Can Wide Scale Diffusion of Resource Efficient Technologies Reduce Groundwater Utilization? Evidence from Water Scarce Regions of Gujarat, India

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Abstract:

Anticipating that a large scale adoption of micro-irrigation could reduce potential use of groundwater, a higher incentive has been given to the farmers in the dark-zone talukas since 2012 for rapid diffusion. While one can expect that extra subsidy can enhance adoption, the impact on water utilization has been less explored at the irrigation system-level in India. The objectives of this study therefore are: (a) to examine the effect of additional subsidy on diffusion of micro-irrigation in the water deficit areas, and (b) to evaluate impact of adoption on groundwater extraction at the tubewell level. Information about adoption were collected for 8,073 villages and towns between 2006-07 and 2014 to validate the first objective, and around 430 micro-irrigation adopted tubewell owners were surveyed for the second one. The findings reveal that additional subsidy and social learning positively influenced the adoption, and the latter has higher impact. For instance, a 10% additional subsidy enhances the likelihood of adoption rate by 1.2% to 1.8% and area by 0.7% to 1.3%. On other hand, adoption alone found as statistically insignificant to decline pressure on groundwater. However, a combination of adoption with electricity meter connection leads to a reduction in groundwater extraction. This study supports for the continuation of additional subsidy policy for large scale adoption, and suggests for compulsory metering of unmetered connections to achieve the desired goals of sustainable use of groundwater. From a larger policy perspective, we emphasize for accounting water at the depletion point, rather than drawing policy conclusion based on measurement at the application point.

Keywords: additional subsidy, discontinuity, water scarce region, micro-irrigation, diffusion, groundwater utilization, Gujarat

JEL Classifications: H23, O13, O33, Q16, Q38

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1.1. Introduction

Over the years, an unsustainable utilization of groundwater has been observed in the state of Gujarat, Western India since the cost of pumping groundwater do not reflect full social cost (Shah et al., 2012; Narula et al., 2011). The over extraction is a case of negative externality for the users, resulting in loss of harvests and farm income, and in turn, threatening intra- and intergenerational water- and food securities. Climate change is likely to foster stresses on the already depleting water resources in the forthcoming decades. Given the consequences, resource efficient technologies like micro-irrigation (MI), which aims to increase irrigation efficiency[1], has been promoted to meet resource preservation challenges, while also maintaining current levels of farm production. MI technologies such as drip and sprinkler are considered to be pillars of 'sustainable intensification' since it likely to reduce water and energy footprint (Fishman et al., 2014). There is always a strong political unwillingness to implement Pigouvian tax on negative externalities associated with water and energy (Fishman et al., 2014). Establishing property rights for groundwater is also a difficult task (Sun et al., 2016), especially in countries like India (Kumar, 2005); while it is the main agenda for political vote bank (Shah et al., 2008), there is a lack of institutions and technology (Fishman et al., 2016). Hence, alternative policy instruments such as subsidizing resource efficient technologies are mostly practiced across the world, particularly in the developing nations (Fishman et al., 2014). It is a 'win-win' situation to escalate such technologies as these expected to cut down groundwater extraction and energy expenditure (for both consumer and government – tariff for agricultural consumption is again subsidized) while also declining greenhouse gas emissions.

Across the Indian states, the respective government subsidizes the irrigation capital cost for a large scale diffusion of MI, and however, the subsidy rate is not uniform (Bahinipati and Viswanathan, 2016). Likewise, various subsidy policies are adopted in Gujarat, and in particular, farmers in the water scarce talukas[2] (named as dark-zone[3]) get additional 10% subsidy[4] since 2012, irrespective of landholding and cropping patterns[5] (Bahinipati and Viswanathan, 2016). Given the other determinants, this creates a sharp discontinuity on the probability of farmers' adoption behaviour between the dark-zone and other talukas. Previous studies find an evidence of higher likelihood of MI adoption in the water scarce areas (Caswell and Zilberman, 1983; Palanisami et al., 2011). There is also a wide belief that a large scale adoption of such technologies could diminish extraction of groundwater in the arid and semi-arid regions, i.e., elimination of common-pool externalities (Kumar, 2016a, b). As a result, several public policies, specially focused on

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[1] According to India's intended nationally determined contribution (INDC) report, the national government is committed to enhance water use efficiency by 20% http://www4.unfccc.int/submissions/INDC/Published%20Documents/India/1/INDIA%20INDC%20TO%20UNFCCC.pdf (accessed on August 8, 2016)

[2] Taluka means sub-division of a revenue district, comprising of a group of villages.

[3] The Government Resolution (GR) dated 19/9/2001 states that the groundwater levels are very low in certain areas (i.e., 54 talukas at present), and therefore, the state government had enforced a ban on electricity connection for agricultural purposes and extraction of groundwater in these talukas in the interest of geo-hydrology and public at large. In 2003, these talukas were declared as dark-zone (see GR. no. GWR-2003-14J1, dated 16/12/2003).

[4] The cost of implementing MI ranges approximately between INR (Indian Rupee) 19,700 and INR 1,27,700, depending on specific system, cropping patterns, crop spacing, etc. All the farmers are eligible to get subsidy to the tune of 50% of MI cost or INR 60,000/ ha, whichever is lower. The dark-zone taluka farmers can avail additional 10%, i.e., 60% of MI cost or INR 60,000/ha, whichever is less (Bahinipati and Viswanathan, 2016).

[5] This was revised in early 2015 with giving further extra subsidy to small and marginal farmers (Bahinipati and Viswanathan, 2016).

water and energy saving technologies, have been launched, and a billion of public and private investments have been made to scaling up these technologies, particularly to improve water use efficiency[6] (Sun et al., 2016). While voluminous studies have already examined the post adoption farm-level resource utilization scenarios, there is a limited understanding at the basin-wide and the irrigation system level (Kumar, 2016a); a study by Ward and Pulido-Velazquez (2008) for Mexico is a noteworthy exception. Given this background, the objective of this study is twofold: (i) to examine the effect of additional subsidy on diffusion of MI in the water scarce regions; and (ii) to evaluate the impact of MI adoption on groundwater extraction at the tubewell level.

The paper is organized as follows. Section II discusses about the review of literature and section three briefly explains diffusion of MI in the state's dark-zone talukas. Section IV discusses the effect of additional subsidy on diffusion of MI in the water scarce region, and section V describes the impact of MI adoption on groundwater extraction; both the sections include data and methods, and results and discussions, separately. Section VI presents the concluding remarks with some policy suggestions.

1.2. Review of Literature

The patterns of diffusion and adoption of modern irrigation technologies is a major empirical research issue in the both developed and developing countries (Foster and Rosenzweig, 2010; Genius et al., 2014). Previous studies find the major determinants of adoption as factors related to economics, farm-organizational, demographic, extension agents, social learning and environmental conditions (Foster and Rosenzweig, 2010; Zilberman et al., 2012; Genius et al., 2013; Taylor and Zilberman, 2015). In spite of having socio-economic and environmental benefits of adoption and several policy interventions, the overall adoption of MI is still low in India. For example, around 14% of total potential area[7] under MI as of 2013 (Palanisami, 2015), and it is less than 5% of the net sown area (NSA) (Mahendra Dev, 2016). Since the mid of last decade, many Indian states have been redesigning the institutions and subsidy policies based on the recommendations provided by the task force (Bahinipati and Viswanathan, 2016). In Gujarat, a special purpose vehicle like Gujarat Green Revolution Company limited (GGRC), for instance, was formed in 2004-05 by the state government to heighten adoption, and the subsidy structure has been revised over the years (Bahinipati and Viswanathan, 2016). Although a few studies have been emerged to explore the reason behind such low adoption (Namara et al., 2007; Palanisami et al., 2011; Government of India, 2014a; Kumar, 2016b), there is a limited studies that assess the effect of subsidy on diffusion of MI (Kumar, 2016b). Moreover, the existing studies justify subsidy from social learning and credit constraint perspectives (see Fishman et al., 2014). This becomes imperative especially in the context of increasing ground water shortages leading to many states adopting policies and financial incentive programmes for promoting MI.

All the farmers are entitled to get subsidy which varies across as well as within the states (Bahinipati and Viswanathan, 2016), and therefore, the impact of additional subsidy on MI adoption can be examined. A recent study by Fishman et al. (2014) finds an evidence of additional subsidies enhancing adoption of MI in Gujarat, i.e., drip irrigation by 32%, the area installed with drip by 30% and the probability of having at least one purchase by 11%. In contrast, Malik et al. (2016) ascertain that the existing subsidy system acts as a negative determinant for expansion of

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[6]Ratio of water used in plant metabolism to water lost by the plant through transpiration.

