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Title: Effects of electric pumps on farm-level agricultural production and groundwater use in West Bengal

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Abstract: How does access to less expensive energy for water lifting affect agricultural outcomes? We address this question in the setting of West Bengal in eastern India where, in 2011, the government relaxed a permit policy for small electric pumps mounted on low-yield tubewells and provided a one-time subsidy on the fixed cost of connecting the pump to the grid in order to ease access to groundwater. Based on purposefully selected primary data, and using propensity score methods, we examine the cultivated areas, yields, value-added, and duration and frequency of irrigation for monsoon and winter rice for electric pump owners compared to diesel pump owners and water buyers in West Bengal. Electric pump ownership increases agricultural outcomes and water use at the extensive and intensive margins in both seasons, suggesting that electrification may have an impact on groundwater levels.

Keywords: irrigation, electric pump, agricultural production, groundwater, propensity score matching

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Abstract: How does access to less expensive energy for water lifting affect agricultural outcomes? We address this question in the setting of West Bengal in eastern India where, in 2011, the government relaxed a permit policy for small electric pumps mounted on low-yield tubewells and provided a one-time subsidy on the fixed cost of connecting the pump to the grid in order to ease access to groundwater. Based on purposefully selected primary data, and using propensity score methods, we examine the cultivated areas, yields, value-added, and duration and frequency of irrigation for monsoon and winter rice for electric pump owners compared to diesel pump owners and water buyers in West Bengal. Electric pump ownership increases agricultural outcomes and water use at the extensive and intensive margins in both seasons, suggesting that electrification may have an impact on groundwater levels.

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1. Introduction

How does access to less expensive energy for water lifting affect agricultural outcomes? In particular, do owners of lower-variable-cost electric pumps in West Bengal cultivate their land more intensely, have higher staple-crop yields and value-added, and irrigate their land more frequently and for longer durations than owners of higher-variable-cost diesel pumps and water buyers? We examine this question in a context where (a) there are no major surface-water irrigation schemes, (b) all farmers historically needed a permit for an electric pump connection and had to pay the full fixed cost of installing the electric pump and connecting it to the grid, and (c) recent policy changes have made it easier for farmers in some areas to acquire electric connections. In 2011, the West Bengal government reduced the transaction costs of acquiring electricity connections by relaxing the permit system in administrative blocks that were considered 'safe' in terms of groundwater recharge, and by introducing a one-time subsidy of INR 8,000 on the (fixed) electric connection installation cost. Permits have never been necessary in order to use (less desirable) fossil fuel pumps, which are small devices powered either by diesel or kerosene. Diesel is not subsidized for agricultural use in West Bengal and hence is an expensive fuel; kerosene is subsidized, in theory for domestic purposes, and is therefore used as an alternative to diesel even if it reduces the life span of the pump engine. The policies introduced by the West Bengal government in 2011 provide us a natural-experiment type of opportunity to estimate the effects of access to electricity – a less expensive and more convenient energy for water lifting – on agricultural outcomes.

Prior to 2011, all farmers in West Bengal needed a permit from the State Water Investigation Directorate (SWID) for extraction of groundwater from their wells in order to apply for an electric pump connection from the West Bengal State Electricity Distribution Company Limited (WBSEDCL). The motivation for relaxing this permit system in 2011 was the observation that growth in the agricultural sector had stagnated due to a slow-down in the growth of electric pump use (Mukherji, Shah and Banerjee, 2012). West Bengal has three agricultural seasons (pre-monsoon, monsoon and winter), with the bulk of agricultural production taking place during the monsoon and winter seasons. Access to groundwater for irrigation is important for both seasons. Winter season cultivation is possible only with access to groundwater; and monsoon season cultivation is increasingly becoming dependent on supplemental irrigation due to (climate-change-induced) south-west monsoon irregularities (Nandargi and Barman, 2018). In the 1980s and 1990s, there was a steady increase in the production, areas under cultivation, and yields of winter rice (Figure 1), which coincided with an increase in the number of electrified tubewells (Figure 2). As the increase in the number of electrified tubewells stagnated in the 2000s, so did the increase in winter rice production, areas under cultivation, and yields (Figures 1 and 2). As a consequence of this, the West Bengal government relaxed constraints on accessing groundwater in an effort to induce growth in the agricultural sector.

Since 2011, farmers residing in administrative blocks identified as 'safe'[1], whose tubewells discharge less than 30 cubic meters per hour, and who intend to use small pumps (less than five horsepower), no longer need permits from the SWID to apply for electric connections to the WBSEDCL (Mukherji *et al*., 2012). Since 2012, the Department of Agriculture has also provided farmers in 'safe' blocks with a one-time fixed-cost subsidy of INR 8,000 for connecting their pumps to the grid (called the 'One Time Assistance for Electrification of Agricultural Pump-sets' (OTA-EAP)). The department does not provide subsidies for the purchase of pumps. Farmers must make these purchases themselves. In administrative areas identified as 'semi-critical' and 'critical', farmers must still acquire permits from the SWID in order to apply for electric connections for pumps, irrespective of the discharge of the tubewell or the size of the pump. Irrespective of whether the farm is in a safe, semi-critical, or critical block, the West Bengal government does not subsidize electricity (i.e. there are no variable cost subsidies), and it requires all electric pumps to be metered and practices volumetric pricing (Mukherji and Das, 2014).[2] This is a noticeable departure from the electricity subsidies provided by state governments in north and west India (Badiani et al., 2012).

Following the introduction of the policies to relax permit requirements and to provide a one-time fixed-cost subsidy, the number of electrified tubewells in West Bengal increased 68% in seven years, from 176,436 in 2011 to 296,405 in 2018. The effects of electric-pump use as opposed to diesel-pump use or water buying, however, are not well known. As such, examining whether electric-pump users' cultivated area, yields, production, value-added and water use during the two main agricultural seasons (monsoon and winter) differ from those of diesel pump owners and water buyers, can provide important information for understanding the effects of these policy changes.

