cultivators in Ghana learn how much fertilizer to apply from farmers in their social networks. Bandiera and Rasul (2006) demonstrate a correlation between the initial adoption of a new seed variety within social networks in villages in Mozambiuqe.

actually leads to reduced use of common property resources or pollution.

This paper analyzes the large scale diffusion of micro-irrigation systems (MIS), including sprinkler and drip irrigation across 18,000 villages in the Indian state of Gujarat, and empirically tests each of the above justifications for subsidizing them. Our focus is on the role of social learning in the spatial diffusion of MIS, but we also present preliminary results on the impact of subsidy levels on adoption, and the impact of adoption on energy and water use.

We find robust evidence, using several identification strategies, that diffusion across villages plays a major role in the rapid proliferation of this technology in recent years, and present evidence that this diffusion is driven by social learning, in the sense that early adopters in a village learn from the decisions of farmers nearby on the likelihood that the new technology is worth the large required investment. We also show that when subsidy levels increase, adoption rates increase substantially. Finally, we find, using administrative energy use data, that the use of electricity for pumping groundwater initially increases after the adoption of MIS, but later declines substantially, potentially reflecting a learning process in which farmers develop confidence in the ability of the technology to perform well with lower rates of water application.

Our analysis of social learning differs from the existing literature in several ways. First, unlike seed or fertilizer, on which most earlier studies have focused, MIS represent a quantum step for farmers, both in terms of how different it is from prevalent cultivation practices and in terms of the required investment. Unlike in the case of seeds or fertilizer, and while it is possible for farmers to gradually expand their use of MIS, even the initial investment requires a substantial fixed cost on a minimal plot size, that is typically 2-5 times the average annual profit per unit land. Moreover, while improved seeds or the use of fertilizer does not require a drastic change in the remaining aspects of cultivation, using MIS for irrigation is wholly unfamiliar method of cultivation that requires substantial adjustment and the operation of relatively sophisticated machinery. Our focus, therefore, is on the role learning has in affecting a farmer's decision to take the high (perceived) risk of investing in the new technology, rather than on how to use it.

Second, our analysis is focused on inter, rather than intra-village diffusion. Diffusion, and learning, across villages is likely to be more restricted than learning within the close community of an Indian village, but it is a crucial component of large scale processes of diffusion, as in the case of an entire Indian state. Most previous studies have focused on within-village learning driven diffusion. An exception is Munshi (2004), who also examines learning across entire districts. The advantage of our data is that its size and spatial detail (we have information on adoption in each village of Gujarat), allows for more precise estimates and causal inference and enables us to make progress on identification challenges that are inherent to studies of diffusion and social learning.

Third, our analysis sheds light on previously less investigated aspects of learning. Previous literature has shown (Conley and Udry, 2010; Bandiera and Rasul, 2006) that farmers tend to learn from others in their social network, rather than from their geographical neighbors, presumably because of the availability and the perceived reliability of information, and because of the ease of communication. Here, we focus on the rational *relevance* of information learned from others' decisions to a farmer's own decisions. A simple model in which a farmer assesses the likelihood that an unknown technology will be profitable suggests that, in her assessment, a farmer will (a) place greater weight on the decisions of farmers who are similar to her in observable attributes that may influence 'success' in the use of the technology, and (b) place greater weight on the decisions of farmers who are as diverse as possible in attributes that may be correlated with unobservable determinants of 'success'. Our empirical results are consistent with these predictions. While we find strong evidence for the impact of past adoptions nearby on the occurrence of the first adoption in a village, these impacts only occur for farmers using the same MIS technology and applying it to the same crop. These results reinforce our interpretation of the observed diffusion as occurring through a learning channel, and suggest against other, non-learning mechanisms that may be driving diffusion.

Our analysis is also constrained by several limitations of our data. We only observe adoption, and not its outcomes. However, the rapid diffusion of MIS and evidence from a number of surveys that indicate most systems installed are still in use, strongly suggests that the majority of farmers are able to use it with some degree of profitability. We also do not observe social networks, but rely on geographical distance (future iterations of this paper will include caste dimensions). We also do not observe the full universe of individual farmers, but we do observe the universe of villages, which is another reason we focus our analysis on inter-village diffusion. Finally, we do not observe purchases of MIS that were not recorded with GGRC, i.e. purchases of MIS that were made without government subsidy. Our implicit assumption is that most MIS purchases were made through government subsidy. Given the ease of applying for the subsidy in Gujarat, the large sums of money involved, and universal eligibility, we feel this is not an unreasonable assumption.

The remainder of the paper is organized as follows. Section 2 is devoted to background information on MIS technologies, the state of Gujarat and the data. In section 3 we establish the correlations between the first adoption of MIS in a village and past adoption in nearby villages. We use the size of of our data to investigate the form of this relationship non-parametrically and identify a suitable functional form. In section 4 we provide evidence for diffusion, i.e. the *causal* effect off past adoption nearby on adoption in a new village. As is well known in studies of 'social effects' (Manski, 1993), correlations between agents' choices do not necessarily indicate the presence of diffusion, but the spatial and temporal detail of our data set allows for improved identification. In section 5 we discuss possible mechanisms driving diffusion and present evidence consistent with a simple model of learning about a wholly unfamiliar technology, but not with other possible channels. In section **??** we preset preliminary evidence on the effect of subsidy levels on adoption rates, and in section **??** we present preliminary evidence on changes in energy use following the purchase of a MIS.

2 Background and Data

Increasing water scarcity is emerging as a global concern and threatens the sustainability of the world's food production. In order to meet increasing demands for food in an increasingly water scarce environment, agriculture will have to dramatically increase its water use efficiency over the coming decade, especially in the semi-arid tropics, where the majority of the world's hungry live and poor, smallholder farmers dominate food production. Micro irrigation systems (MIS), like drip and sprinkler irrigation, are considered to be a pillar of 'sustainable intensification'. In addition to substantially increasing crop yields, MIS are also recognized as leading examples of 'sustainable intensification' technologies, because of their proven ability to increase yields while reducing water, and hence energy, requirements (Goldberg et al., 1976; Postel et al., 2001; Keller and Bliesner, 1990; Postel, 2000; Foley et al., 2011).

However, the spread of these technologies, especially in developing countries, has been slow till now, due to an array of potential economic, behavioral and technical reasons (Friedlander et al., 2013), including high capital costs(upfront costs can amount to about 2-5 times annual profit). In India, whose agriculture feeds a sixth of the world's population but is critically dependent on irrigation from dwindling water resources, more than 95% of irrigators still flood their fields through open channels, a technically inefficient use of water and energy that contrasts with the rapidly increasing scarcity of these resources. The urgency of the water crisis has led India's government to promote MIS adoption through various subsidy programs ranging between 50% and 90% of total costs(Palanisami et al., 2011). Despite proven potential economic and environmental benefits (Kumar and Palanisami, 2011) and substantial subsidy support, the extent of MIS uptake by Indian farmers has to date mostly remained low. At the time of the last released Minor Irrigation Census (2001), these technologies were used by less than 5% of Indian micro-irrigators. More recently, it was estimated that they covered only 9% of the suitable (crop wise) potential area (Palanisami et al., 2011). However, in some areas, particularly in the states of Gujarat and Andhra Pradesh, MIS have been rapidly diffusing in recent years (Pullabhotla et al., 2012).

In 2004-5, The Government of Gujarat (GoG) established the Gujarat Green Revolution Company (GGRC) to spread MIS in the state and administer subsidies through a more efficient transparent process. The securing of government subsidy funds for several years, as well as the rapid and reliable payments delivery to MIS providers is widely credited with incentivizing MIS commercial providers and for the rapid diffusion of MIS in the ensuing years. Since 2005, 450,000 purchases of MIS were made. A farmers wishing to purchase a subsidized MIS comes in contact with one of the private MIS suppliers, and pays 50% of the quoted estimate. Upon verification of installation and payment, GGRC transfers the remaining portion directly to the company. The entire process is carefully monitored by GGRC through its own staff as well as third party verification agencies.

Our data consists of records of each individual MIS purchase between 2006-2012 made through the government subsidy system managed by GGRC, and consists of about 275,000 observations (120,000 of which are for drip purchases) in 18,000 villages [2] (figure 1). Each observation consists of the village in which the purchase took place, its year, the type of crop MIS was installed for, and the size of the plot on which it was installed. This data was collapsed at the village level, geo-referenced and merged with two rounds of Indian census data and micro-irrigation census data.

As is shown in figure 2 for example, in the case of drip irrigation, adoption of MIS occurs through most of the state of Gujarat. In 2006, there were 13,000 drip purchases in 1800 villages. In 2007, number of villages increased to 4800 and the total purchases were 45,000. In 2008, the numbers were almost doubled.