[7] Coverage of MI in India is about 6 million ha out of total potential area is around 42 million ha as on March 2013 (Palanisami, 2015).

MI coverage in Madhya Pradesh, India. As outlined above, the dark-zone taluka farmers get additional 10% subsidy when adopting MI. To empirically test the impact of extra subsidy on MI adoption, a Regression Discontinuity Design (RDD) approach was employed in this study. Both the dark-zone talukas and its counterpart adjacent talukas (i.e., control group) were covered in the empirical analysis. This is based on information related to village-wise diffusion of MI for the period between 2006-07 and 2014 for 8073 villages and towns, covering 110 talukas.

The main aim of subsidizing such technologies is to promote wide spread adoption that could reduce groundwater extraction, energy consumption and stabilize water tables (Dhawan, 2000). Reviewing several papers based on Indian case study, Saleth and Amarasinghe (2010) ascertain that these technologies enhance water use efficiency which save water between 48% and 67% and reduce energy costs by 44% to 67%. With reference to Gujarat, Fishman et al. (2014) find an increasing energy consumption in the short-term (i.e., 1-2 years after adoption), while a substantial reduction is observed in the long-term (i.e., 4-5 years); such outcome rely on small fraction of consumers who were metered and billed volumetrically. Extrapolation based on farm-level estimation could have over-estimated potential saving of water at the aggregate level, i.e., irrigation system. While the plot-level estimation is mostly based on the technological potential, farmers' ex-post adoption behaviour matters for calculation of realistic saving of water and energy at larger scale (Fishman et al., 2015). What farmers do with the saved water due to adoption of MI? What about pressure on groundwater after wide scale adoption of MI? Instead of accounting water at the application point, it is imperative to calculate at the depletion level (Ward and Pulido-Velazquez, 2008).

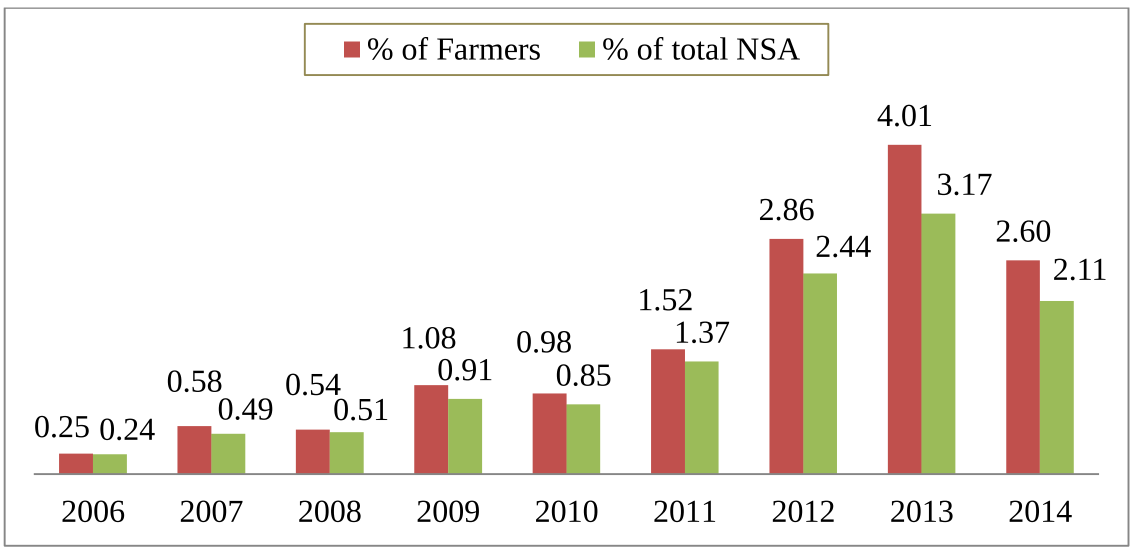
The marginal cost of water and energy (subsidized energy price/ levied at a flat rate) is often less or negligible for farmers in the state, and on the other hand, a large proportion of land is still un-irrigated. It is, henceforth, very unlikely that utilization of water could be reduced after the wide scale adoption of MI as compared to the baseline level. A few studies also pointed out that adoption of water efficient technologies lead to higher water use and faster resource depletion – 'Jevons Paradox', i.e., resource efficiency curse (Ward and Pulido-Velazquez, 2008). In order to maximize profit, farmers could undertake following options after adoption: (i) expansion of irrigated area, (ii) increase frequency of irrigation, (iii) shifting to water intensive crops, (iv) sharing water with neighbourhood farmers, and (v) lack of knowledge to utilize potential of MI (Fishman et al., 2014). However, these responses can offset the social objective intended at a reduction of water extraction, i.e., net effect of adoption of MI on water use could be nil or insignificant at the irrigation system level. There is a lack of empirical research, particularly in the arid and semi-arid regions of India (Kumar, 2016b).

Namara et al. (2007) and Fishman et al. (2014) pointed out, without robust empirical analysis, that farmers objective is not to conserve groundwater with adopting MI, but to increase irrigation intensity and/or provide more water to the irrigated crops. Fishman et al. (2015) compare between 'naïve' (no change) and 'realistic' (irrigated area expanded until the baseline level of water extraction reached or until the cultivated area saturated) behavioural scenarios of water efficient technologies, i.e., drip, sprinkler and laser land leveling, across the Indian districts. It notices an evidence of increasing number of over-extraction districts in the latter scenario, and the total amount of unsustainable water extraction drops by half. However, it fails to capture farmers' actual behaviour. Based on a survey of 430 tubewells where MI technologies have been installed at least one year before, across the dark zone talukas of the state, this study has investigated the impact of MI adoption on groundwater utilization.

1.3. Diffusion of MI across Dark-Zone Talukas: Background

In Gujarat, GGRC acts as a nodal agency to promote MI within the state (see Bahinipati and Viswanathan, 2016 for detail business/ institutional models being tried in the state), and according to Palanisami (2015), GGRC's operational model performs better in the context of diffusion of MI as compared to the other Indian states. This section briefly discusses about trends of MI adoption in the dark-zone talukas. Figure 1 shows year-wise percentage of MI adopted farmers and percentage of NSA[8] under MI in the dark-zone talukas. This depicts new adopters and incremental area under MI in the reported year as percentage of total farmers and NSA, respectively. An increasing trend was found for both the percentage of farmers and area under MI. In 2006, around 0.25% of the total farmers adopted MI with a total NSA of 0.24%. The share of new adopters progressively increased to 1.08%, 1.52% and 4.01% in the years 2009, 2011 and 2013, respectively. The estimated percentage of additional area under MI was 0.91%, 1.37% and 3.17% respectively during the same reference period. It is noted that a majority of farmers have adopted MI between 2012 and 2014, and similar evidence was also noticed in the case of percentage of area under MI. This signifies that the extra subsidy given to the dark-zone farmers could have positively influenced such increasing adoption and the resultant area expansion under MI in the recent years. The further empirical analysis with adopting RDD approach is attempted in the next section.

Figure 1.Year-wise percentage of farmers and NSA under MI in dark-zone talukas



Note: The year 2006 represents the financial year, i.e., April 2006 to March 2007, and it is same up to 2013, and the data for 2014 cover between April and December; NSA- Net Sown Area
Source: Authors' figure based on data compilation from GGRC

1.4. Additional Subsidies and Diffusion of MI

[8] The figures for taluka-wise total number of farmers and net sown area were collected for the year 2011 from the agricultural census, Government of Gujarat, Gandhinagar, India. Based on 2011 data, the percentage figure was calculated for both farmer and area between 2006 and 2014.