Estimating the effect of electric-pump ownership on agricultural outcomes is likely to be confounded by two factors. The first is the non-random relaxation of the permit system, where the permit was relaxed in blocks where groundwater was not very 'developed' and where water levels easily recharged after the monsoons (i.e. 'safe' blocks), while the permit system continued in blocks where groundwater was already developed or where water levels did not recharge well ('semi-critical' blocks). We address this bias in our sampling strategy by selecting blocks that are just above and just below the threshold that separates 'safe' from 'semi-critical' blocks. This design controls for block-level features that may drive differences in agricultural outcomes. The second is selection into pump ownership, where farmers who historically have had better outcomes may also be more likely to have electric pumps. To address this bias, we use propensity score matching (PSM) methods to build a counterfactual group of water buyers and diesel pump owners with observable characteristics that are similar to those of electric pump owners.

Using primary data collected through a survey of 1,396 farming households, where 370 households own electric pumps, 398 own just diesel pumps and 628 are water buyers, the results indicate that for the monsoon season (*kharif*), electric-pump owners allocate more of their cultivated land to rice (*aman*), and have higher rice yields and value-added than diesel-pump owners. They also irrigate their rice plots more times in the season and for longer durations than both diesel-pump owners and water buyers. For the winter season, electric-pump owners allocate more of their cultivated land to rice (*boro*) than both diesel-pump owners and water buyers, and they irrigate their rice plots more times in the season and for more hours than water buyers. Finally, electric-pump owners have higher cropping intensities on their most irrigated plots than both diesel-pump owners and water buyers. In short, electric pump ownership affects agricultural outcomes and water use at the extensive and intensive margins in both seasons.

A limitation of this article is that it does not directly examine the effects of the groundwater and electrification policy changes on agricultural outcomes, and only indirectly provides insights on the potential effects of the pumps' electrification. This would have required a block-level analysis of all 341 administrative blocks, with panel data on agricultural production, electric prices, groundwater hydrology, and other confounding observable factors (*a la* Badiani-Magnusson and Jessoe, 2018, who perform such an analysis at the district level for all districts in India for the period 1995-2004). This was challenging to put together in West Bengal at the block level. Conducting such an analysis with the current dataset is not feasible, as the dataset only covers 24 blocks. Despite the limitations of this study, the results at the farm level reflect findings from district-level analysis carried out across India.

The paper is structured as follows. We present a conceptual framework in section 2. In section 3, we describe the data, and describe the empirical strategy in section 4. We present the results in section 5, and discuss their implications in section 6.

2. Conceptual Framework

Indian agriculture is heavily dependent on groundwater for irrigation, which is usually accessed by means of private tubewells and pumps (Mukherji, 2007; Badiani et al., 2012). Over 70 percent of Indian food grain production requires irrigation and groundwater accounts for 60 percent of the irrigated area in the country (Gandhi and Namboodiri, 2009). Many state governments in India have subsidized the cost of energy for agriculture (either diesel or electricity, or both), thus reducing barriers to accessing groundwater (Briscoe and Malik, 2006). These policies, however, are not uniform across all of India. States that have historically provided most of the energy subsidies are located in the north, south, and west (Badiani et al., 2012). States in eastern India – Assam and West Bengal – have shied away from such policies, however, and farmers there have historically tapped groundwater using either expensive unsubsidized diesel or unsubsidized electricity (Mukherji and Das, 2014). As a consequence, farmers in these states have under-utilized groundwater, and the high agricultural-production costs have adversely affected their incomes (Mukherji 2007).

In West Bengal, electricity is less expensive than diesel as an energy source for agricultural water lifting. Based on household survey data described below, while the variable cost of using a five-horsepower diesel pump was around INR 41 per hour in 2013, the cost of operating a similar five-horsepower electric pump was around INR 26 per hour during the daytime and only INR 7 per hour at night.[3] The use of electric pumps is not only less expensive but also more convenient by relaxing the need to buy diesel regularly for example. As became apparent to the West Bengal government when relatively few new electricity connections were made between 1994 and 2010 (Figure 2), the state's permit system for electricity connections imposed on farmers a substantial transaction cost on accessing a cheaper and more convenient source of energy. By relaxing the permit system and providing one-time connection subsidies in blocks where groundwater is not heavily developed and where significant post-monsoon recharge of groundwater levels occurs, the state government eased access to cheaper energy in areas that were not at risk of groundwater depletion.

Research into the effects of energy prices on agriculture has mostly focused on variable-cost-reducing subsidies on electricity tariffs and has found that these subsidies tend to increase farm value-added (Bardhan *et al*., 2014) and the amount of cultivated area allocated to water-intensive crops (Badiani and Jessoe, 2018). However, they also tend to increase groundwater use (Badiani and Jessoe, 2018; Birner *et al.* 2011; Janakarajan and Moench, 2006; Moench, 2007; Sarkar, 2011; Somanathan and Ravindranath, 2006; Balali *et al.* 2011). The benefits of an irrigation subsidy policy can be limited when social and environmental effects are accounted for, especially under climate change (Kahil *et al.* 2015).

Some recent work has examined strategies for lowering water use in agriculture. Non-price measures to encourage reductions in power and groundwater use, such as compensation to farmers for every unit of electricity they "save" from an entitlement, are politically more feasible especially in developing countries; but they may not yield reductions in either power or water use (Fishman et al., 2016). On the other hand, an increase in energy prices can affect both the extensive and intensive margins, and reduce extraction of groundwater (Pfeiffer and Lin, 2014); but are likely to be contentious in a context where small and marginal farmers dominate the agricultural sector.).

This paper contributes to the literature on agriculture and energy prices by examining the effects of lowering the transaction costs associated with accessing unsubsidized but cheaper energy on agricultural production and groundwater use. Other work on examining the effects of transaction costs has looked at the effects of imposing water quantity constraints on agricultural growth (e.g. Chaudhry and Barbier, 2013); and the effects of the public provision of groundwater on its depletion in areas with high fixed-costs of acquiring private wells (e.g. Sekhri, 2011). The effect of the 2011 and 2012 policy changes in West Bengal has been to lower the transaction costs of applying for and installing electricity connections, thus reducing the fixed-costs of installing electric pumps and easing access to a cheaper energy source for water lifting. Access to this cheaper energy increases both agricultural production and groundwater use, in line with the literature.