3 Diffusion

Since our focus is on inter-village diffusion, we investigate the determinants of the event of the first purchase of a MIS system in a village, focusing on drip irrigation for now. We are interested in estimating the relationship between the probability that a village in which there were no prior purchases of drip will have its first adopter in a given year, and 'nearby' adoptions of drip in the previous year. [3] Formally, we are interested in estimating

$$Prob(A_{i,s,T} = 1) = f(\{A_{j,T-1}, N_{j,T-1}\}) + Controls + \epsilon_{iT} \tag{1}$$

where $A_{i,s,T}$ is the dummy for (any) adoption in village i, at sub-district s, at year T, and $N_{i,s,T}$ indicates the number of adopters in village i, at sub-district

[2] Of the 18,000 villages in Gujarat, 13,138 villages have at least one MIS purchase in 2006-2012

[3] looking at nearby adoption in all previous years does not change our results in a substantial way.

s, at year T. The sample at each year is limited to those villages in which there was no prior adoption. Our controls will include village demographic and labor force attributes from administrative data as well as fixed effects for sub-district administrative units (see below).

Rather than choosing a functional form for the relationship captured by the function f on theoretical or rather arbitrary grounds, the extent and spatial detail of our data allows us, unlike previous studies of diffusion, to choose a functional form on the basis of non-parametric analysis. In the next sub-section, we will investigate descriptively some of the properties of the function f, particularly its dependence on the number and distance of past adopters, and use it to specify a functional form that will be used for parametric analysis in the remainder of the paper. After the descriptive analysis, we will move on to establish the causal nature of the observed relationship in the following sub-section.

We begin with an investigation of the form of the relationship between past 'nearby' adopters and the probability of adoption in villages which has no prior purchases of drip. If drip irrigation defuses geographically, we expect to find an increasing relationship between this probability and both the number of past adopters, and their geographical closeness to the village in question. Below, we will confirm these predictions and investigate the mathematical form of the relationship through non-parametric regressions.

3.1 Number of adopters

We begin with an investigation of the relationship between the probability of first adoption and the number of adopting villages/individuals nearby. Table 1 reports the average number of adopting and non-adopting villages and individuals at each year of our sample. Clearly, the number of villages nearby an average village which have adopted drip in the past increases over time. The number of villages that have adoptions in the previous year is around 5-7, depending on the year.

To investigate the form of the relationship, we estimate a non-parametric regression

$$Prob(A_{i,s,T} = 1) = \sum_i \omega_i \mathbb{1} NA_{2km<d<10km,T-1} = i + \delta_{s,T} + \epsilon_{i,s,T} \qquad (2)$$

where $NA_{2km<d<10km,T-1}$ is the number of adopters or number of villages in T-1 less than 10km away. We will see below that adoption that occurs farther than 10km from a village does not seem to have any effect. The cutoff of 2km is meant to exclude villages that are formally separate in the Indian census but in effect are part of the same settlement, and our results are not sensitive to this cutoff. The regression pools cross-sections from all years in our sample together. $\delta_{s,T}$ are interacted fixed effects for combination of sub-districts s (of which there are 220) and years T. Errors are clustered at the sub-district level.

Figure 3 displays a plot of the coefficients ω_i against i, when the number of past adoptions is counted at the level of individuals (top panel) or villages (bottom panel), meaning that only villages in which there was at least one adoption are counted. The plot indicate an approximately linear, statistically significant increasing relationship, at least up to about 30 adopters, after which the relationship may be flattening.

3.2 Dependence on distance

We next investigate the relative influence of earlier adopters depending on their distance from the village in question. To do so, we estimate, non-parametrically:

$$Prob(A_{iT} = 1) = \sum_{d>2km} \omega_d NA_{d,T-1} + \delta_{s,T} + \epsilon_{iT} \tag{3}$$

where: $NA_{d,T-1}$ is the number of past adopters in T-1 in villages at distance (bracket) d from village i. We group past adoptions in concentric rings of 1km width, and as above, omit adopters in villages that are less than 2km away from the village in question.

A plot of the coefficients ω_d against d, displayed in figure 4, shows that the influence of past adopters declines with distance from the village in question. We will discuss the possible mechanisms driving this relationship below. For now, we note that the relationship can be approximately fit with an inverse distance function $\omega \approx 1/d$.

3.2.1 Parametric Regressions

Based on the above results, we define the 'exposure' of a village to past adoption of drip as:

$$E_{i,T} = \sum_{d>2km} \frac{NA_{d,T-1}}{d} \tag{4}$$

In the remainder of the paper, we will investigate the relationship between this measure of exposure and the probability of first adoption in greater detail. Our definition of exposure is based on the actual form of the observed relationship, which the size of our data allows us to estimate rather precisely. Previous studies of diffusion have had to assume specific functional forms that were not grounded in the data itself. Interestingly, our measure of exposure is similar to that used by other authors to represent exposure to 'treatment' in impact evaluations (Miguel and Kremer, 2004).

In estimating the relationship between exposure and first adoption, we will utilize both spatial and temporal variation in $E_{i,T}$. Spatially, we will regress, cross sectionally, in a given year,

$$Prob(A_{i,s,T} = 1) = \nu + \omega E_{i,s,T} + \beta NE_{i,s,T} + \kappa X_i + \delta_s + \epsilon_i \tag{5}$$

where T is fixed to be one of the years 2007-2012. The sample is restricted to those villages which have had no purchase of drip until year T. X_i is a vector of village level controls from administrative census data (mostly demographic and labor force indicators); δ_s are sub-district fixed effects (there are 220 sub-district administrative units in Gujarat). The errors, ϵ_{iT} are clustered at the sub-district level.

In order to test whether observed correlations are not driven by the overall number of villages near the village in question, but only by adopting villages, we also control, in regressions using the number of adopting villages, for a measure of exposure to non-adopting villages: [4]

$$NE_{i,T} = \sum_{d>2km} \frac{NNA_{d,T-1}}{d} \tag{6}$$

where $NNA_{d,T-1}$ are the number of non-adopting (at year T-1) villages or individuals in distance bracket d from village i.

We will mostly pool samples from different years in a single regression

$$Prob(A_{i,s,T} = 1) = \omega E_{i,s,T} + \beta NNE_{i,s,T} + \kappa_T X_i \times \mu_T + \nu_T + \delta_{s,T} + \epsilon_{i,s,T} \tag{7}$$

where, as above, X_i is a vector of village level controls (including a constant), but it is allowed to interact with year dummies μ_T, and where $\delta_{s,T}$ are interacted sub-district and year fixed effects. The error terms $\epsilon_{i,s,T}$ are clustered the sub-district level.

[4] we are unable to do this for regressions based on individual adoption because we do not have data on non-adopting individuals

The cross-sectional regression is our preferred model. However, we also utilize temporal variation in exposure and adoption to estimate

$$Prob(A_{i,s,T} = 1) = \omega E_{i,s,T} + \beta NE_{i,s,T} + \lambda_i + \delta_{s,T} + \epsilon_{iT} \tag{8}$$

where we also control for village fixed effects λ_i as well as interacted fixed effects for sub-district and year. This regression estimates, in effect, the average change in a village's exposure during the year of first adoption in comparison to the previous year. In an abuse of terminology, we will refer to this regression as the 'time series' regression.

Tables 2 and 3 reports the results of these regressions when the independent variable is counted at the level of individuals or villages, repsectively. Column 1 reports results for the pooled cross-sectional regression, and column 2 reports results of the 'time-series' regression. The probability that a previously non-adopting villages will see its first adoption in a given year increases by 0.37% or 0.41%, depending on the specification, per individual purchase of drip in the previous year (weighted with inverse distance), and by 2.6%-3.6% per additional village in which there was some purchase of drip in the previous year. We note that estimates from cross sectional and time series regressions are quite consistent.

4 Causal Inference

The results presented above establish a statistically significant correlation between the probability of a first adoption of drip in a village and (distance weighted) numbers of individuals or villages in which there were some drip purchases in the previous year. This is suggestive of a process of diffusion, by which we mean a causal effect of nearby past adoption on adoption in a given village.

However, as noted originally by Manski (1993), studies of correlated choices amongst agent suffer from difficult identification challenges. Specifically, the observed correlation may be an artifact of spatially-correlated characteristics of farmers, rather than reflecting actual diffusion in the sense of an influence of one village on nearby villages. In the case of the adoption of agricultural technologies, in particular, geophysical conditions may well influence the profitability and demand for these technologies, like soil, climate, proximity to water sources, etc... While temporal variation in data helps address identification issues (Conley and Udry, 2010; Foster and Rosenzweig, 2010), it does not fully resolve it, since factors affecting adoption may be correlated in time as well as space.

The spatial detail of our data allows up to make progress on the identification of diffusion. The next two sub-sections describe two empirical strategies we use to establish the causal effect on nearby adoption in villages.

4.1 Dealing with unobservable geographical factors

The adoption of MIS may be driven by a host of geographical variables that may be unobservable to us and which may be driving the observed correlations. The unique size and spatial detail of our data set allows us to adopt a novel approach, by which we examine the sensitivity of our estimates to the inclusion of an increasingly finer set of spatial fixed effects that can capture unobservable geographical variables.