1.4.1. Data and Methods

The first objective, outlined in the introduction section, is to investigate the effect of extra subsidy on diffusion of MI in state's water deficit talukas where farmers are more likely to adopt such technologies (see Palanisami et al., 2011). Previous studies pertaining to India have been reported that hydrological parameters and cropping patterns are the major determinants (Namara et al., 2007; Palanisami et al., 2011). Instead of taking all the talukas, both the dark-zone talukas and its' immediate neighbourhood talukas (referred as 'adjacent taluka' in the remainder of the manuscript; see figure 2) are considered for the empirical analysis of this study. We anticipate that the above two determinants are unlikely to be significantly different between both the regions[9]. In sum, our study covers 110 talukas[10] (52 talukas in the dark-zone and 58 talukas in the adjacent category) with 8073 villages and towns[11], of which 4019 were from dark-zone talukas and the rest (4053 villages and towns) from the adjacent talukas (see Figure 2). The village-wise MI technology diffusion information, i.e., number of farmers adopted drip and sprinkler irrigation and total area under MI (in ha), were collected from GGRC for the period 2006-07 and 2014[12]. The data related to the socio-economic indicators (e.g., village area in ha and total number of households) were gathered from district census handbooks (2011). Further, taluka-wise SGWD (stage of groundwater development - ratio of annual ground water draft and net annual ground water availability in percentage) figures were composed from district level groundwater brochure published by the Central Ground Water Board, Government of India[13].

In the second step, the study has generated a sub-sample of villages and towns situated along the administrative boundary line drawn between the dark zone and adjacent talukas[14]. The empirical analysis for this sample was carried out to do a robust check of the results found, based on the analysis of larger sample (i.e., all the villages and towns). There is a higher chance that the difference in cropping patterns and hydrological parameters among the border villages and towns between dark-zone and adjacent talukas are not statistically significant; the empirical test is unlikely to be carried out due to paucity of data at the village level. In total, it includes 1456 villages and towns, of which, 855 are in dark-zone and the rest (601 villages/towns) from the adjacent talukas. Further, another study sample was created based on village pair-wise difference in adoption and area under MI; this sub-sample selection was constructed based on the paper by Somanathan et al. (2009). There are around 827 pairs of villages and towns. Thus, the empirical analysis was conducted at three levels: (i) all the villages and towns in the dark- and adjacent talukas, (ii) border villages and towns in both the regions, and (iii) village/ town pair-wise differences in the adoption and area under MI.

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[9] Due to lack of such information at the village level, it is not possible to do a statistical check these determinants.

[10] As of now, there are 54 dark-zone talukas and we have found another 64 talukas are adjacent to dark-zone, and among them, 8 talukas are notified as tribal; since there is different subsidy policy for tribal farmers in tribal talukas, we have excluded tribal talukas from the empirical analysis of this study.

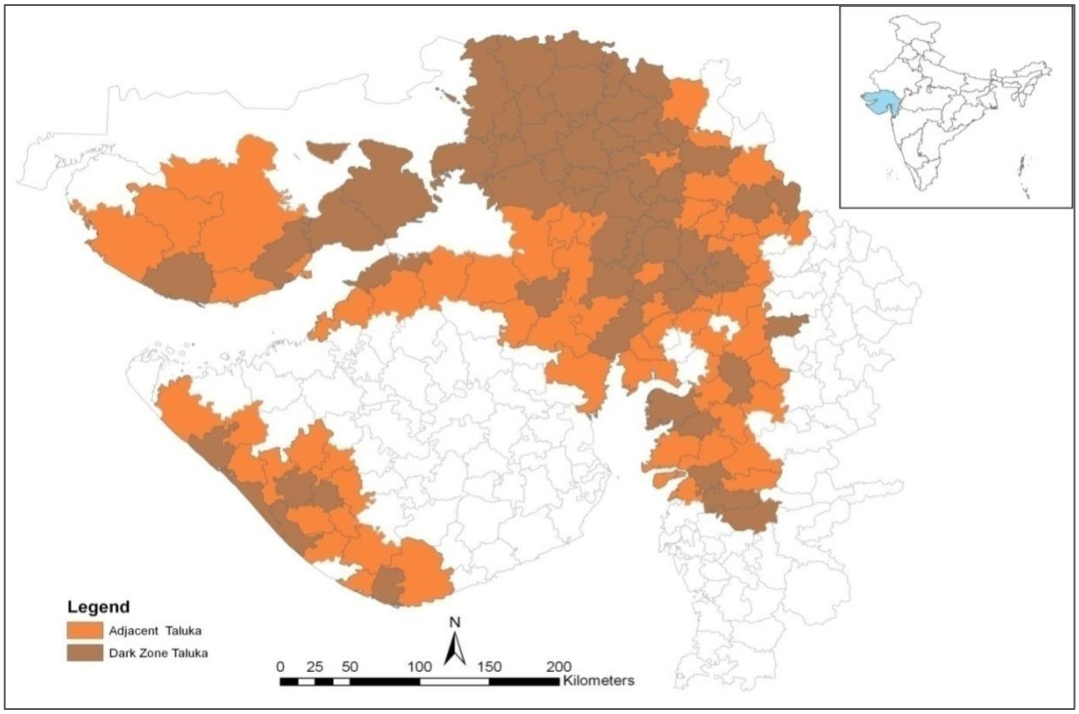
[11] Agricultural is being practiced in the peri-urban areas where farmers adopted MI technologies. Since it is impossible to accumulate data for these areas separately within the city, we have considered the whole city in the analysis.

[12] The government has introduced a new subsidy policy in January 2015 for small and marginal farmers in the dark-zone talukas (Bahinipati and Viswanathan, 2016), and therefore, this study's empirical analysis pertains to the data collected up to 2014.

[13] http://www.cgwb.gov.in/District_Profile/Gujarat_districtprofile.html; accessed on June 28, 2016.

[14] Those villages were considered who share border with a village in adjacent taluka.

Figure 2: Map of Dark-Zone and Adjacent Talukas in Gujarat



Source: Authors' figure

A 'regression discontinuity design (RDD)' method (see Hahn et al., 2001; Lee and Lemieux, 2010 for a survey) was adopted to evaluate the effect of additional subsidy on diffusion of MI in water deficit regions of the state. Although this approach was largely applied in the field of education research to evaluate impact of attending summer school and scholarship on the performance of students (Matsudaira, 2008), other fields of economics recently used it to evaluate the effect of various programmes and policies (Hahn et al., 1999; Lee and Lemieux, 2010; Jacob et al., 2012; Singhal, 2016). Moreover, the RDD is infrequently used in the economics literature as such type of data design is rare (Hahn et al., 2001). According to Hahn et al. (2001), RDD requires mild continuity assumption for locating the effects of treatment as compared to any other non-experimental or natural experimental approaches (difference-in-difference). RDD approach has similarity with the randomized control trials, and thus, popularly known as quasi-experimental design (Singhal, 2016). The regression model can be written as:

$$Y_{vt} = \alpha_0 + \alpha_1 T_{vt} + \alpha_2 X_{vt} + u_{vt} \ldots\ldots(1)$$

Where Y_{vt} is the outcome variable (i.e., adoption rate of MI and area under MI[15]) in village $'v'$ at time 't'; T_{vt} refers to treatment variable in binary terms, i.e., equal to '1' if the village $'v'$ is

[15]While the former was estimated dividing total number of new MI adopters in a village in a particular year by total number of households in the village as per Census 2011, the later was calculated by dividing total incremental area under MI in the reported year by total area in the village as of Census 2011.

entitled to extra subsidy at time 't', otherwise '0'; X_{vt} captures other covariates that possibly influence adoption; and u_{vt} represents the error term. The coefficients $\alpha_s^{'}$ are the parameters to be estimated and the major interest lies with α_1, as it measures the causal effect of extra subsidy on outcome.

By construction, the collected information represents a panel dataset, i.e., data for 8073 villages and towns for 9 periods (2006-07 to 2014)[16]. With adopting an ordinary least square (OLS) fixed effects model, this study first estimated impact of extra subsidy on diffusion of MI technologies.

The OLS fixed effects regression is:

$$Y_{vt} = \beta_0 + \beta_1 T_{vt} + \varepsilon_v + \gamma_t + u_{vt} \ldots\ldots(2)$$

Previous studies ascertain that the diffusion of technologies occurred through social learning, i.e., farmers tend to learn about the technologies from the early adopters (Conley and Urdy, 2010; Foster and Rosenzweig, 2010; Fishman et al., 2014). We have, therefore, taken lagged dependent variables as one of the covariates to capture the effect of social learning. When the lagged dependent variable has become an explanatory variable, the estimation model violates the strict exogeneity assumption, i.e., the idiosyncratic error in the current time period will be correlated with the explanatory variables in the past. It rules out the application of standard random and fixed effects panel estimation. Therefore, this study employs a linear dynamic panel data estimation as developed by Arellano and Bond (1991). The Arellano-Bond model utilizes a generalized method of moments framework by using further lagged values of the explanatory variables as instruments and resolves the correlation of the idiosyncratic error by using an efficient weighting matrix, thereby yielding consistent and efficient estimator (Wooldridge, 2010; Spielman and Ma, 2016). Hence, this study employs Arellano-Bond dynamic panel regression model.