3. Data

The analysis is based on a sample of 1,396 farming households surveyed in six districts in West Bengal in May and June 2013. These households reside in 93 villages that are located in blocks which were purposively selected from administrative units that the Government of India categorized as 'safe' and 'semi-critical' in terms of groundwater development and recharge. As we describe below, the purpose of this sampling design is to address the endogeneity of electric pump use that is associated with the non-random differences in the fixed costs of acquiring an electric pump in these respective areas. In the resulting sample, 54% of the households reside in safe blocks, and 46% reside in semi-critical blocks. While the potential for groundwater recharge differs slightly in the chosen 'safe' and 'semi-critical' blocks, the farmers residing there all face very similar conditions in terms of access to and availability of groundwater.

Using a census of diesel and electric pump-owning households conducted for each sample village, we selected 15 households per village for the survey based on a proportional random sampling. For villages with fewer than 15 pump-owning households, we randomly selected water-buying households so that there were 15 households surveyed in each village. This procedure resulted in a sample in which 26.5% are electric pump owners, 28.5% are diesel pump owners, and 45.0% are water buyers. Although the sample is not representative of the population of rural farmers in West Bengal as a whole, the sample is large enough to provide adequate statistical power for comparisons of electric pump-owning households with other farming households.

We gathered detailed information from each household about agricultural production over the course of the previous agricultural year. The one-year recall covered three cropping seasons: the *kharif* (May-October 2012), *rabi* (November 2012 - January 2013) and summer (January-April 2013) seasons. For logistical reasons, we limited our very detailed questions about production during each cropping season to just one of the household plots. These plots were those with the easiest access to irrigation and were generally the largest plots cultivated by the household, accounting for an average of 42.2% of the total cultivated area.

In the presence of climate change, monsoons have been arriving later than usual and weather shocks (excess of rains, floods, droughts) have become more frequent in West Bengal. Yet, the cropping seasons covered by our data are not terribly out of the ordinary. While 2012 was a year with a moderate deficit in monsoon rainfalls compared to the 1971-1990 mean, 2013 was a normal year (Kothawale and Rajeevan, 2017). We, therefore, do not expect our results to be driven by mitigation strategies linked to major climatic shocks (Rosenzweig and Udry, 2019).

4. Empirical Strategy

The effect of electric pump ownership on on-farm outcomes is likely to be confounded by two factors: (1) the non-random differences in transaction costs associated with acquiring an electric pump connection in ‘safe’ and ‘semi-critical’ blocks, and (2) the non-random selection into pump ownership, where farmers who have better outcomes are also more likely to have electric pumps. We address the former with a purposeful sampling strategy, and the latter with a PSM approach.

4.1. Non-random cost differences

To address the bias associated with the non-random relaxation of the electricity-connection permit requirement and the provision of a one-time capital cost subsidy for connecting to the grid, we initially select blocks that are just above and just below the hydrological threshold that separates ‘safe’ from ‘semi-critical’ blocks, and then select households in these block for the final sample. The idea is that the hydrological conditions that affect on-farm outcomes such as cropping choices, yields, value-added, and irrigation of farming households in blocks that are just above and just below the threshold, are not very different on average. Hence, these on-farm outcomes should not differ on average due to differences in the hydrological conditions for households in these ‘safe’ and ‘semi-critical’ blocks. There is, however, a discrete difference in the transaction costs of acquiring an electricity connection for those below the threshold (i.e. in ‘safe’ blocks) compared to above the threshold (i.e. in ‘semi-critical’ blocks). This exogenous difference in cost is likely to affect electric-pump ownership but not on-farm outcomes.

The Government of India uses two criteria to categorize administrative blocks as ‘safe,’ ‘semi-critical’ and ‘critical’ in terms of groundwater potential for development: (a) the stage of groundwater development (SOD), and (b) long-term changes in pre- and post-monsoon groundwater levels. The SOD is defined as the extraction of water as a percent of the net renewable recharge. A SOD that is greater than 100%, for example, means that more water is being extracted from the stock of groundwater than is flowing in, and thus the groundwater level is likely to fall. Following guidelines developed by the Ground Water Estimation Committee (GEC, 1997), the government classifies administrative blocks according to the assignment rule illustrated in Table 1, which includes combinations of SOD and “significant long-term declines in groundwater levels” before and after the monsoons. A long-term decline is defined as groundwater levels falling by at least 20 cm per year on average over the previous 10 years. This assignment rule in Table 1 is used to categorize administrative blocks all over India and cannot be manipulated. At the time of the survey, the categorization for West Bengal was based on data collected by the State Ground Water Department and the Central Ground Water Board in 2009, which was before the policy change.

The challenge for our sampling strategy, where we select blocks that are just above and just below the threshold that separates ‘safe’ from ‘semi-critical’ blocks, is that the ‘threshold’ here depends on three indicators, not just one. This means that, for our sampling purposes, we must determine the appropriate criteria for all three indicators to define what levels are 'just' above and 'just' below. Fortunately, as illustrated in Figures 3 and 4, we can simplify the inclusion criteria to just two indicators: SOD and post-monsoon groundwater declines. Although SOD and pre-monsoon groundwater-decline levels do not cleanly distinguish 'safe' from 'semi-critical' blocks (Figure 3), SOD and post-monsoon groundwater-decline levels do. To illustrate this, note that in Figure 4, all of the blocks in West Bengal that have SOD levels above 90% and/or post-monsoon groundwater-levels that declined by more than 20 cm per year on average over the previous decade are categorized as 'semi-critical'. Conversely, all of the blocks with SOD below 90% and groundwater declines of less than 20 cm (southwest quadrant of Figure 4) are categorized as 'safe'. Based on these two criteria, the two groups are mutually exclusive. Our criteria for 'close' to the thresholds are then determined as follows. For those blocks for which the SOD is less than 90 percent, we sample blocks within 5 cm of the 20 cm post-monsoon groundwater-decline threshold (i.e. Zone 1 in Figure 4). Similarly, for those blocks for which the post-monsoon groundwater-decline is less than 20 cm per year, we sample blocks that are within 10 percentage points of the 90% SOD threshold (i.e. Zone 2 in Figure 4). From these two zones, we sample 24 blocks, 14 of which were 'safe' and 10 of which were 'semi-critical'.