We divide the map of Gujarat with an increasingly finer mesh of horizontal and vertical gridlines (figure 5), and define a corresponding set of dummy variables, each representing one cell in the associated grid $\left\{\vec{l}\right\}$, which we label $\kappa_{\vec{l}}$. We then re-estimate our pooled cross-sectional regression while controlling for these dummies:

$$Prob(A_{i,s,T,\vec{l}} = 1) = \omega E_{i,s,T} + \beta NE_{i,s,T} + X_i \times \mu_T + \delta_{s,T} + \kappa_{\vec{l}} \times \mu_T + \epsilon_{iT} \quad (9)$$

The new geographical dummies are interacted with year fixed effect μ_T to allow for time dependent unobservable attributes at each cell. As we refine the mesh, the number of fixed effects included in the regression increases gradually, and we examine the dependence of the estimated coefficient of interest ω on the number of fixed effects, or equivalently, on the size of each cell in the grid. If the observed correlation captured by the point estimate of ω is driven by unobservable geographical variables, one would expect the point estimate to decline as the set of fixed effects absorbs the associated geographical variation. Alternatively, stability of the point estimate suggests the correlation is not driven by unobservable geographical correlates.

Figure 5 presents plots of the point estimate ω against the diameter of a cell in an increasingly finer grid down to about 2 km (the number of fixed effects included in the regression increases from X to Y as the diameter decreases from 80km to 2km). Regression point estimates of ω remain relatively stable in magnitude as the number of geographical fixed effects increases, up to a grid with diameters of about 2km. Clearly, as more and more fixed effects are included, the statistical confidence intervals of the point estimate are likely to expand. However, and remarkably, even with grid cells of 3km diameter, we are still able to reject a zero value of ω. The evidence is strongly indicative of the presence of a causal effect adoption in a village on future adoptions in nearby villages, barring geographical unobservable correlates occurring on a scale of less than 2-3 km on substantial portions of Gujarat, which we believe to be highly unlikely.

4.2 Instrumental Variable Approach

As an additional approach to identification, we present results from an instrumental variable estimation. As we have seen, past adoption farther than 10km away from a village does not seem to be correlated with the probability that village will begin adopting in a given year. We therefore attempt to instrument the adoption of drip in a radius of 10km from a village at year $T-1$ with the number of adopters that are farther than 10km (10km-20km) away from the village at year $T-2$ (figure 6). The exclusion restriction is satisfied as long as adoption farther than 10km away from a village have no effect on adoption at a village other than through its impact on adoption nearer to the village in subsequent years.

Tables 6 and 7 report IV estimation results when using individual and village level adoption, respectively. Both results indicate a statistically significant relationship between first adoption in a village and the previous year adoption within 10km, but the point estimates are smaller than those obtained from OLS: the probability of first adoption in a village increases by 0.8% per additional village adopting nearby, whereas the OLS estimate was 2.5%.

5 Is MIS Diffusion Driven by Social Learning?

Diffusion may occur through a number of mechanisms, social learning is only one of which. We use the term (spatial) diffusion to refer to the causal impact of past purchases of drip in the vicinity of a village on the probability of first adoption in that village in a given year. We use the term social learning to refer to a process of diffusion that is driven, at least in part, by rational inference by farmers in the village on their perceived likelihood that the MIS technology will be profitable for them. Spatial diffusion may be driven by non-informational mechanisms. For example, MIS companies' agents may be going from village to village to promote and sell MIS, and their movement patterns may result in diffusion. And even informational mechanisms can differ from social learning as we define it above. For example, farmers may learn from the decisions and experiences of others not on the performance of the technology, but on the reliability of GGRC or the MIS companies.

In this section we present three main results that are consistent with a model of rational social learning but not with the other mechanisms mentioned above. Consider a simple model of a farmer in a village in which there is no past adoption of MIS, who is considering whether to take the risk of investing in MIS. In deciding whether to invest in MIS, a farmer needs to assess the expected profitability of the investment, on the basis of the information available to her from the decisions and experiences of other farmers. Profitability depends on a potentially large and unknown set of farmer and plot attributes. Some of these attributes are known to the farmer, like the crop for which MIS was applied, for example, and the type of MIS technology used (drip or sprinkler). But the farmer does not know what all important attributes are, and she cannot observe them. For example, the performance of MIS may depend on certain unknown set of soil properties.

In assessing the likelihood of MIS turning out to be profitable for her, the farmer clearly has the most to learn from the experiences of farmers that are similar in terms of the important determinants of profitability. In the case of known and observable attributes, like crop choice, this means that the farmer is more likely to be influenced by the experiences of farmers who have applied MIS to the same crop. [5] However, when it comes to attributes that are not known, the farmer needs to assess how similar other successful farmers are likely

[5]We implicitly assume here that crop choice is independent of MIS investments. Consistent anecdotal evidence from interviews with farmers, government officers and agricultural experts confirm that farmers tend to apply MIS to the same crops they are used to cultivate.

to be to her, by using probable correlates of these unknown attributes, many of which are likely to be correlated with geographical location. For that reason, the experiences of farmers that are nearer are more informative. But beyond that, the perceived likelihood of profitability increases when a more diverse group of other farmers has been successful, because that increases the likelihood that MIS is successful in a wide range of circumstances, and therefore is more likely to be successful for her. We therefore expect that a farmer will be more likely to adopt an MIS system if:

- There are more farmers nearby who have adopted (and presumably profited from) the same MIS technology
- There are more farmers nearby who have applied (and presumably profited from) the MIS technology to the same crop
- Given the same numbers of past adopters and their attributes, they are more spread out geographically (reside in different villages).

In addition, another prediction of a theory of learning is that the effect of past adoption nearby diminishes over time (Comin et al., 2012). Below, we present empirical results that show that the observed strength of spatial diffusion (a) diminishes over time; (b) only occurs between farmers purchasing the same MIS technology; (c) only occurs between farmers applying MIS to the same crop; (d) is much stronger if past adopters are in different villages and more geographically disperse, keeping all else constant. These results are consistent with a model of social learning, but not of the other possible mechanisms of diffusion we considered above, and lend support to the role of learning in the adoption of MIS.

5.1 Does diffusion diminish over time?

In Tables 4 and 5 we report the results of the cross-sectional regression, estimated separately for every year. The results are also summarized in figure 7 which shows how the effect of exposure to adopters declines with time. The same figure also shows the mean value of exposure. Even though the value of exposure rises with time, it is unlikely to be driving the decrease in the effect of exposure, because as table 1 shows, the mean number of nearby adopting villages remains within the domain in which the relationship between adoption and the number of nearby adopters is approximately linear. exposure to non-adopting villages in panel data.)

5.2 Is there diffusion across MIS types?

To assess whether the impact of past adoption occurs across MIS categories, the most prevalent of which are drip and sprinkler irrigation system, we estimate the following model:

$$Prob(A_{i,s,T,M} = 1) = \omega E_{i,s,T,M} + \gamma E_{i,s,T,\bar{M}} + X_i \times \mu_{T,M} + \delta_{s,T,M} + \epsilon_{iTM} \quad (10)$$

where

$$M \in \{Drip, Sprinkler\}.$$

The dependent variable is the probability of adoption of a certain micro irrigation system. We separately control for the exposure to the adoptions of the same system, $E_{i,s,T,M}$, and the exposure to the adoptions of the other system, $E_{i,s,T,\bar{M}}$, as defined above. We interact the controls and the sub-district year fixed effects with dummies of the MIS type $\delta_{s,T,M}$.

Tables 8 and 9 report the results when exposure is counted in terms of individuals or villages, respectively. Column 1 reports estimates of the above, combined regressions, and columns 2 and 3 report results of estimates for the separate samples of drip and sprinkler adoptions, respectively. Over all, an increase in one unit of exposure (in terms of villages) to the same MIS system increases the probability of adoption by 2.3%, while exposure to the other system increases it by a much smaller, statistically insignificant amount of 0.1% (the difference between the two coefficients is clearly statistically significant). Similar patterns occur for the separate sample estimation.

5.3 Is there diffusion across crops?

Drip can be applied to a variety of crops. Anecdotally, crop choice is 'sticky', in the sense that farmers apply drip to crops they have grown before, rather than adapting their crops to suit drip irrigation. To assess whether the impact of past adoption occurs across MIS categories, the most prevalent of which are drip and sprinkler irrigation system, we estimate the following model:

$$Prob(A_{i,s,T,c} = 1) = \omega E_{i,s,T,c} + \gamma E_{i,s,T,\bar{c}} + X_i \times \mu_{T,c} + \delta_{s,T,c} + \epsilon_{iTc} \qquad (11)$$

where c is a crop index, and as above, we control separately for $E_{i,s,T,c}$, the exposure to drip purchases for the same crop, and $E_{i,s,T,\bar{c}}$, the exposure to drip purchases for all other crops. We have 12 categories for crops, including (1) Bottle Guard, (2) Banana, (3) Castor, (4) Cotton, (5) Green Gram, (6) Groundnut, (7) Lemon, (8) Mango, (9) Papaya, (10) Sugar Cane, (11) Wheat, and (12) Other. As before, we interact all controls and fixed effects with crop specific dummies.

Regression estimates are reported in table 10, when exposure is defined in terms of individuals (column 1) or villages (column 2). The results show diffusion is much stronger within the same crop type.