The Arellano-Bond linear dynamic panel regression is:

$$Y_{vt} = \beta_0 + \alpha_1 Y_{v,t-1} + \alpha_2 Y_{v,t-2} + \beta_1 T_{vt} + \beta_i X_{vt} + \gamma_t + u_{vt} \ldots\ldots(3)$$

In equations 2 and 3, X_{vt} captures other possible covariates that might influence the adoption (water scarcity region dummy in the present study context, i.e., overexploited, critical, semi-critical and safe categories[17]). $Y_{v,t-1}$ and $Y_{v,t-2}$ represent first and second lags of the dependent variable. ε_v is the village-level fixed effects, and γ_t is the time fixed effects. u_{vt} refers to idiosyncratic error term and β_i and α_i are the parameters to be estimated and the major thrust of the analysis lies with β_1. Based on equations 2 and 3, this study has estimated results for the first two samples, i.e., all the villages and only the border villages and towns.

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[16]We have dropped 0.07% and 0.91% of total sample in case of MI adoption and area, respectively due to outliers, and therefore, it denotes an unbalanced panel.

[17] Over exploitation: SGWD > 100%; critical: SGWD is between 85-100%; Semi-critical: SGWD is between 65-85%; and safe: SGWD < 65% (Government of India, 2014b).

As outlined above, this study also reconfirmed the findings obtained based on the above equations (2 and 3) with constructing a sample of pair-wise border village matching. Following Somanathan et al. (2009), the estimated regression model is:

$$\Delta Y_{pt} = \alpha_0 + \alpha_1 T_t + u_{pt} \ldots\ldots(4)$$

Where ΔY_{pt} is the difference in adoption rate of MI and area under MI of different village pair $'p'$ at time $'t'$. In this context, the coefficient (α_1) of the variable T_t is the main interest of the analysis. And u_{pt} refers to idiosyncratic error term. This model was estimated following OLS regression with random effects.

Table 1 reports the descriptive statistics of variables used in the regression model. In the case of total sample, on an average 1% of the total households adopt MI every year, with a minimum adoption rate of 0% and maximum rate of 49%. Per year adoption rate was found as higher in the dark-zone talukas (1.4%) as compared to the adjacent talukas (0.8%). About 0.8% of the total village area was covered under MI each year during the study periods with a maximum of 54%. Likewise, the mean MI installed area per year was high in the dark-zone talukas, i.e., 1.1% of the total area as compared to 0.5% in the adjacent talukas. Out of the total study villages, 30%, 12%, 18% and 40% fall in over-exploited, critical, semi-critical and safe categories, respectively.

1.4.2. Results and Discussions

Figures 3 and 4 present year-wise adoption rate of MI and area under MI between the dark-zone and the adjacent talukas, respectively. Note the mean difference of MI adoption rate between both the regions is statistically insignificant during 2006 to 2011, whereas a significant difference was noticed between 2012 and 2014 – we have also got similar observation for the border villages (see Appendix 1 and Figure 3). On other hand, the mean difference of adoption rate of area under MI is statistically significant for both the periods, i.e., 2006 to 2011 and 2012 to 2014 – however, the difference was reported as high in the later (see Appendix 1). This indicates that the mean differences in adoption rate of MI and area under MI were significantly higher during the later period (2012 to 2014) as compared to the earlier period, i.e., 2006 to 2011. This finding warrants identification of the drivers which could have played a major role causing a sharp increase in the diffusion of MI in the water scarce areas in the recent past years. We have hypothesized that the additional subsidy could be one of the major determinants for observing this significant difference – the results of the empirical investigation are presented in the following section.

Table 1. Descriptive Statistics of variables

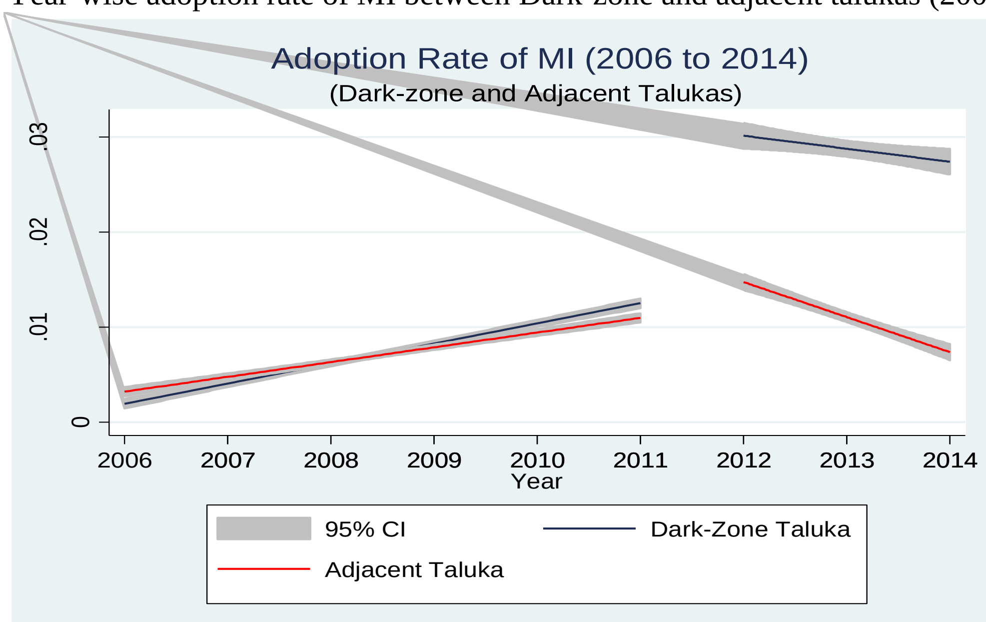
	Full Sample			Dark-zone	Adjacent	Border Village	Difference*
Parameter	Mean (SD)	Min	Max	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Adoption Rate of MI	0.011 (0.031)	0	0.49	0.014 (0.035)	0.008 (0.025)	0.011 (0.030)	0.005 (0.060)

Adoption Rate of Area under MI	0.008 (0.021)	0	0.54	0.011 (0.025)	0.005 (0.015)	0.008 (0.019)	0.005 (0.023)
Extra Subsidy	0.163 (0.370)	0	1	0.328 (0.470)	0 (0)	0.192 (0.394)	-
Overexploited	0.304 (0.460)	0	1	0.61 (0.488)	0 (0)	0.30 (0.459)	-
Critical	0.121 (0.326)	0	1	0.124 (0.33)	0.118 (0.323)	0.157 (0.364)	-
Semi-Critical	0.179 (0.383)	0	1	0.096 (0.294)	0.261 (0.439)	0.184 (0.387)	-
Safe	0.396 (0.489)	0	1	0.17 (0.375)	0.621 (0.485)	0.358 (0.48)	-

Note: SD- standard deviation; *- village pair-wise difference between dark-zone and adjacent talukas

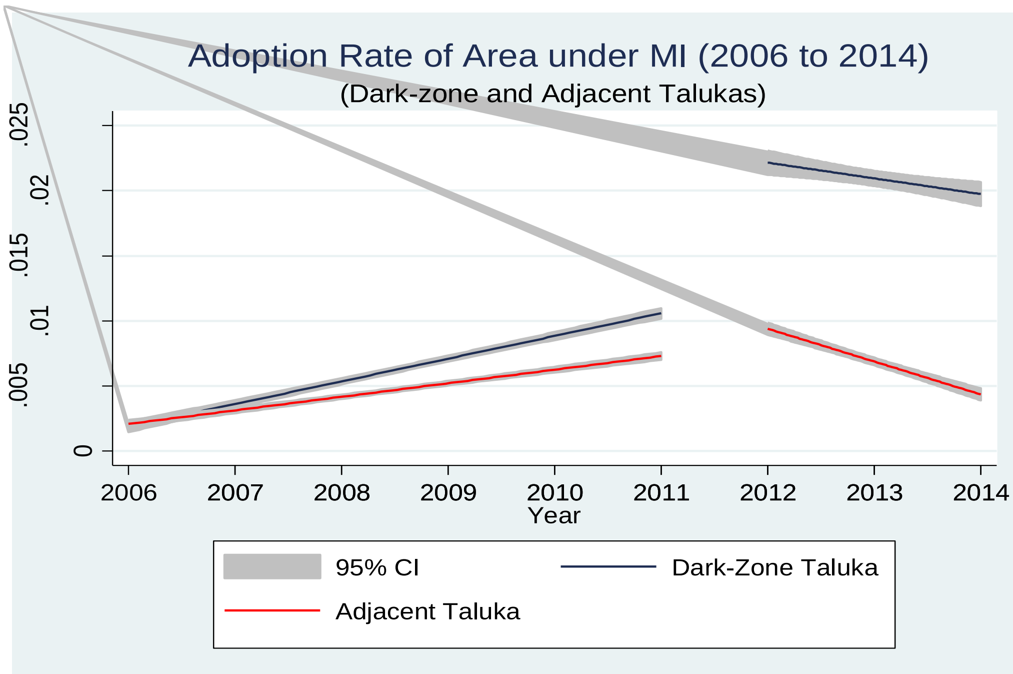
Source: Authors' Computation from secondary data