4.2. Non-random selection into pump ownership

While the sampling design addresses selection bias at the block level, it does not account for selection into pump ownership at the farmer level. Even in the same block where all farmers face the same conditions vis-à-vis access to electricity, not all farmers will acquire electricity connections for irrigation. Indeed, farmers with better outcomes may also be more likely to acquire electric pumps, thus biasing our estimator for the relationship between electric-pump ownership and these outcomes if we do not account for this likelihood. To the extent that acquiring an electric pump is correlated with a set of observable farmer characteristics ($\boldsymbol{X}$) that are also correlated with the farm outcome variables of interest (Y), a comparison of the average differences in outcomes for electric-pump owners ($T = 1$; the 'treated' group) and non-electric-pump owners ($T = 0$; the 'counterfactual' group) with the same set of observable characteristics ($\boldsymbol{X}$), provides an unbiased estimator for the average treatment effect (*ATE*). Of course, it is impractical to find a sufficient number of electric-pump-owner and non-electric-pump-owner pairs with identical observable characteristics ($\boldsymbol{X}$) to be able to estimate the ATE. Fortunately, Rosenbaum and Rubin (1983) show that the matching between the two groups can be done on the basis of the probability of being 'treated' conditional on observable characteristics. In our case, this means matching electric-pump owners with non-electric-pump owners who have similar probabilities of being electric-pump owners ('treated') conditional on observable characteristics. That is, following Rosenbaum and Rubin (1983), we compare outcomes of electric-pump owners with non-electric-pump owners that have similar propensity scores (i.e. Prob($T = 1 \mid \boldsymbol{X}$)).

We estimate propensity scores using a logit model in which the dependent variable is an indicator of whether the farm has an electric connection for agriculture, and hence has an electric pump. We include three sets of observable household/farm characteristics as predictors. First, we use variables that capture the need for access to irrigation, and hence for low-variable-cost electric pumps. These include the area of land cultivated by farmers, a productive asset index constructed using principal component analysis[4], and the proportion of household members involved in agriculture. Second, we include information on the household head (age, education, religion, and caste) and on the number of household members as measures social capital that may affect the household's ability to obtain an electric connection. The third set of variables represents households' economic capacities to invest in electric pumps, including a wealth asset index constructed using principal component analysis[5] and an indicator of whether the household has any off-farm sources of income.

Important observable predictors of electric-pump ownership are not limited to household characteristics. As such, we include village characteristics such as pre- and post-monsoon groundwater depth, status as a 'semi-critical' block (vs. being a 'safe' block), and whether there exist electricity connections for domestic purposes. Finally, we include three variables that measure how close the administrative blocks are to the thresholds that differentiate 'safe' from 'semi-critical' blocks. The first is the difference between the blocks' actual SOD measured in 2009 and the 90% SOD threshold. The second and third are the difference between the 20 cm threshold in the decline in groundwater depth and the blocks' actual pre- and post-monsoon measured declines, respectively. The addition of these variables complements the sampling design and reduces placement bias at the block level.

Summary statistics for all the variables used in the analysis are presented in Table 2, and the results of the logit regression for the pooled sample (electric-pump owners, diesel-pump owners, and water buyers) appear in Table 3. These regression estimates are generally as expected. We find a statistically significant positive relationship between electric pump ownership and farmers' net cultivated area and their productive asset index. We also find that the domestic asset index is a significant and positive predictor of farmers' electricity connections for irrigation. The set of variables related to environmental and technical determinants highlights some interesting results. While the effect of pre-monsoon groundwater levels on the electric pump ownership is non-linear, taking on an inverted-U shape with a turning point at 103.4 feet, post-monsoon groundwater levels have a linear negative association. Further, the ceteris paribus positive association between residing in a semi-critical block and owning an electric pump may follow from permits for connections in those semi-critical blocks being liberally provided prior to the policy change. Finally, none of the distance from the block assignment thresholds is significant, which confirms the quasi-experimental implementation of the electrification policy in the sample selected near the cutoffs.

We use the coefficients from the logit treatment model to estimate conditional probabilities for each farmer in the sample. This 'propensity score' is the predicted probability that the individual farmer owns an electric pump conditional on the observable characteristics included as regressors in the logit model. We match the two groups using the nearest-neighbor methodology, where each treated farmer (electric-pump owner) is matched with the five counterfactual farmers (diesel-pump owners and water buyers[6]) that have the closest propensity scores that are within a 0.01 probability band from the treated farmer's propensity score. We exclude from the sample all treated and counterfactual farmers for which there are no nearest neighbors within the 0.01 probability band. From the original 1,396 observations included in the sample, we keep 1,363 of them in the analysis after matching. We also experimented with alternate matching methods (first nearest neighbor, kernel matching, radius matching) and different calipers (from 0.01 to 0.2), and present the results with the cropping intensity as outcome in Appendix Figure A.1. We note that each approach gives similar results, and we thus proceed with the five nearest-neighbors matching method.

The validity of the PSM methodology for causal inference relies on two necessary assumptions: conditional independence and common support. The conditional independence states that given a vector of observable characteristics (X) not affected by the treatment, the potential outcome Y is independent of treatment assignment T. This is akin to assuming that pump ownership (T) is exogenous. That is, it is only determined by the observable characteristics (*X*) or that the outcome (*Y*) and the treatment (*T*) are not jointly determined by unobservable characteristics. We test for conditional independence using Durbin-Wu-Hausman tests where the outcome (*Y*) is regressed on the propensity score and the residuals from the treatment model for the sub-sample selected by PSM. We present the results of these tests in Appendix Table A.1 for a selection of outcomes. We find that the significance of the residual coefficients is rejected for 8 out the 13 outcomes tested. In other words, we cannot reject conditional independence for these cases. In the three other cases in which conditional dependence is rejected, we must proceed with caution in our interpretation of the results. We also check for unobserved heterogeneity using the bounding approach proposed by Rosenbaum (2002). This indicates how sensitive the matching analysis is to hidden bias due to unobserved variables influencing both the likelihood of using an electric pump and the expected outcomes. We present Rosenbaum-bound significance levels in Appendix Table A.2. For the various outcomes considered, and with a significance level of 0.1, we find that the analysis is insensitive to biases that would increase the odds of treatment by 10% to 100%. Given that we already control for observables, this indicates that the analysis is reasonably robust to hidden bias (Abou-Ali, et al., 2010).