5.4 Learning from Villages or from Individuals?

Up to this point, we have defined exposure in two ways: by counting past individual MIS purchases, and by counting villages that at least one MIS purchase. As we have seen, the results obtained by using the two measures of exposure were not significantly different. The above considerations predict the marginal influence of one adopter in a village to be larger than any additional adopters in the same villages - the additional information gained from another successful MIS adopter is smaller than the information that would be gained from knowing about the same adopter in another village in which there are no other adopters, since it proves MIS to be profitable in a greater variety of circumstances. Figure 8 shows a plot of the estimated coefficients of a regression that controls for a series of indicators, each indicating the number of adopting, past, nearby villages with a given number of adopters, plotted on the horizontal axis. If the impact of a village would scale proportionally to the number of farmers adopting in that village, we would expect the plot to be linear, but we see the plot is lower than the linear extrapolation of the impact of a village with a single adopters (indicated by the dotted black line).

Similar indications are provided by the results reported In table 13. In columns 1 and 2 we reproduce the estimates of models which control for each of them separately. In column 3 we report results of a regression that simultaneously controls for exposure as counted by number of individuals and by number of villages. The coefficient in the first row can be interpreted as the marginal impact of an additional adopter in a village that already has other adopters, and the coefficient in the second row can be thought of as the maringal impact of an adopting farmer who is the only one in her village. We see that the former coefficient reduces to an insignificant and low value when the number of adopting villages is controlled for, indicating that the additional information gained from additional past adopters in the same villages is negligible.

6 The Effect of Subsidies

In this section we present preliminary results on the effect of subsidies on MIS adoption. The subsidies might be wasteful from a public perspective if MIS adoption rates would have been similar without them. Since the establishment of the subsidy and of GGRC occurred simultaneously in the entire state, a direct evaluation of its effect is difficult. Instead, our empirical strategy utilizes variation in subsidy levels that results from the occasional occurrence of special additional subsidy schemes, typically cooperations between a NGO and a particular MIS company working in a particular sub-district for a limited time period. These schemes usually offer additional subsidies in the range of 5%-30% on MIS.

We collapse the data on MIS purchases, Y_{sct} by sub-district (s), MIS company (c), and time (m, monthly), and estimate a triple difference regression (separately for drip and sprinkler):

$$Y_{sct} = A_{sc} + B_{st} + C_{ct} + \beta \times S_{sct} + \epsilon_{sct} \tag{12}$$

where S_{sct} indicates the presence of additional subsidy (in the range 10%-30%) in sub-district s, in year t, with company c.

Results are presented in table 14 for Drip irrigation purchase. In columns 1-3, we examine three types of outcomes (Y_{sct}): the logarithm of the number of purchases (applications), $\log MIS_{act}$, the logarithm of the area installed, $\log MIS_{act}$, and the probability of having at least one application (i.e. $MIS_{act} >$

0. The results indicate that additional subsidies increase drip purchases by 32%, the area installed with drip by 30%, and the probability of having at least one purchase by 11%. In columns 4-6 we repeat the estimations but now separating schemes into drip irrigation schemes and sprinkler schemes. One would expect a much lower, if any, impact of sprinkler schemes on drip irrigation purchases, making it a sort of placebo treatment. As can be seen, sprinkler subsidies have insignificant effects on the number or area of drip purchases, and a small negative impact on the chance that there are any drip purchases. The impacts of drip irrigation subsidies is much larger, positive and statistically significant.

We also examined whether farmers adopting Drip irrigation under an extra subsidy scheme differ from other adopters in significant ways. One may imagine that, to the extent that cost and credit constraints are more binding for poorer populations, more of them might adapt drip when additional subsidies are available. We do not have income data, but we do have data indicating the total landholding size of each applicant, and whether she belongs to a scheduled tribe (ST), often more socially marginalized populations. In table 15, we report results of comparisons of these two indicators, as well as the probability that the farmer utilized a special loan to finance her part of the cost, amongst the two populations. We find that farmers adopting under additional subsidy schemes are 4% more likely to be from tribal populations (doubling their prevalence in the general sample). However, we do not find any difference in landholding size. We do find that farmers adapting under extra subsidies are also 4% less likely to utilize loans. These results provide some evidence that subsidies may relieve credit constraints and help more vulnerable farmers to access MIS, but are not entirely conclusive.

7 Is Drip Irrigation Saving Water and Electricity?

MIS hold the potential to preserve, or even increase crop yields while cutting water use (and hence the energy used for pumping it) by 30%-40% for some crops. However, naive projections, which are based solely on engineering based studies or technical potential, and fail to take into account farmers' behavior may severely overestimate the associated savings of water and energy (Greenstone and Jack, 2013). Exiting studies of the effects of drip adoptions are mostly observational and cross sectional in nature (Kumar and Palanisami, 2011). Careful analysis in the energy sector, for example, have shown that actual energy savings triggered by subsidization of energy efficient appliances can even be negative (Davis et al., 2013). In the context of groundwater use, there are four principal responses by farmers that can offset the reduction in water requirements: First, farmers may choose to use the same amount of water to expand the irrigated area, rather than maintaining irrigated area while using less water. Second, farmers may sell any excess water to neighboring farmers in pervasive informal water markets in Gujarat. Third, farmers may increase the use of the resource when it becomes more profitable. Fourth, and perhaps most basic, farmers may fail to utilize the potential of MIS because they may not know how to use it properly, or may not trust the suggested irrigation schedules' capacity to increase yields while using less water. For these reasons, the overall effect, and even its sign, is a matter of empirical research.

To provide some new evidence on the issue, we matched administrative electricity billing data from UGVCL to drip adopters. Most agricultural electricity consumers in Gujarat are billed on a flat rate basis and are un-metered. We therefore had to rely on the small fraction of consumers who are metered and billed volumetrically. This may present issues of external validity, but we note that the rate paid by these consumers is highly subsidized, and available evidence suggests it is still far below the marginal value of water. Nevertheless, this issue needs to be kept in mind when interpreting the results. We also note that without a counterfactual, we are unable to identify the **impact** of Drip adoption. However, we can test whether adoption is associated with reductions in electricity (water) use.

To investigate this question, we estimate the following regressions. The most basic model is

$$\log(w_{c,m,d}) = \sum a_i Y_i + \omega_m + \lambda_c + \epsilon_{c,m,d} \tag{13}$$

where m are year-month combinations, c is a consumer identifier, and Y_i are dummies for years occurring i years after adoption ($-5 \leq i \leq 5$).

We also estimated a model which includes division d (a part of the energy grid) specific quadratic time trends

$$\log(w_{c,m,d}) = \sum a_i Y_i + \omega_m + \lambda_c + \beta_d m + \gamma_d m^2 + \epsilon_{c,m,d} \tag{14}$$

and a model which includes division specific year and month fixed effects

$$\log(w_{c,m,d}) = \sum a_i Y_i + \omega_m + \lambda_c + \beta_{d,y} + \gamma_{d,m} + \epsilon_{c,m,d}$$

The results are reported in table 16 and summarized (for the last, and most stringent model) in figure 9. In all models, we find a short-term *increase* of about 5% in electricity use in the first 1-2 years after adoption. However, we find some indications of substantial reductions in usage 4-5 years after adoption, of around 10-20%. In our most stringent model, this effect is insignificant. As data collection continues and sample size increases, we hope to gain stronger evidence along these lines. However, we note that these results are consistent with a gradual learning by farmers of the proper usage of drip, as described to us qualitatively by drip company field staff. Initially, farmers use drip as a conveyance system, and do not alter their irrigation schedule. Possible expansion of irrigated area and enhanced use of more productive water may dominate at this stage. However, with time, through continuos interaction with MIS company extension agents, farmers may learn to reduce the flow of water through the drip system, and this effect may dominate in the long-term. Further research is needed to shed light on these questions.

8 Conclusion

Meeting the challenge of feeding 10 billion people in a changing environment and dwindling natural resources is a formidable challenge. A crucial component of this task involves closing yield gaps in developing countries, even as water resources become depleted and weather patterns less reliable. Meeting this challenges will necessitate the widespread adoption of dramatically more efficient and more productive cultivation technologies, on a scale that rivals that of the green revolution. These kinds of technologies, of which MIS are but one example, tend to be more expensive, and more difficult to operate, than improved seeds, for example. The results of this paper show that even when such technologies are generously subsidized by governments, significant informational barriers continue to hinder adoption, as indicated by the important role of social learning driven spatial diffusion of MIS among neighboring villages. The results have important implications for government policy, that has tended to focus on subsidies and continue to neglect the public extension system. Our results also provide new evidence on the role of learning in diffusing new technologies on large geographical scales. Additional research (under progress) investigates the impacts of the subsidy level itself, and the effect of drip adoption on productivity and water use.