Figure 3. Year-wise adoption rate of MI between Dark-zone and adjacent talukas (2006 to 2014)



Source: Authors' figure

Figure 4. Year-wise adoption rate of area under MI between Dark-zone and adjacent talukas (2006 to 2014)



Source: Authors' figure

Table 2 depicts the effect of additional subsidy on adoption rate of MI, and its' impact on adoption rate of area under MI is presented in Table 3. In both the tables, second and third columns show the estimated coefficients based on the full sample, while columns (iv) and (v) present the results based on the border villages and towns. Whereas second and fourth columns report coefficients computed based on equation 2 (OLS fixed effects), calculated coefficients based on equation 3 (Arellano-Bond dynamic panel regression) are presented in columns (iii) and (iv). Column (vi) shows the outcomes derived on the basis of pair-wise sample, i.e., worked out on the basis of equation 4. Fixed effects model was employed in the case of OLS to control time-invariant effects, i.e., village level effects, and year dummies were taken to capture time-variant essences. The values of Wald χ^2 are significant in the dynamic panel models, indicating that there are no errors in the estimation of the models. The higher orders of the first difference are found as not significant in all the models (except column 'v' of Table 3), indicating that there is no serial correlation.

In all the models outlined in Tables 2 and 3, the estimated parameters β_1 are found as statistically significant at 1% level, and this indicates that an additional subsidy specific to dark-zone farmers has positively influenced the wide scale diffusion of MI technologies. For instance, additional 1.2% to 1.8% of the total households per year are likely to adopt MI when the subsidy amount enhanced by 10%. Similarly, an extra 10% subsidy brings 0.7% to 1.3% of additional village area under MI per year. Although these figures are small, the rate of adoption and area under MI could be significantly higher as these are percentage of total households and area in a village/ town. The village level adoption is positively correlated with the extent of adoption in the village during previous years. This highlights the evidence of social learning, i.e., farmer-to-farmer social networking plays a major role in the diffusion of technologies; previous studies also outlined similar observation (see Foster and Rosenzweig, 2010). The coefficients of lagged dependent variables are found as higher than the additional subsidy. This underscores the importance of social learning for the rapid diffusion of MI. Keeping this in mind, previous studies justified for providing incentive to early adopters for scaling up these technologies (Fishman et al., 2014). While conducting field work for the second objective, a large number of farmers reported that subsidy is not the major influencing factor for their adoption behaviour. Nonetheless, they have undertaken such technologies because of two reasons: (i) awareness about water use efficiency from the early adopters, and (ii) economically viable option.

Table 2. Effects of Additional Subsidy on Adoption Rate of MI

Independent Variables	Adoption Rate of MI				Δ adoption rate of MI
(i)	(ii)	(iii)	(iv)	(v)	(vi)
Extra Subsidy	0.018***	0.012***	0.016***	0.012***	0.018***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
$(\text{ARMI})_{t-1}$	-	0.055	-	0.334***	-
		(0.137)		(0.074)	
$(\text{ARMI})_{t-2}$	-	0.015	-	0.108***	-
		(0.070)		(0.019)	
Region Dummy[a]					
Overexploited	-	0.096	-	-0.001	-
		(0.091)		(0.022)	
Critical	-	0.251***	-	0.051	-
		(0.088)		(0.048)	
Semi-Critical	-	0.012	-	0.005	-
		(0.068)		(0.040)	
Constant	0.003***	-0.050*	0.003***	0.002	-0.001
	(0.000)	(0.029)	(0.000)	(0.012)	(0.001)
R^2 / Wald χ^2	0.124	1835.12***	0.130	1158.07***	0.018
AR(1) z statistics (Pr>z)	-	-3.155 (0.002)	-	-5.874 (0.000)	-
AR(2) z statistics (Pr>z)	-	0.766 (0.444)	-	0.782 (0.434)	-
No. of Obs.	72597	56460	13080	10172	7443
No. of Villages/ Pairs	8073	8073	1456	1454	827
No. of Instruments	-	42	-	42	-
Year FE	Yes	Yes	Yes	Yes	No
Model	OLS(FE)	Arellano-Bond	OLS(FE)	Arellano-Bond	OLS(RE)
Sample	Full	Full	Border	Border	Border

Note: a- the omitted category is safe; Figures in the parentheses indicate village level cluster robust standard error in case of OLS model and WC- robust estimator in the case of Arellano-Bond Model; FE- Fixed Effects; RE- random Effects;*** p<0.01, ** p<0.05 and * p<0.1 respectively.
Source: Authors' Computation from secondary data

We have also observed a significant coefficient value for critical and semi-critical parameters. This reveals that farmers in these regions are more likely to adopt MI as compared to the safe category. Based on the previous literature, it is expected that farmers in the over-exploited region are more likely to adopt MI (see Palanisami et al., 2011). More importantly, we have not noticed a significant relationship for this covariate. Property of non-exclusivity and not reflecting scarcity value of water lead to 'use it or lose it' rule in water, which could have reduced the incentive to use resource efficient irrigation technologies (Zilberman et al., 1994). Because of this, farmers in the overexploited region might not have shown interest in adopting MI as it requires initial capital investment both for digging or deepening the tubewells and for installation of MI systems.

Table 3. Effects of additional Subsidies on Adoption Rate of Area under MI

Independent Variables	Adoption Rate of Area under MI				Δ adoption rate of MI
(i)	(ii)	(iii)	(iv)	(v)	(vi)
Extra Subsidy	0.013*** (0.000)	0.008*** (0.001)	0.010*** (0.001)	0.007*** (0.001)	0.011*** (0.001)
$(\text{ARMI})_{t-1}$	-	0.460*** (0.033)	-	0.203*** (0.077)	-
$(\text{ARMI})_{t-2}$	-	0.137*** (0.026)	-	0.027 (0.046)	-
Region Dummy[a]					
Overexploited	-	0.003 (0.008)	-	-0.030 (0.026)	-
Critical	-	0.044** (0.022)	-	0.129*** (0.048)	-
Semi-Critical	-	0.039*** (0.015)	-	0.016 (0.056)	-
Constant	0.002*** (0.000)	-0.017*** (0.006)	0.003*** (0.000)	-0.009 (0.009)	0.001*** (0.0003)
R^2 / Wald χ^2	0.126	5235.30***	0.120	716.97***	0.052
AR(1) z statistics (Pr>z)	-	-16.589 (0.000)	-	-5.118 (0.000)	-
AR(2) z statistics (Pr>z)	-	0.493 (0.622)	-	2.424 (0.015)	-
No. of Obs.	71927	55944	13034	10136	7317
No. of Villages/ Pairs	7993	7992	1450	1448	813
No. of Instruments	-	42	-	42	-
Year FE	Yes	Yes	Yes	Yes	No
Model	OLS(FE)	Arellano-Bond	OLS(FE)	Arellano-Bond	OLS(RE)
Sample	Full	Full	Border	Border	Border

Note: a- the omitted category is safe; Figures in the parentheses indicate village level cluster robust standard error in case of OLS model and WC- robust estimator in the case of Arellano-Bond Model; FE- Fixed Effects; RE- Random Effects;*** p<0.01, ** p<0.05 and * p<0.1 respectively.