The common support assumption states that treated farmers have counterfactual observations with similar propensity scores. If this is not the case, then inferring causality becomes risky. Heckman, et al. (1997) suggest dropping the observations with weak common support. We present kernel density estimates of the propensity scores for the treated and counterfactual farmers in Appendix Figure A.2. The distributions confirm that there is a large overlapping support. We drop less than 1% of the observations due to weak common support.

Finally, test for balancing. Using t-test of differences, we compare the observable characteristics (*X*), outcome variables and propensity scores of the treatment and counterfactual farmers before and after the matching. We present the balancing tests in Appendix Table A.3 and find that whereas there are differences in observable characteristics in the initial unmatched sample, the differences are minimal and not significant in the matched sample. To illustrate these differences independent from the sample size (Imbens and Wooldridge, 2009), we plot the standardized percentage bias[7] before and after matching in Appendix Figure A.2. This confirms that the differences between the two groups on the matched sample are minimal.

Assuming that the assumptions of conditional independence and common support hold, we can interpret the mean difference in outcomes over the common support between the treated and the non-treated groups weighted by the propensity score for each unit as the average treatment effect (ATE)[8]. Because the standard confidence intervals computed for matching estimators are likely to be biased; in our results below, we present analytical standard errors (Abadie and Imbens, 2006; Abadie and Imbens, 2008).

In order to complement the ATE estimates and to test the robustness of these coefficients, we also present results from weighted OLS regressions. That is, we estimate the following model,

$$Y_i = \alpha + \beta T_i + \gamma X_i + \varepsilon_i \,,$$

where Y, T and X are the outcome variable, the pump-ownership variable, and control variables, respectively, as defined above. When we use OLS with weights of 1 for electric pump owners and $P(T = 1 \mid \boldsymbol{X})/(1 - P(T = 1 \mid \boldsymbol{X}))$ for the control observations, we get a consistent and fully efficient estimator for our relationship of interest, β (Hirano, Imbens and Ridder, 2003; Chen, Mu and Ravallion, 2009). We apply the weighted OLS estimator to the entire sample, not just to the sample with common support from the PSM. In doing so, we can view this as a robustness check in which we impose fewer restrictions and use more information from the observations that were excluded from the common support (Lechner, 2001).

5. Results

We present the estimated effects of electric pump ownership on cropping patterns, rice yields and value-added, and irrigation for rice production in Tables 4, 5 and 6, respectively. We estimate each model on three different samples. The first is the pooled sample of electric pump owners, diesel pump owners, and water buyers. We interpret the coefficient estimates for this sample as the average difference in outcomes (dependent variables) for electric-pump owners compared to both diesel-pump owners and water buyers conditional on the set of control variables. The second is a truncated sample that includes just electric- and diesel-pump owners (i.e. excludes water buyers). For this sample, the estimated effects can be interpreted as the conditional average differences in outcomes for electric-pump owners compared to just diesel-pump owners. Finally, the third sample includes only electric-pump owners and water buyers (i.e. excludes diesel-pump owners). For this sample, we interpret the estimated effects as the difference between conditional averages of outcomes for electric pump-owners compared to water buyers.[9]

For each outcome variable, we present two parameter estimates corresponding to the two methods that we use to estimate the impact of access to less expensive energy for water lifting on agricultural outcomes: the PSM ATE estimates and the weighted OLS estimates. In the analysis below, we interpret the ATE estimates and use the weighted OLS estimates as robustness checks. As a rule of thumb, we consider estimates to be robust when both coefficients are statistically significant.

Finally, given that we estimate effects for 11 outcomes, we cannot ignore the fact that the probability of committing Type I errors (falsely rejecting the null hypothesis) increases with the number of hypotheses tested. We, therefore, test for multiple hypotheses using the family-wise error rate (FEW; i.e. the probability of one or more false rejections) to adjust the p-values. We present p-values adjusted for multiplicity based on different methods for each model in Appendix Table A.4. The classical method developed by Bonferroni (1935) adjusts the p-values for the number of outcomes considered, while Holm (1979) proposed a slightly more powerful method by ordering the tests based on the p-value. Finally, List, et al. (2016) suggest incorporating information about the joint dependence structure of the tests for a more restrictive test. All of the statistically significant estimates that we discuss below are also statistically significant when using multiplicity adjusted p-values to determine significance.

5.1.Electric pumps and cropping patterns

Electric-pump owners use their land more intensively than both diesel-pump owners and water buyers. While the average cropping intensity (gross cropped area/net sown area) of 195.1 percent in the pooled sample (Table 2) indicates that farmers in West Bengal generally use their plots twice a year for production, electric-pump owners use their land 13.5 percentage points more than otherwise-similar diesel-pump owners, and 27.0 percentage points more than otherwise-similar water buyers (Table 4).

In addition to using their land more intensively, farmers with access to electricity for irrigation also choose to allocate more of their land to rice production, especially in the dry winter season. Electric-pump owners allocate 25.5 percentage points more of their net cultivated area to winter rice than diesel-pump owners, and 21.2 percentage points more than water buyers (Table 4). Considering that only 43 percent of the land is used to produce rice in this season (Table 2), these large differences suggest that the lack of access to less expensive energy for water lifting has hindered rice production in the winter.

Interestingly, while there is no statistically significant difference compared to water buyers in the monsoon season, electric-pump owners also allocate 13.0 percent more of their land to monsoon rice compared to diesel-pump owners (Table 4). This is a season where farmers in West Bengal allocate 73 percent of their land to rice production (Table 2), which is mainly due to the reliability of the rains. The fact that we find a difference in land allocated to rice by electric- and diesel-pump owners may follow from evidence in recent years suggesting that farmers in West Bengal tend to need additional irrigations for monsoon rice at the end of the growing period. With a less-expensive source of energy than diesel-pump owners, electric-pump owners are in a position to allocate more land to rice during the monsoon period in the presence of this uncertainty.

5.2.Electric pumps and rice yields and value-added

While there is no robust statistically significant evidence that access to electric pumps for irrigation affects rice yields and value-added in the winter season, we do find that electric-pump owners have higher rice yields and values added than otherwise-similar diesel-pump owners in the monsoon season. Monsoon season rice yields of electric-pump owners are 126.8 kg per acre greater than for diesel-pump owners, and that their values added are INR 2,045 per acre greater (Table 5). This is consistent with our discussion above about the increasing need for West Bengali farmers to irrigate at the end of the monsoon-season growing period. The greater flexibility that farmers have around irrigation when they have lower energy-cost electric pumps accords them more of the opportunity to irrigate more appropriately when the monsoon rains are less predictable than owners of diesel pumps.