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Table 1: Summary Statistics (Mean) for Drip Adopters within 2-10km

Year (T)	2007	2008	2009	2010	2011	2012	Pooled
Percentage of villages starting to adopt (%)	11.80%	16.02%	8.74%	7.87%	9.00%	4.55%	10.23%
Adopting villages (2-10km), previous years	3.70	6.88	9.35	10.80	12.18	13.57	8.75
Adopting individuals (2-10km), previous years	10.05	23.91	39.88	53.25	66.66	87.82	41.88
Adopting villages (2-10km), last year	3.70	5.40	6.01	5.96	5.83	7.17	5.49
Adopting individuals (2-10km), last year	10.05	14.90	18.55	17.65	18.26	27.06	16.84
Num. of villages with no adoption to date	16,255	14,336	12,039	10,987	10,121	9,209	

Table 2: Basic Results: Nearby Adopters (Individuals at T-1)

	Cross Section	Panel
Exposure (Individuals, T-1)	0.0038***	0.0041***
	(0.0005)	(0.0006)
Exposure (Non-Adopting villages, T-1)	0.0002	
	(0.0005)	
Mean (Indep.Var)	6.84	6.84
Median (Indep.Var)	2.62	2.62
R-squared	.21	.61
Num. of obs	72,947	72,947
Demographic Controls	Yes	No
Village F.E.	No	Yes
Sub-District × Year F.E.	Yes	Yes

Dependent variable: Probability of adoption.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 3: Basic Results: Nearby Adopters (Villages at T-1)

	Cross Section	Panel
Exposure (Villages, T-1)	0.0258***	0.0362***
	(0.0025)	(0.0044)
Exposure (Non-Adopting Villages, T-1)	-0.0009	
	(0.0005)	
Mean (Indep.Var)	2.12	2.12
Median (Indep.Var)	1.31	1.31
R-squared	.21	.62
Num. of obs	72,947	72,947
Demographic Controls	Yes	No
Village F.E.	No	Yes
Sub-District $\times$ Year F.E.	Yes	Yes

Dependent variable: Probability of adoption.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * p<0.05, ** p<0.01, *** p<0.001

Table 4: Results by Each Year (Individuals at T-1)

	2007	2008	2009	2010	2011	2012
Exposure	0.0126***	0.0078***	0.0043***	0.0048***	0.0027**	0.0007*
(Individuals, T-1)	(0.0015)	(0.0015)	(0.0010)	(0.0008)	(0.0008)	(0.0004)
Exposure	-0.0006	-0.0007	-0.0002	0.0009	0.0011	0.0006
(Non-Adopting Villages, T-1)	(0.0009)	(0.0012)	(0.0009)	(0.0007)	(0.0008)	(0.0009)
Mean	3.86	3.84	7.59	7.25	7.64	11.33
Median	1.56	3.16	2.80	2.76	2.71	4.35
R-squared	.16	.35	.16	.13	.13	.09
Num. of obs	16,255	14,336	12,039	10,987	10,121	9,209
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Village F.E.	No	No	No	No	No	No
Sub-District F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Dependent variable: Probability of adoption.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * p<0.05, ** p<0.01, *** p<0.001

Table 5: Results by Each Year (Villages at T-1)

	2007	2008	2009	2010	2011	2012
Exposure	0.0427***	0.0321***	0.0278***	0.0288***	0.0217***	0.0069**
(Villages, T-1)	(0.0078)	(0.0063)	(0.0041)	(0.0039)	(0.0038)	(0.0024)
Exposure	-0.0013	-0.0019	-0.0012	-0.0008	0.0001	0.0001
(Non-Adopting Villages, T-1)	(0.0010)	(0.0012)	(0.0010)	(0.0009)	(0.0008)	(0.0008)
Mean (Adopters)	1.40	2.06	2.33	2.32	2.27	2.79
Median (Adopters)	.83	1.50	1.50	1.47	1.37	1.83
R-squared	.16	.35	.16	.13	.13	.09
Num. of obs	16,255	14,336	12,039	10,987	10,121	9,209
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Village F.E.	No	No	No	No	No	No
Sub-District F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Dependent variable: Probability of adoption.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 6: Results from IV Analysis (Individuals at T-1)

	First Stage	Second Stage
	Individual T-1 (2-10km)	Adoption
L.Individual T-1(11-20)	0.1819***	
	(0.0197)	
Individual T-1 (2-10)		0.0015***
		(0.0003)
F	9.9467e+13	.0286
R-squared	.62	.21
Num. of obs	56,692	56,692
Demographic Controls	No	No
Village F.E.	No	No
Sub-District × Year F.E.	Yes	Yes

Instrumental variable: Number of adopters with 11-20km in T-2.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 7: Results from IV Analysis (Villages at T-1)

	First Stage	Second Stage
	Village T-1 (2-10km)	Adoption
L.Village T-1(11-20)	0.2475***	
	(0.0158)	
Village T-1 (2-10)		0.0079***
		(0.0010)
F	4.2537e+14	8.6348e+12
R-squared	.77	.22
Num. of obs	56,692	56,692
Demographic Controls	No	No
Village F.E.	No	No
Sub-District $\times$ Year F.E.	Yes	Yes

Instrumental variable: Number of adopting villages with 11-20km in T-2.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * p<0.05, ** p<0.01, *** p<0.001

Table 8: Diffusion across Different Types of MIS (Individuals at T-1)

	All	Drip	Sprinkler
Exposure (Same)	0.0025***	0.0038***	0.0020***
	(0.0003)	(0.0004)	(0.0004)
Exposure (Other)	0.0003**	0.0004***	-0.0000
	(0.0001)	(0.0001)	(0.0003)
R-squared	.24	.21	.26
Num. of obs	149,437	72,947	76,490
Demographic Controls	Yes	Yes	Yes
Village F.E.	No	No	No
Sub-District $\times$ Year $\times$ MIS F.E.	Yes	Yes	Yes

Dependent variable: Probability of adoption.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 9: Diffusion across Different Types of MIS (Villages at T-1)

	All	Drip	Sprinkler
Exposure (Same)	0.0229***	0.0250***	0.0214***
	(0.0019)	(0.0025)	(0.0027)
Exposure (Other)	0.0015	0.0025*	-0.0005
	(0.0011)	(0.0010)	(0.0026)
R-squared	.24	.21	.27
Num. of obs	149,437	72,947	76,490
Demographic Controls	Yes	Yes	Yes
Village F.E.	No	No	No
Sub-District $\times$ Year $\times$ MIS F.E.	Yes	Yes	Yes

Dependent variable: Probability of adoption.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 10: Diffusion across different types of crops

	Individual	Village
Exposure (Same Crop)	0.0050***	0.0297***
	(0.0006)	(0.0020)
Exposure (Other Crops)	0.0001***	0.0003
	(0.0000)	(0.0003)
R-squared	.17	.17
Num. of obs	1,236,655	1,236,655
Demographic Controls	No	No
Village F.E.	No	No
Sub-District $\times$ Year $\times$ Crop F.E.	Yes	Yes

Dependent variable: Probability of adoption.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 11: Diffusion across different types of crops (Individuals at T-1)

	BOTTLEGUARD	BANANA	CASTOR	COTTON	LEMON	MANGO	OTHER	PAPAYA	SUGARCANE
Exposure	0.0106***	0.0041***	0.0068**	0.0043***	0.0145***	0.0196***	0.0112***	0.0114**	0.0058***
(Same Crop)	(0.0019)	(0.0006)	(0.0025)	(0.0007)	(0.0033)	(0.0032)	(0.0020)	(0.0035)	(0.0012)
Exposure (Other Crops)	0.0001	-0.0000	0.0000	0.0008	0.0000	-0.0000	0.0003***	0.0001*	0.0001
(Other Crops)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
R-squared	.29	.08	.12	.20	.14	.07	.12	.09	.11
Num. of obs	102,693	103,825	105,417	84,883	105,523	103,231	98,301	104,498	103,441
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village F.E.	No	No	No	No	No	No	No	No	No
Sub-District × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Dependent variable: Probability of adoption.
Standard errors in parentheses, errors clustered by sub-district.
Stars denote statistical significance: * p<0.05, ** p<0.01, *** p<0.001

Table 12: Diffusion across different types of crops (Villages at T-1)

	BOTTLEGUARD	BANANA	CASTOR	COTTON	LEMON	MANGO	OTHER	PAPAYA	SUGERCANE
Exposure	0.0339***	0.0223***	0.0239**	0.0349***	0.0373***	0.0382***	0.0294***	0.0195***	0.0197***
(Same Crop)	(0.0060)	(0.0031)	(0.0073)	(0.0040)	(0.0081)	(0.0061)	(0.0036)	(0.0057)	(0.0022)
Exposure	0.0007	-0.0007	0.0001	-0.0020	0.0003	-0.0004	0.0016*	0.0007	0.0008
(Other Crops)	(0.0004)	(0.0006)	(0.0004)	(0.0030)	(0.0002)	(0.0004)	(0.0007)	(0.0004)	(0.0010)
R-squared	.29	.078	.12	.21	.14	.069	.12	.091	.11
Num. of obs	102,693	103,825	105,417	84,883	105,523	103,231	98,301	104,498	103,441
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village F.E.	No	No	No	No	No	No	No	No	No
Sub-District × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Dependent variable: Probability of adoption.
Standard errors in parentheses, errors clustered by sub-district.
Stars denote statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 13: Learning from Villages VS. Learning from Individuals

	Individual	Village	Both
Exposure (Individuals, T-1)	0.0037***		-0.0003
	(0.0005)		(0.0007)
Exposure (Villages, T-1)		0.0258***	0.0270***
		(0.0025)	(0.0042)
Exposure (Non-Adopting Villages, T-1)		-0.0009	-0.0009
		(0.0005)	(0.0005)
R-squared	.21	.21	.21
Num. of obs	72,947	72,947	72,947
Demographic Controls	Yes	Yes	Yes
Village F.E.	No	No	No
Sub-District $\times$ Year F.E.	Yes	Yes	Yes

Dependent variable: Probability of adoption.