Source: Authors' Computation from secondary data

Similar to the results observed in other columns of Tables 2 and 3, column (vi) reports that an extra subsidy is the major determinant for observing higher adoption of MI in the dark-zone talukas than that of the adjacent talukas. While an extra 10% subsidy has enhanced difference in

MI adoption between dark-zone and adjacent talukas by 1.8%, the gap in MI installed area was likely to increase by 1.1%. The findings support the hypothesis that additional subsidy positively influenced farmers' behaviour on adopting MI. More generally, subsidy influences adoption behaviour in two ways: (i) directly remove the risk of credit barrier in adopting technologies, and (ii) indirectly influences adoption through social learning (Fishman et al., 2014).

1.5. Adoption of Micro-Irrigation and Resource Utilization

1.5.1. Data and Methods

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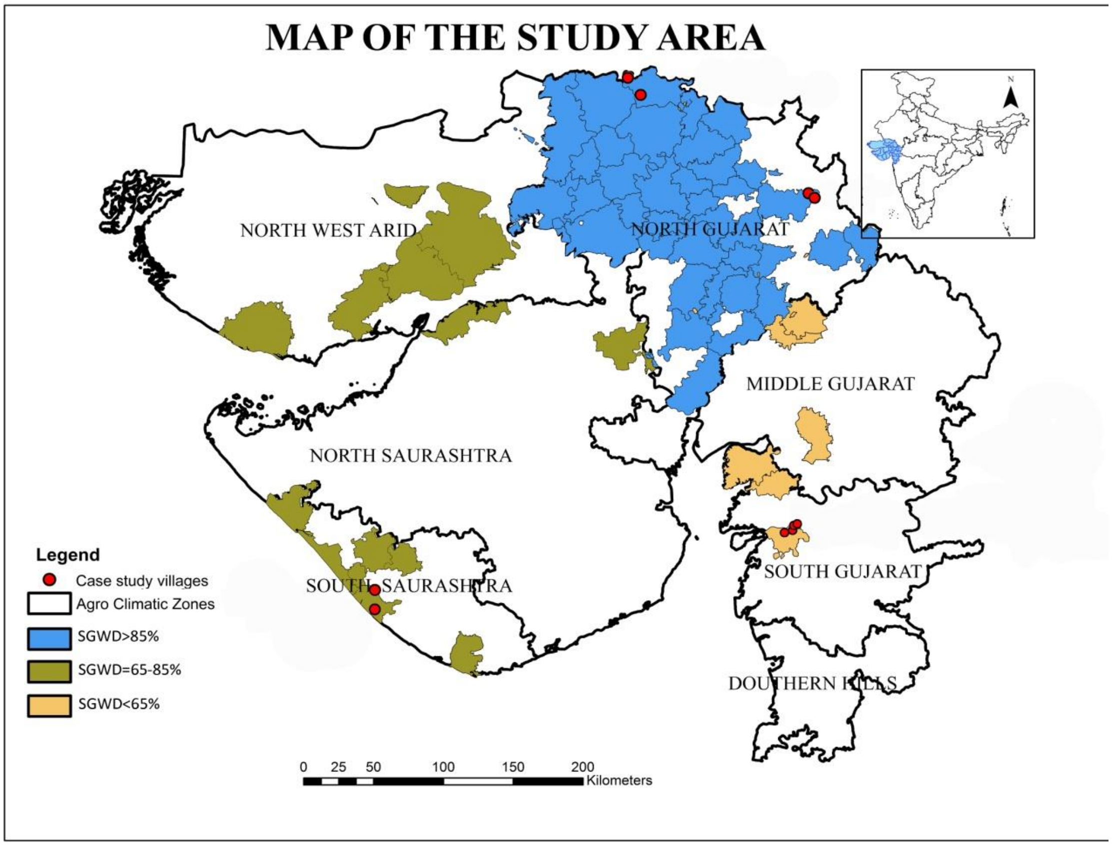
In order to investigate the impact of MI adoption on groundwater extraction at the tubewell level, we have conducted a primary survey in the dark-zone talukas. All the dark-zone talukas are falling under the six agro-climatic zones: north Gujarat (36 talukas), south Saurashtra (5 talukas), middle Gujarat (4 talukas), north Saurashtra (2 talukas), south Gujarat (3 talukas) and north-west arid (4 talukas). A stratified random sampling approach has been followed to select tubewell owners for survey. The first stage of classification was carried out to select districts, talukas and villages. We have classified the agro-climatic zones into three categories based on SGWD, e.g., (i) over-exploited and critical categories, (ii) semi-critical and (iii) safe categories. Whereas most parts of north Gujarat are notified as over-exploited and critical regions, the talukas in south Saurashtra, north Saurashtra and north-west arid regions are known as semi-critical, and the remaining zones like middle Gujarat and south Gujarat fall under safe category. The study districts, talukas and villages were selected on the basis of adoption status of MI, and we have selected those villages where a higher adoption was noticed. While we have purposively selected two districts from the first category, e.g., Banaskantha and Sabarkantha[18], one district each has been picked out from second and third categories, viz., Junagadh and Bharuch. One taluka from each district has been chosen: Dhanera (Banaskantha), Idar (Sabarkantha), Mangrol (Junagadh) and Ankleshwar (Bharuch). From these study talukas, 10 villages were chosen for primary survey, namely, Nenava, Dhakha, Gorol, Mudeti, Shepa, Divrana, Diva, Mandvabuzarg, Kansiya, and Andada (see Figure 5). We have specifically selected four villages from the Ankleshwar taluka since the adoption of MI is lower across the villages as compared to the talukas in other categories. Following a random sampling method, we have surveyed 430 tubewell owners where MI was already installed at least one year before. It should be noted that there are no other sources of irrigation except borewell and tubewell in all the study villages.

Figure 5. Map of the Study Villages

[18] Around 67% of total dark-zone talukas are falling under this category, and therefore, two districts were considered for survey purposes.



Source: Authors figure

We had used structured questionnaires for villages and tubewells to get responses from the tubewell owners regarding their resource utilization behaviour after adopting MI. At the village level, we have collected detailed information about irrigation sources, cropping patterns and overall infrastructure. Further, the tubewell owners were specifically asked to report the technical details about the tubewell for two time periods, i.e., survey year (2015-16) and before adopting MI. The tubewell specific information related to irrigation practices, cropping patterns, energy consumption, and extraction of water were also collected during the survey. The tubewell owners were particularly asked to provide data for the tubewell rather than for own cultivated land. We have also gathered detailed socio-economic information of the tubewell owner, and in addition, they were asked to share their opinion/ perception on impact of MI adoption on resource utilization, i.e., water and energy.

In order to capture the rate of groundwater extraction before and after adoption, we have taken proxy variables as change in depth of water level, number of added column pipes and change in pumpset HP (horse power); these are the dependent variables. In order to capture the impact of MI adoption, the variables like the proportion of gross irrigated area (GIA) under MI and number of years since MI adoption were included as explanatory variables in the regression model. The effect of these variables on extraction of groundwater resources may be confounded with the effect of other drivers such as gross irrigated area before MI adoption, electricity meter connection, GIA under MI multiplied with meter connection, water recharge measures, depth of the groundwater level before MI adoption, age of tubewell, years of schooling of tubewell owner, and tubewell owners' age. Further, we have also taken binary dummy variable for surveyed villages to capture unobserved heterogeneity effects at the village level[19]. Obtaining reliable estimates requires controlling for these factors.