The higher value-added that we observe for electric-pump owners' rice production compared to diesel-pump owners in the monsoon season may follow from a combination of yield and price effects. The higher rice yields that electric-pump owners have during this season, contributes to greater value of production per acre. Combine this with lower costs of inputs such as electric-pump-lifted water used for production (though, admittedly, more water pumped at lower cost per unit can result in higher overall cost), and it is not surprising to find higher value-added associated with access to electricity.

5.3.Electric pumps and irrigation practices

Electric-pump owners irrigate their rice plots more frequently and for longer durations than both diesel-pump owners and water buyers. Although there is evidence that this is the case in the winter season, the results are more robust for the monsoon season. We find that electric pump owners conduct 3.7 more irrigations on their monsoon rice plots on average than do otherwise-similar diesel-pump owners, and 4.6 more than otherwise-similar water buyers (Table 6). In doing so, they also irrigate their rice plots for a total of 39.1 more hours per acre than diesel-pump owners, and 27.4 more hours per acre than water buyers during the monsoon season. These differences are especially large when we consider that, during the monsoon season, the average number of irrigations on rice plots is 8.7, and the average total duration is 57.3 hours per acre (Table 2).

We also find that during the winter season, electric-pump owners conduct 7.7 more irrigations on their rice plots and irrigate for 45.8 more hours per acre compared to the pooled group of diesel-pump owners and water buyers (Table 6). These differences are not as economically significant as during the monsoon season considering that farmers conduct substantially more irrigations (34.1) for longer durations (203.0 hours/acre) during the dry winter season than during the monsoons (Table 2). Moreover, when we disaggregate the counterfactual sample, we only find a robust significant effect of electric-pump ownership on the number of irrigations for winter rice plots compared to water buyers. Electric-pump owners conduct 10.9 more irrigations on their rice plots than water buyers in the winter season (Table 6).

We must qualify these results – electric-pump owners irrigate their rice plots more frequently and for longer durations than diesel-pump owners and water buyers – with a word of caution. The implicit assumption is that these results indicate that electric-pump owners thus use more water. While this may seem likely, we cannot conclude this with great certainty. In order to do so, we would need to measure the quantities of water applied to the crops during the appropriate cropping cycles. Doing so with survey data is extremely challenging and costly, and was not possible for our survey.

6. Conclusion and discussion

In this article, we address the question of how access to less expensive energy for water lifting affects agricultural outcomes? In particular, we ask if owners of lower-variable-cost electric pumps in West Bengal cultivate their land more intensely, have higher staple-crop yields and value-added, and irrigate their land more frequently and for longer durations than owners of higher-variable-cost diesel pumps and water buyers? We examine this question in a context where (a) there are no major surface-water irrigation schemes, (b) all farmers historically needed a permit for an electric pump connection and had to pay the full fixed cost of installing the electric pump and connecting it to the grid, and (c) recent policy changes have made it easier for farmers in some areas to acquire electric connections. In 2011, the West Bengal government reduced the transaction costs of acquiring electricity connections by relaxing the permit system in administrative blocks that were considered 'safe' in terms of groundwater recharge, and by introducing a one-time subsidy of INR 8,000 on the fixed installation cost. Permits have never been necessary in order to use less desirable fossil fuel pumps, which are small devices powered either by diesel or kerosene. The policies introduced by the West Bengal government in 2011 provide us a natural-experiment type of opportunity to estimate the effects of access to electricity – a less expensive energy for water lifting – on agricultural outcomes.

Most of the research on the effects of energy prices on agriculture have focused on variable-cost-reducing subsidies on electricity tariffs. Less has been done on understanding the agricultural-production and groundwater-use effects of the transaction costs associated with accessing water with unsubsidized energy. The effect of the 2011 and 2012 policy changes in West Bengal has been to lower the transaction costs of applying for and installing electricity connections, thus reducing the fixed-costs of installing electric pumps and easing access to a cheaper energy source for water lifting. This article examines the effect of that cheaper energy source on farm-level outcomes and water use.

Estimating the effect of electric-pump ownership on agricultural outcomes is likely to be confounded by two factors. The first is the non-random relaxation of the permit system, where the permit was relaxed in blocks where groundwater was not very 'developed' and where water levels easily recharged after the monsoons (i.e. 'safe' blocks), while the permit system continued in blocks where groundwater was already developed or where water levels did not recharge well ('semi-critical' blocks). To address this bias, we purposefully sampled blocks that are just above and just below the threshold that separates ‘safe’ from ‘semi-critical’ blocks. This sampling design controls for block-level features that may drive differences in agricultural outcomes. The second is selection into pump ownership, where farmers who historically have had better outcomes may also be more likely to have electric pumps. To address this bias, we use PSM methods to build a counterfactual group of water buyers and diesel pump owners with observable characteristics that are similar to those of electric pump owners.

Using primary data collected through a survey of 1,396 farming households, the results indicate that for the monsoon season (*kharif*), electric-pump owners allocate more of their cultivated land to rice (*aman*), and have higher rice yields and value-added than diesel-pump owners. They also irrigate their rice plots more times in the season and for longer durations than both diesel-pump owners and water buyers. For the winter season, electric-pump owners allocate more of their cultivated land to rice (*boro*) than both diesel-pump owners and water buyers, and they irrigate their rice plots more times in the season and for more hours than water buyers. Finally, electric-pump owners have higher cropping intensities on their most irrigated plots than both diesel-pump owners and water buyers. In short, electric pump ownership affects agricultural outcomes and water use at the extensive and intensive margins in both seasons.

A back-of-the-envelope calculation gives a sense of the additional value-added that electric pump owners benefit from. Electric pump owners accrued an additional value-added of INR 1,273 per acre for monsoon rice, and INR 2,659 per acre for winter rice (Table 5, Panel A). With an average farm size of about 2 acres, the additional value-added in 2013 for electric pump owners was INR 7970. The subsidy of INR 8000 per farm that the government of West Bengal has provided to reduce the fixed cost of electric pump connections would be transferred to the farmer through additional benefit from agriculture production within one year. This back-of-the-envelope calculation does not take into consideration the additional income electric pump owners receive from water selling; electric pump owners received INR 12,000 more as compared to diesel pump owners from selling water to neighboring farmers in 2013. These results provide an economic rationale for subsidizing fixed costs of electric connections, as a pro-smallholder strategy in a context of financial constraint.