Standard errors in parentheses, errors clustered by sub-district.

Stars denote statistical significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 14: The effect of additional subsidies on Drip Irrigation purchases

	(1) (Log) Applications	(2) (Log) Land	(3) Any applications	(4) (Log) (Applications	(5) (Log) Land	(6) Any applications
Extra Subsidy	0.324***	0.308***	0.105***			
	(0.0502)	(0.0588)	(0.00391)			
Sprinkler Subsidy				0.0592	0.282	-0.0374***
				(0.287)	(0.336)	(0.00958)
Drip Subsidy				0.337***	0.269***	0.155***
				(0.0638)	(0.0747)	(0.00527)
Drip+Sprinkler Subsidy				0.325***	0.371***	0.0918***
				(0.0791)	(0.0926)	(0.00710)
Observations	41812	41811	1348380	41812	41811	1348380

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: properties of adopters under additional subsidies to adopters under standard subsidies

	(1) Tribal Caste	(2) Land Holding Size (Ha)	(3) Loanee
Extra Drip Subsidy	0.0440***	0.669	-0.0427***
	(0.00334)	(2.660)	(0.00781)
Observations	193096	181519	193096
Mean Dep. Var.	0.04	4.16	0.13

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Changes in (log) electricity consumption before and after drip adoption.

	(1)	(2)	(3)	(4)
-5	0.0439	0.0874	0.0695	0.00835
	(0.0645)	(0.0642)	(0.0640)	(0.0641)
-4	0.0724	0.115^{*}	0.0993	0.0377
	(0.0522)	(0.0519)	(0.0518)	(0.0519)
-3	0.0196	0.0459	0.0276	-0.00715
	(0.0402)	(0.0400)	(0.0399)	(0.0400)
-2	0.00224	0.0150	-0.0000529	-0.0156
	(0.0286)	(0.0285)	(0.0284)	(0.0285)
-1	0.00952	0.0154	0.00586	0.00686
	(0.0184)	(0.0182)	(0.0182)	(0.0181)
0	0	0	0	0
	(.)	(.)	(.)	(.)
1	0.0416^{*}	0.0417^{*}	0.0488^{**}	0.0591^{**}
	(0.0187)	(0.0186)	(0.0185)	(0.0184)
2	-0.00167	-0.00321	0.0153	0.0434
	(0.0285)	(0.0284)	(0.0284)	(0.0284)
3	-0.0760	-0.0582	-0.0400	-0.00230
	(0.0406)	(0.0405)	(0.0404)	(0.0404)
4	-0.165^{**}	-0.106	-0.0948	-0.0403
	(0.0543)	(0.0542)	(0.0541)	(0.0540)
5	-0.251^{**}	-0.176^{*}	-0.175^{*}	-0.0939
	(0.0833)	(0.0831)	(0.0831)	(0.0827)
Observations	65176	65176	65176	65176
Year x Month F.E.	Yes	Yes	Yes	Yes
Division LTT	No	Yes	Yes	No
Division QTT	No	No	Yes	No
Division x Year F.E.	No	No	No	Yes
Division x Month F.E.	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

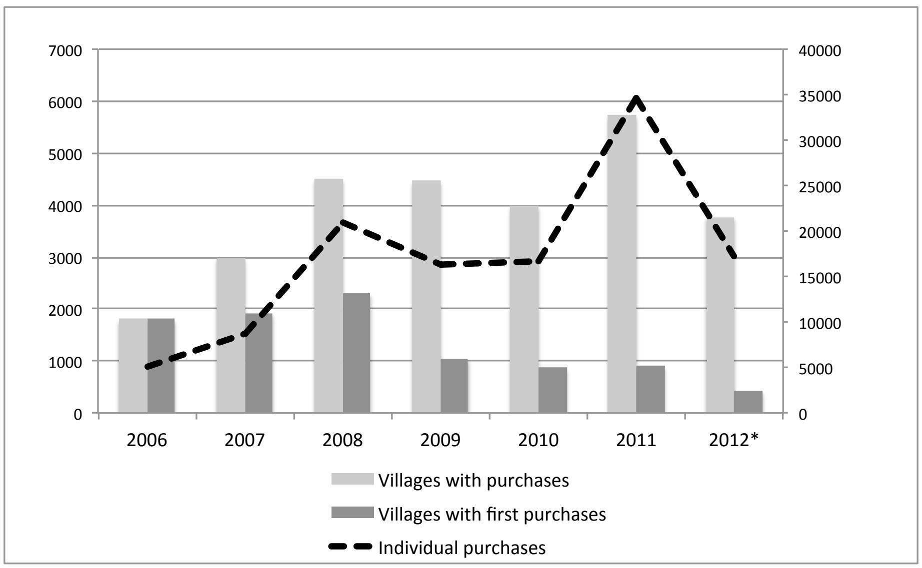


Figure 1: Individual drip purchases (dotted line, right axis), number of villages in which there was at least one purchase (light grey bars, left axis) and number of villages in which the first purchase of drip occurred (dark grey bars, left axis) in every year between 2006-2012. * Observations were only available for part of 2012.

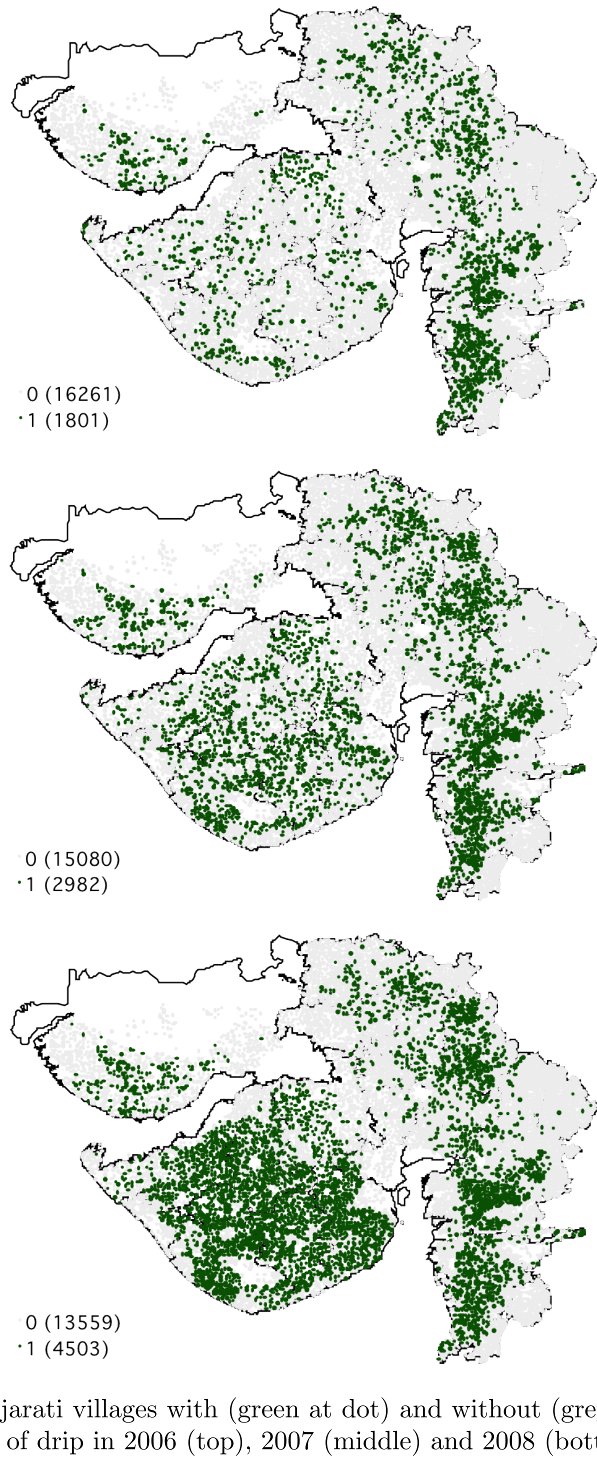
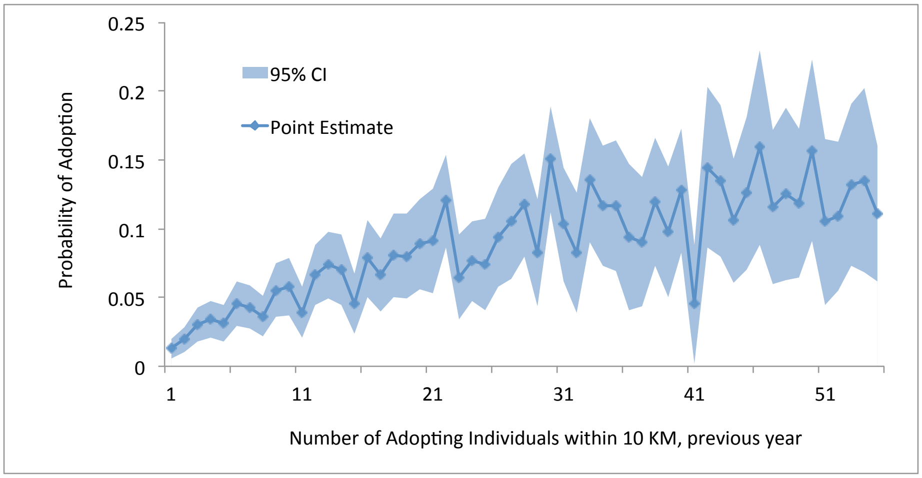