The estimated equation is specified as:

$$\begin{aligned}\Delta DWL_i / \Delta CP_i / \Delta Pump_i = \beta_0 + \beta_1 GIAMI_i + \beta_2 YearMI_i + \beta_3 GIABMI_i + \beta_4\, Meter_i \\ + \beta_5 (GIAMI * Meter)_i + \beta_6 WRM_i + \beta_7 Ln(DWater)_i \\ + \beta_8 AgeTubewell_i + \beta_9 EduOwner_i + \beta_{10} AgeOwner_i \\ + \beta_{11} V_i + \varepsilon_i \ldots\ldots(5)\end{aligned}$$

Table 4 provides description and summary statistics of the variable (both dependent and explanatory) used in the econometric analysis of this study. While the average depth of groundwater level has increased by 11 feet between surveyed year and before adoption, around 2 column pipes were added and HP of the pumpset has enhanced by 2 during the same reference period. The empirical analysis of this study has taken confounded variables related to MI adoption, farm and tubewell characteristics, water regulatory measures and tubewell owners' characteristics. Given the objective for wide scale diffusion of these technologies, it is expected that the indicators representing MI adoption status, e.g., proportion of GIA under MI and number of years of MI adoption, could have negative impact on groundwater extraction. A substantial number of studies have empirically estimated that these technologies reduce the use of water at the farm-level as compared to the conventional method of irrigation (see Kumar, 2016b). It is found that the mean of 76% of total irrigated area under MI, and the average number of years the farmers undertaken MI are four at the time of survey. Farm characteristics include GIA before MI adoption and water recharge measures. The variable $GIABMI_i$ was taken to control the water extraction scenario at the baseline level. Various water recharge measures, (e.g., check dams, bori bundhs[20], farm ponds[21], etc.), have been undertaken at individual- and community levels across the state over the years (Kishore, 2013). There is a provision to avail incentives from the state government to construct these measures (Kishore, 2013). These activities could enhance groundwater recharge and improving water supplies at the basin level. In the present study context, around 60% of farmers have undertaken water recharge measures. The factors representing tubewell characteristics are $Ln(DWater)_i$ and $AgeTubewell_i$. The variable $Ln(DWater)_i$ captures baseline water level which could influence farmers' extraction behaviour.

Table 4. Descriptive Statistics of the Variables used in the Analysis

[19] Amount as well as variation of rainfall is also a major determinant for the observed groundwater level. Due to non-availability of village-level rainfall information, this variable was not directly taken into model, but the influence of it could have been captured by the village-level effect variables.
[20] It is a type of check dams made of sand bags.
[21] The state government had launched Sardar Patel participatory water conservation scheme in January 2000, and it was planned to construct a large number of check dams, especially in the water scarce regions (Kishore, 2013).

Sl. No.	Dependent Variables	Description	Mean (SD)
1	ΔDWL_i	Δ Depth of Water Level (in feet)	11.47 (17.07)
2	ΔCP_i	Δ Column Pipe (in no.)	2.09 (4.61)
3	$\Delta Pump_i$	Δ Pumpset HP	2.19 (4.16)
	Independent Variables		
	Adoption of MI		
4	$GIAMI_i$	GIA under MI (%)	0.76 (0.23)
5	$YearMI_i$	No. of years adopted MI	4.41 (2.84)
	Farm and Tubewell Characteristics		
6	$GIABMI_i$	Gross Irrigated Area Before MI adoption	6.03 (4.67)
7	WRM_i	Water Recharge Measures	0.60 (0.49)
8	$Ln(DWater)_i$	Ln(Depth of water level before MI adoption)	4.48 (0.89)
9	$AgeTubewell_i$	Age of the Tubewell	18.09 (9.87)
	Water Regulatory Measures		
10	$Meter_i$	Meter Connection (Yes/ No)	0.35 (0.48)
11	$(GIAMI * Meter)_i$	Gross Irrigated Area under MI*Meter Connection	2.31 (4.54)
	Tubewell Owners' Characteristics		
12	$EduOwner_i$	Years of schooling of Tubewell Owner	7.13 (4.87)
13	$AgeOwner_i$	Tubewell Owners' Age	51.47 (12.34)
14		N	430

Note: SD- Standard Deviation
Source: Authors' Computation

In 1989, Gujarat electricity board has changed from meter tariff system to flat-rate tariff to avoid high transaction costs (Shah et al., 2008). Earlier studies ascertain that the marginal cost for pumping groundwater is almost zero, and this, in turn, increased the demand for electricity connections in tubewells, resulting over-extraction of groundwater (Dubash, 2007; Shah et al., 2012; Fishman et al., 2016). As part of the power sector reforms, Asian Development Bank had advised the government of Gujarat to metering of farm power supply during the early last decade, and it also becomes mandatory according to the Indian Electricity Act of 2003 (Fishman et al., 2015). Due to political resistance, the government move slow in fixing meter on the old connections, but made meter tariff mandatory for all new connections for tubewells (Shah and Verma, 2008; Shah et al., 2012). Because of this, a large percentage of farmers across the state are still charged on the basis of flat-rate tariff linked to the HP of pumps (Viswanathan, 2014). About 35% of the total surveyed tubewell, for example, had meter connection. Having a meter connection expected to reduce the extraction of groundwater – because, the marginal cost of extracting groundwater is higher for farmers with meter connection that that of farmers with unmetered connections who pay a flat rate (Shah et al., 2008). According to economic theory, efficient allocation of water could be achieved, if farmers are charged as per the marginal pricing of water including full social cost – this may slow down water resource depletion (Shah et al., 2012; Fishman et al., 2016). In order to capture the influence of meter connection, the variables like $Meter_i$ and $(GIAMI * Meter)_i$ are taken in the model. Earlier studies emphasize to account water at the depletion point (Ward and Pulido-Velazquez, 2008), and this variable, in fact, captures water extraction at the tubewell level.

This study has considered two proxy variables to capture tubewell onwers' characteristics those could have possible impact on water extraction, namely, $EduOwner_i$ and $AgeOwner_i$. Since the cross section econometric analysis is associated with the problem of multi-collinearity and heteroskedasticity, a variance inflation factor (VIF) for the covariates was estimated to check multicollinearity, and a robust standard error was calculated to address the possibility of heteroskedasticity (Wooldridge, 2002). The VIF value for the explanatory variables was below 10 (i.e., 2.51, spreading between 1.11 and 4.96) and hence, negate the problems of multi-collinearity.

1.5.2. Results and Discussions

Previous studies pointed out that MI enhances water use efficiency as compared to the conventional method of irrigation (Saleth and Amarasinghe, 2010), and as a consequence, it is anticipated that we can reduce water footprint in agriculture by adopting such technologies at a larger scale (Kumar, 2016b). Nevertheless, the impact of MI adoption on water extraction at the irrigation system level is less explored, while several studies had investigated this at the farm-level (Kumar, 2016b). Technological potential could reduce water footprint at the farm-level, but the overall extraction of groundwater mostly depend on farmers' post-adoption behaviour. It is found that farmers change the agricultural management practices after adopting MI; some of them are outlined in the review of literature section. These measures could offset the real potential saving of water, i.e., strategic externality. Estimating water saving potential based on the technology capacity is a clear cut example of asymmetric information. Based on the primary survey, it is found that 26% of farmers have increased the GIA, and enhanced frequency of irrigation by 80% of the tubewell owners (Table 5). While post adoption cropping intensity is increased by 32%, around 37% of farmers diversified towards water intensive crops (Table 5). These ex-post activities could offset the water saving potential which would have otherwise achieved due to adoption of water conservation technologies.

Table 5. Tubewell Owners' Behaviour after adopting MI

Sl. No.	Post Adoption Behaviour	Mean (SD)
1	Increase Gross Irrigated Area (GIA)	0.26 (0.44)
2	Increase frequency of Irrigation	0.80 (0.40)
3	Increase Cropping Intensity	0.32 (0.47)
4	Shifting Water Intensive Crops	0.37 (0.48)

Note: SD- standard deviation
Source: Authors' table based on field survey

The results of impact of MI adoption on groundwater extraction are presented in Table 6. Columns (iii), (iv) and (v) show the coefficients of the explanatory variables for three dependent variables, e.g., change in depth of water level, change in column pipes and change in capacity of pumpset (HP), respectively. In these models, it is found that the goodness of fit (R^2) varies between 0.39 and 0.46, i.e., these models explain 39-46% of the total variation in the dependent variables.

When the main thrust of the empirical analysis is with the covariates of MI adoption, the coefficients of $GIAMI_i$ were found as non-significant. Surprisingly, we observed a positive relationship for the covariate $YearMI_i$ with column pipes added, and it is statistically significant. This reveals that the additional year under MI enhances the probability of adding column pipes by 13%. In contrast to the expected results, these findings suggest that the adoption of MI does not have a significant impact on reduction of groundwater – the major policy onus for wide scale diffusion of these technologies is to stabilize groundwater level in arid and semi-arid regions of India (see Dhawan, 2000). Moreover, we have observed a negative relationship with statistically significant coefficient for the variable $(GIAMI * Meter)_i$. For instance, this covariate reduces the likelihood of increasing depth of water level by 49%, additional column pipes by 15%. This finding suggests that the wide scale adoption of MI does not have significant impact on the reduction of groundwater extraction, as long as connection is not metered. In other words, adoption of MI with metered connection reduces the depletion of groundwater. Similarly, Shah et al. (2008) conclude that increasing water price charges due to '*Jyotigram*[22]' scheme diminishes groundwater extraction. Several studies also ascertain that charging electricity price as per meter is likely to mitigate the rate of groundwater extraction (Dubash, 2007; Shat et al., 2012). Testing an alternative voluntary approach, i.e., invite farmers to install electricity meters and receive compensation for every unit they save, Fishman et al. (2016), however, found no impact on water usage, while there was an unprecedented voluntary shift to meter based billing. We have also observed similar result as the coefficients of meter connection were reported as insignificant. Note that neither meter connection nor water saving technologies alone can decline groundwater depletion. Moreover, this study finds that the combination of both has the potential to reduce the pressure on groundwater.