It should however also consider the risk of overusing irrigation and be coupled with economic and social incentives to avoid depletion of the groundwater resource.

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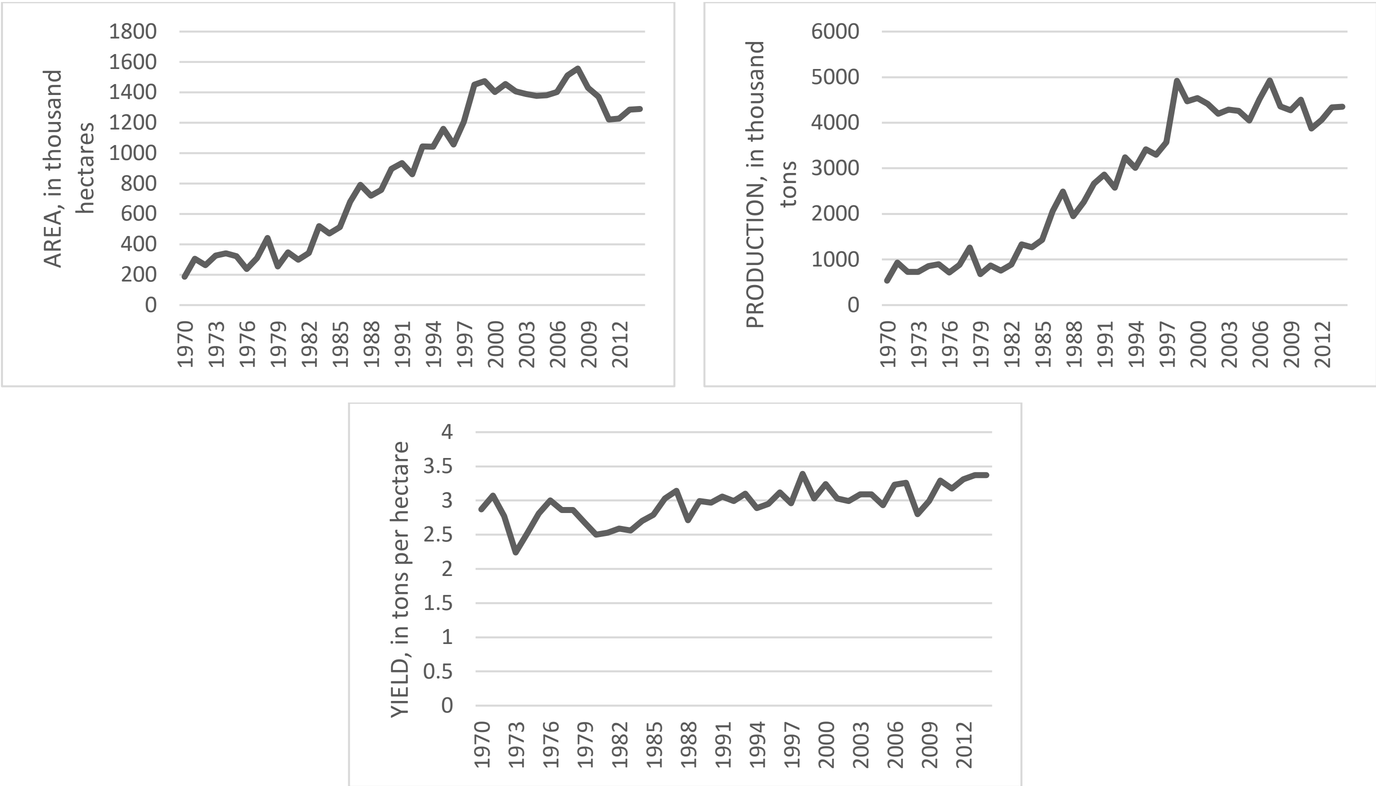


Figure 1. Area, production and yields of winter rice produced in West Bengal

Source: Own calculation from authors based on data published by the Bureau of Applied Economics and Statistics, Department of Statistics and Programme Implementation, Government of West Bengal.