Figure 2: Gujarati villages with (green at dot) and without (grey dot) at least one purchase of drip in 2006 (top), 2007 (middle) and 2008 (bottom)



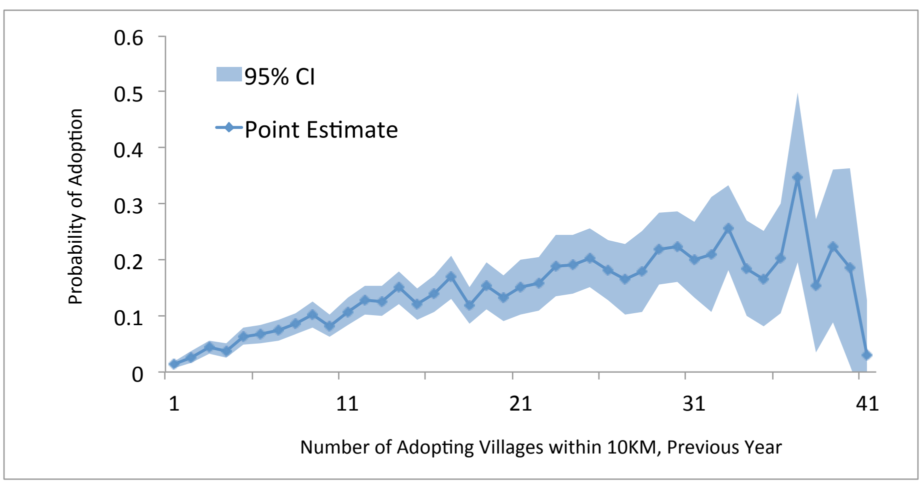


Figure 3: Non-Parametric relationship between probability of adoption in a given year and the number of individual (top) or villages (bottom) adoptions in the previous year within 10 KM. The shaded region represents 95% confidence intervals.

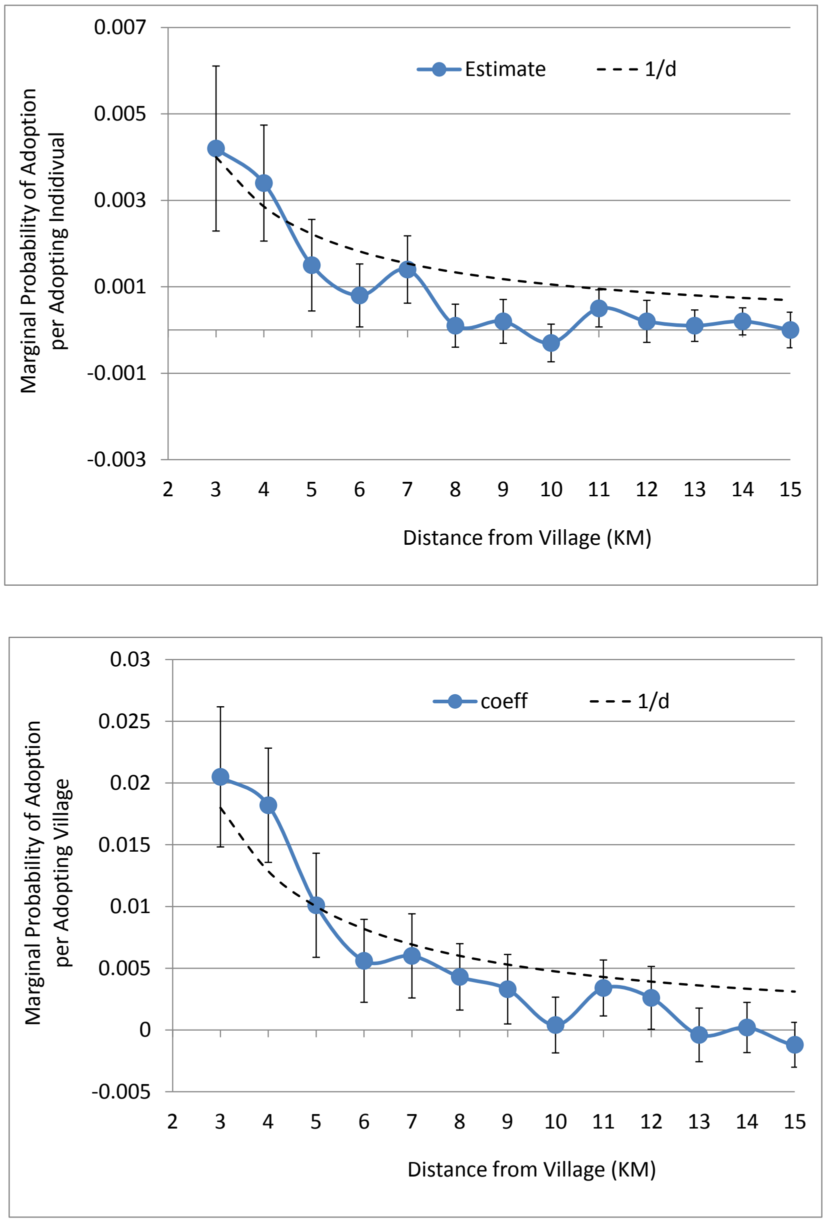


Figure 4: Non-parametric estimation of the relationship between probability of first adoption and the number of past adopting individuals (top panel) or villages (bottom panel) at various 1km distance brackets from the village in question. Each point represents an estimated regression coefficient and error bars represent 95% confidence intervals. The dotted line represents an inverse distance fit.