This reveals the fact that accounting water at the depletion level has become a strong determinant in reducing extraction of groundwater along with adoption of water saving technologies. From the broader policy perspective, it advocates accounting water at the depletion point rather than at the application point. The specific policy suggestion is that the government may expedite the process of fixing meters for all the agricultural power connections in order to reduce the groundwater extraction, in addition to the diffusion of MI. The other covariates found as significant are: gross irrigated area before MI adoption, depth of water level before adoption and tubewell owner's age. It can be inferred that the probability of groundwater extraction is higher if water depth level was high before adoption of MI. Again the empirical analysis through primary data proves 'use it or lose it' hypothesis (see Zilberman et al., 1994).

Table 6. Impact of MI adoption on Groundwater Extraction

Independent Variables	ΔDWL_i	ΔCP_i	$\Delta Pump_i$

[22] This scheme was implemented between 2004 and 2007, and the onus is effective rationing of the power supply to the agriculture sector. Under this, a separate three phase high voltage electricity connection has been provided to agriculture sector for a pre-announced 6-8 hours per day (see Kishore, 2013).

Sl. No.		Coef. (Robust SE)	Coef. (Robust SE)	Coef. (Robust SE)
(i)	(ii)	(iii)	(iv)	(v)
	Adoption of MI			
1	$GIAMI_i$	-5.08 (3.43)	-0.42 (0.91)	0.59 (0.81)
2	$YearMI_i$	0.38 (0.24)	0.13** (0.06)	0.05 (0.05)
	Farm and Tubewell Characteristics			
3	$GIABMI_i$	0.37** (0.18)	0.09* (0.05)	0.03 (0.04)
4	WRM_i	1.19 (1.81)	0.44 (0.51)	0.04 (0.46)
5	$Ln(DWater)_i$	0.23 (1.68)	0.97** (0.41)	0.27 (0.30)
6	$AgeTubewell_i$	-0.03 (0.07)	0.01 (0.02)	0.01 (0.01)
	Water Regulatory Measures			
7	$Meter_i$	-0.08 (1.96)	0.41 (0.45)	-0.44 (0.43)
8	$(GIAMI * Meter)_i$	-0.49** (0.19)	-0.15*** (0.06)	-0.05 (0.05)
	Tubewell Owners' Characteristics			
9	$EduOwner_i$	-0.04 (0.16)	-0.00 (0.04)	-0.01 (0.04)
10	$AgeOwner_i$	-0.02 (0.06)	0.01 (0.01)	0.02** (0.01)
11	Constant	27.79*** (9.86)	0.54 (2.63)	4.77*** (1.73)
12	R^2	0.39	0.46	0.46
13	F (19, 410)	17.56***	9.67***	14.92***
14	Village Effects	Yes	Yes	Yes
15	N	430	430	430
16	Model	OLS	OLS	OLS

Source: Authors' Computation

Note: Robust standard errors are in the parentheses; *** p<0.01, ** p<0.05 and * p<0.1 respectively

1.6. Concluding Observations

While a large number of studies have been constantly warning about the looming water scarcity in the state of Gujarat, an unsustainable extraction of groundwater has been widely observed due to the common-pool nature and the absence of appropriate pricing of groundwater based on marginal pricing principles (Shah et al., 2012). There is always a strong political unwillingness to enforce Pigouvian tax on negative externalities associated with water and energy, and therefore, government subsidizes the capital cost for large scale diffusion of water saving technologies like MI (Fishman et al., 2014). While the subsidy rates varied across social categories of farmers in the state, the dark-zone farmers are entitled to get additional 10% subsidy since 2012 (Bahinipati and Viswanathan, 2016). This fosters a sharp discontinuity on the probability of farmers' adoption behaviour. On the other hand, it is expected that a large scale adoption of such technologies would reduce water footprint in agriculture sector, which occupies a larger share. Although this has been widely studied at the plot-level, it is less explored at the irrigation system level. Thus, this study aimed to empirically examine the extent to which extra subsidy influenced the adoption of MI in water scarce regions and to examine the impact of MI adoption on groundwater utilization at the tubewell level. The secondary data for 8,073 villages and towns, including dark- and adjacent talukas, between 2006-07 and 2014 were collected to do the former analysis, and around 430 tubewell owners with adopted MI, were surveyed in the water scarce region for the analysis of the latter.

In order to analyze the effect of additional subsidy on diffusion of MI, the study adopted RDD approach and the empirical analysis was carried out in three samples: (i) all the villages and towns, (ii) border villages and towns, and (iii) village/ town pair-wise differences in adoption of MI. In addition to subsidy, there could be a possibility that social learning influences farmers' adoption behaviour, and hence, the lagged dependent variables were taken as one of the explanatory variables – in this case, Arellano-Bond dynamic panel model was employed. The major findings after analyzing data for the first objective are: (i) additional subsidy and social learning act as major determinants in enhancing diffusion of MI in the dark-zone regions; and (ii) social learning has made higher influence on diffusion as compared to the extra incentives. Analyzing the impact of MI adoption on water utilization, a statistically insignificant relationship was noticed, i.e., MI adoption does not necessarily reduce groundwater extraction. In contrast to widely held beliefs, our result reveals that subsidy on water conservation technologies is unlikely to diminish extraction of groundwater for irrigation purposes – this is in similar with observation by Ward and Pulido-Velazquez (2008). Likewise Fishman et al. (2016), this study outline that meter connection alone does not have significant impact on groundwater extraction. At the same time, it was found that MI adoption with metered connections reduce the extraction of groundwater to a considerable extent. This, for example, reduces the probability of increasing depth of water level and additional column pipes by 49% and 15%, respectively.

Hence, the policy suggestion emerging from the study is that the government should continue to provide additional subsidy for a large scale diffusion of micro-irrigation in the dark zone areas. In particular, with a clear focus on achieving a greater success with its ongoing process of metering of unmetered connections on a priority basis so as to make sustainable impacts to reduce the over extraction of groundwater in water scarce regions. This has also another advantage of reducing rampant power thefts in the case of un-meter connection across the state (Viswanathan, 2014). From a broader policy perspective, we suggest that it is imperative to design institutions and accounting measures in order to achieve real water saving. We also need to rethink of widely belief that irrigation efficiency alone will solve the water crisis. Instead of focusing on water application, it is important to define water rights, water use and water accounting overall in water depletion (Ward and Pulido-Velazquez, 2008). In sum, MI technologies has the advantage of enhancing irrigation efficiency and food security (see Kumar 2016a, b), however does not necessarily save water while estimated at irrigation system level.

Nevertheless, the results of this study also need to be interpreted with some caution. The first has to do with considering explanatory variables while estimating the effect of additional incentive. There is a possibility of considering various other determinants which we may have missed out in the analysis due to paucity of secondary data at the village-level. Second is to do with proxy variables undertaken to capture groundwater extraction and analysis based on a cross-section survey.

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Appendix

Appendix 1. Dark-zone and Adjacent Taluka Sample: Summary Statistics

	Full Sample	Border Village

Parameter	Sample Period	Difference (Adjacent – Dark) Mean	Difference (Adjacent – Dark) Mean
Adoption Rate of MI	2006-14	-0.006***	-0.005***
Adoption Rate of MI	2006-11	-0.0001	0.0001
Adoption Rate of MI	2012-14	-0.018***	-0.016***
Adoption Rate of Area under MI	2006-14	-0.006***	-0.004***
Adoption Rate of Area under MI	2006-11	-0.002***	-0.001***
Adoption Rate of Area under MI	2012-14	-0.014***	-0.011***

Source: Authors' computation

Note: *** p<0.01, ** p<0.05 and * p<0.1 respectively