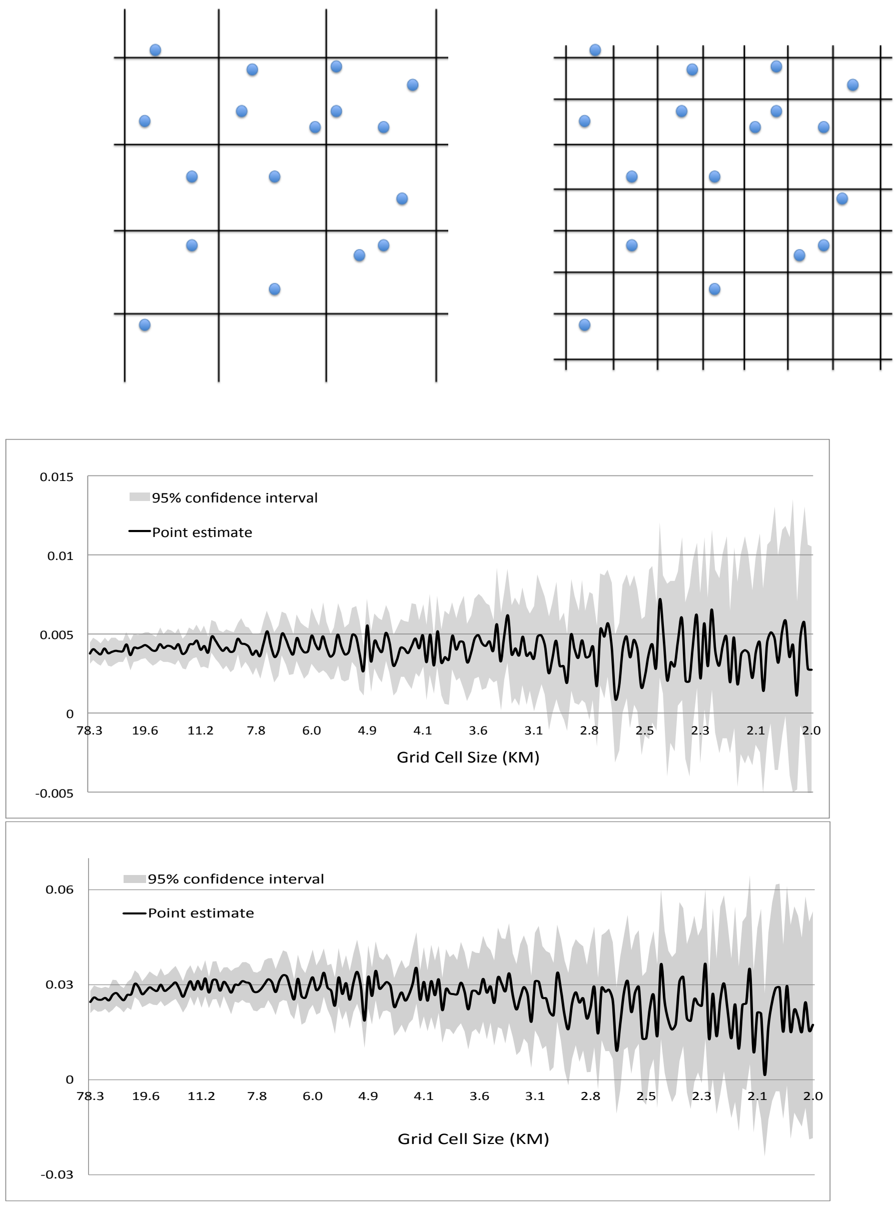


Figure 5: The effect of including increasing numbers of spatial fixed effects on the point estimate of ω. Top panel: an illustration of two grids superimposed on a map of the study region (with point representing villages). A different dummy indicator corresponds to each cell in the grid, taking a value of 1 if a village lies within that cell and 0 otherwise. The grid on the right hand side represents a finer grid with a smaller cell diameter. Mid and bottom panels: plots of the point estimate (solid line) of ω from a regression that includes grid cell dummies, against the diameter of each cell in the grid. The grey shaded area represents the 95% confidence interval.

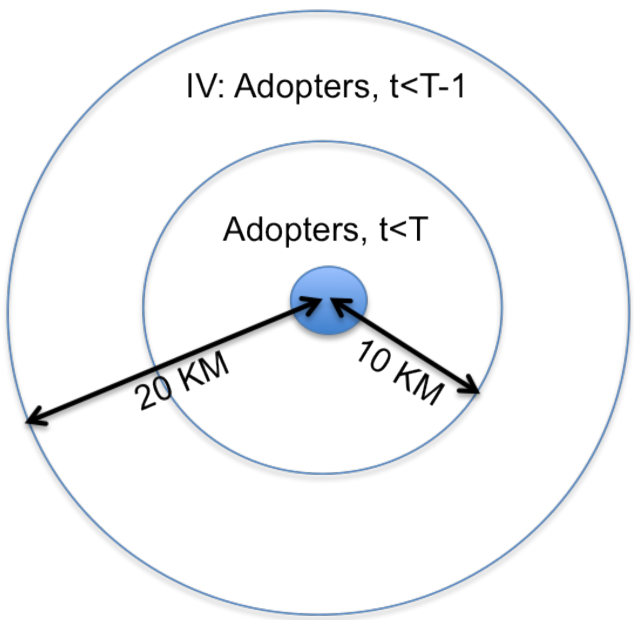
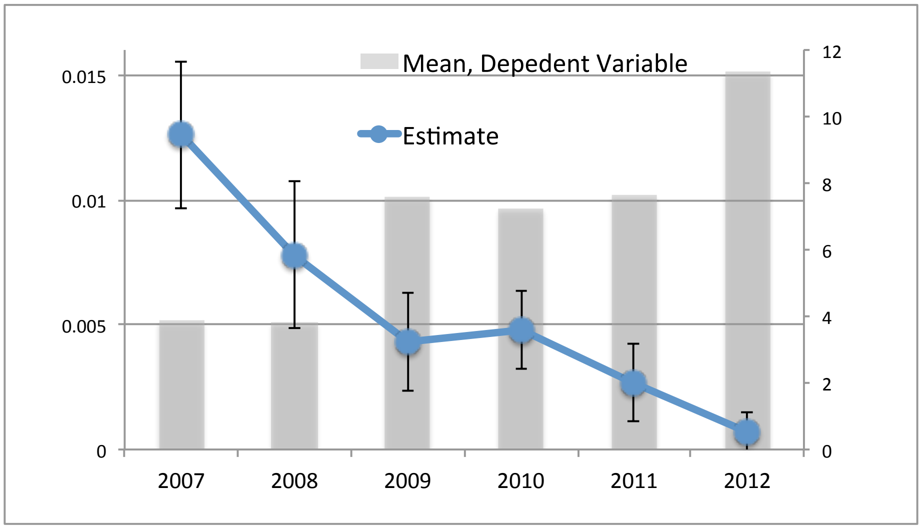


Figure 6: Instrument Exposure by Past Exposure of Further Neighbors



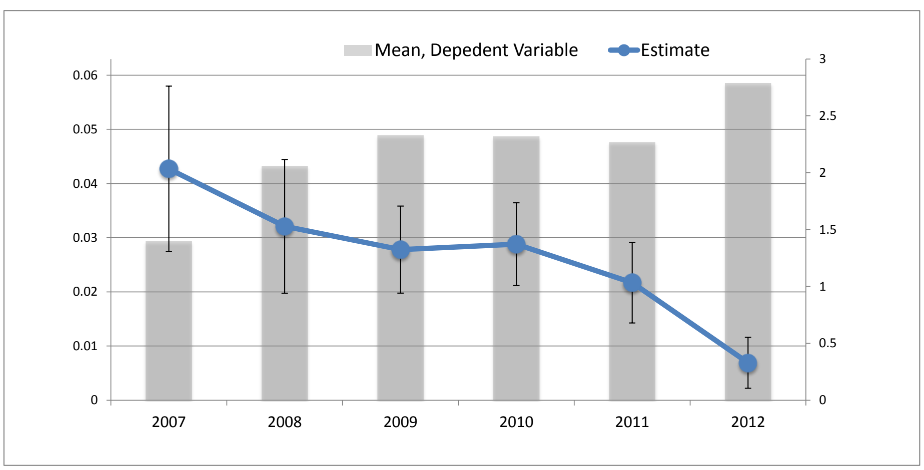


Figure 7: The importance of spatial diffusion over time. Point estimates (dots) of the impact of exposure to past adopters (counted in terms of individuals, top panel, or villages, bottom panel) estimated for samples of different years, plotted by year. Error bars represent 95% confidence intervals. Grey bars indicate the mean level of exposure in each year.

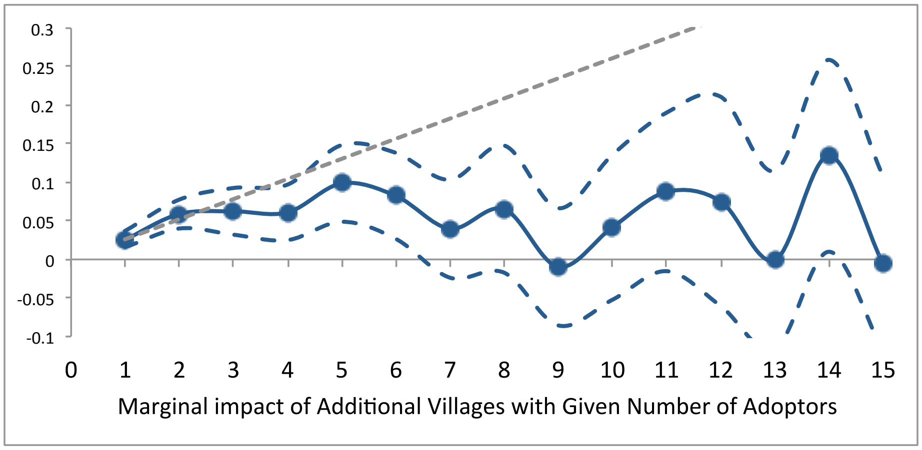


Figure 8: Marginal Impact of Additional Villages with Given Number of Adopters. Estimated coefficients (vertical axis) of a regression that controls for a series of indicators, each indicating the number of adopting, past, nearby villages with a given number of adopters (horizontal axis). Dotted blue lines represent 95% confidence intervals. The dotted black line is a linear extrapolation of the coefficient from villages with one adopter.

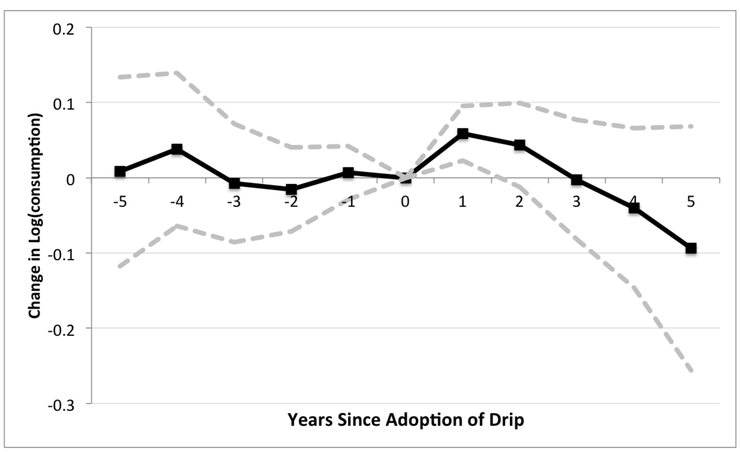


Figure 9: Estimated change in electricity usage (in percent) in 5 years before and after adoption (year 0). Dotted lines represent 95% confidence intervals.