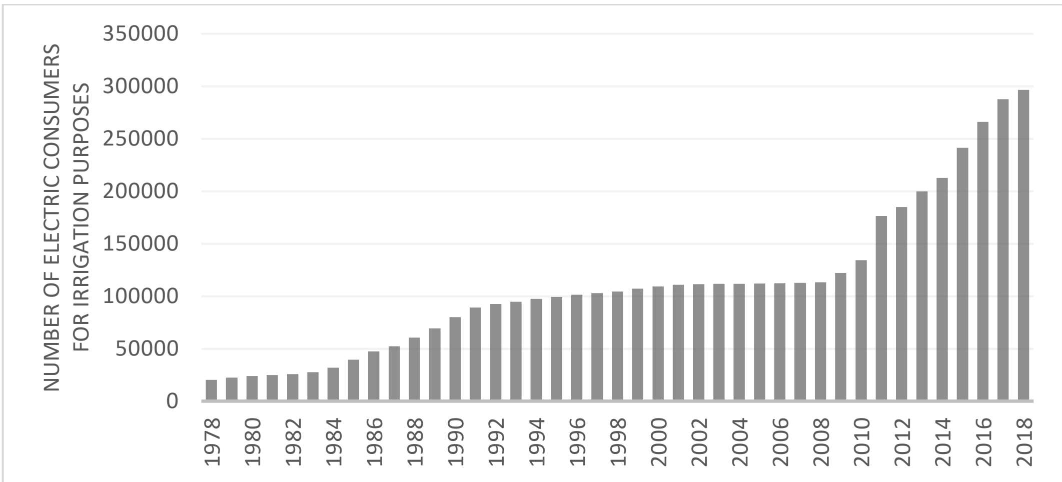


Figure 2. Number of tubewells permanently electrified in West Bengal

Source: Own calculation from authors based on WBSEDCL Annual reports

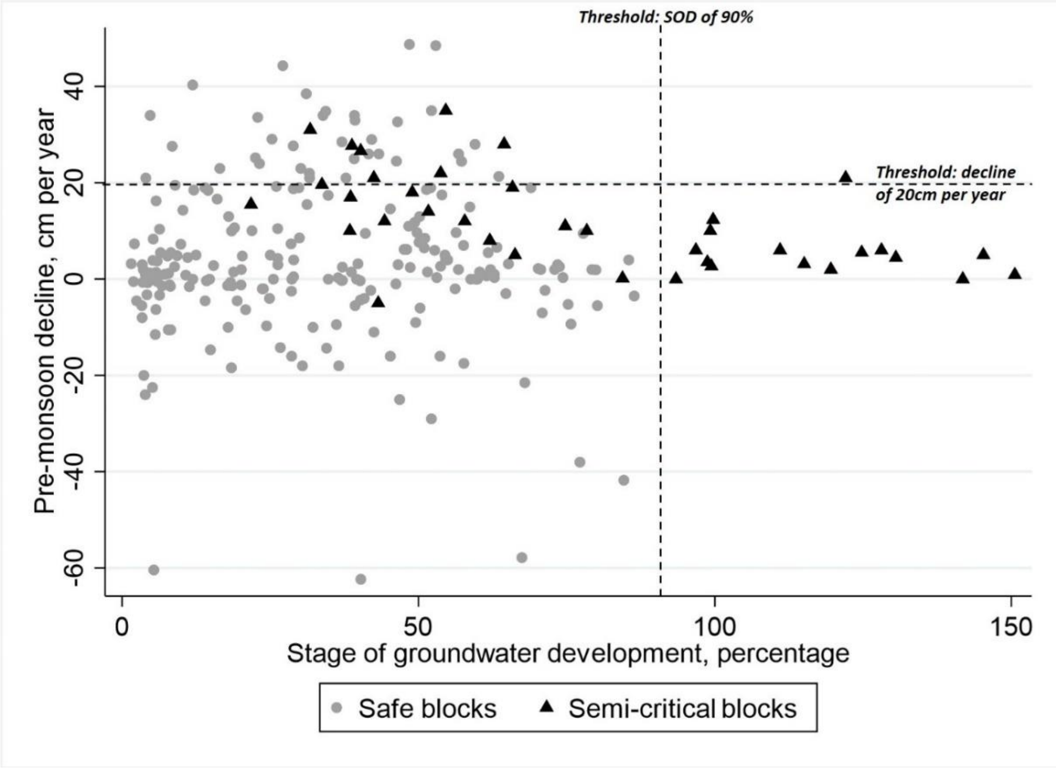


Figure 3. Stages of groundwater development and pre-monsoon groundwater decline of administrative blocks in West Bengal

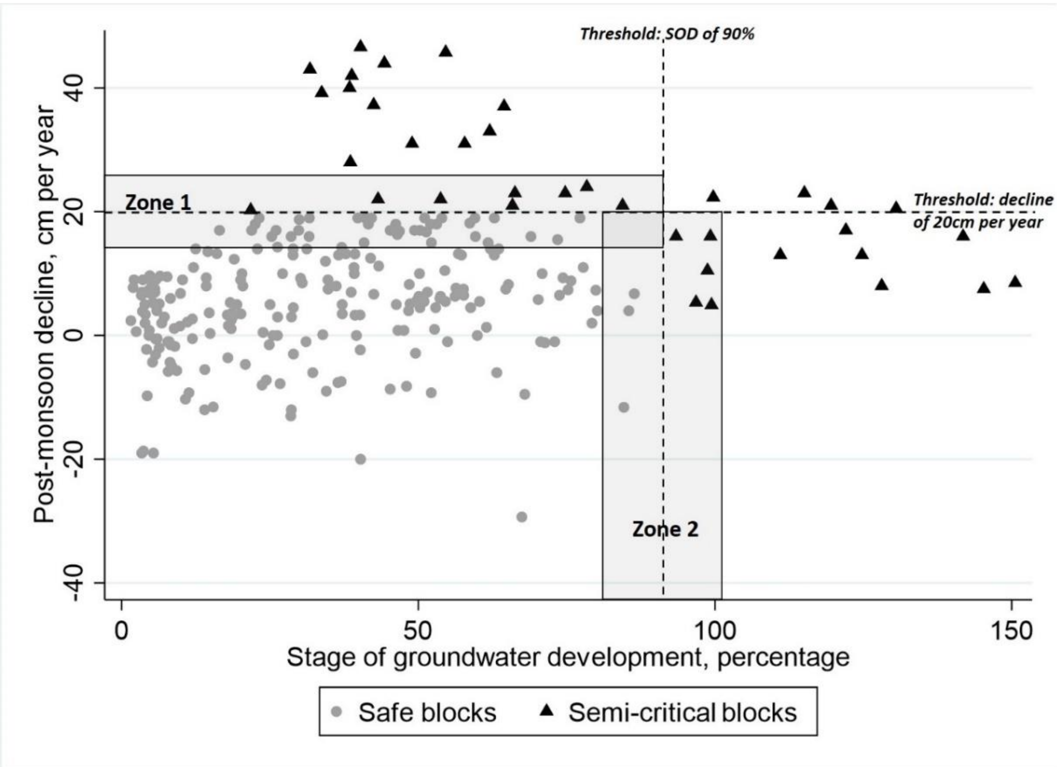


Figure 4. Stages of groundwater development and post-monsoon groundwater decline of administrative blocks in West Bengal

Table 1. Criteria Adopted for the Categorization, GEC 1997 Methodology

Stage of groundwater development	Significant long term decline of groundwater level		Categorisation
	Pre monsoon	Post monsoon	
≤ 70%	No	No	Safe
≤ 70%	Yes	No	Safe
≤ 70%	No	Yes	Semi critical
≤ 70%	Yes	Yes	Semi critical
>70% and ≤90%	No	No	Safe
>70% and ≤90%	Yes	No	Semi critical
>70% and ≤90%	No	Yes	Semi critical
>70% and ≤90%	Yes	Yes	Critical
>90% and ≤100%	No	No	Semi critical
>90% and ≤100%	Yes	No	Semi critical
>90% and ≤100%	No	Yes	Semi critical
>90% and ≤100%	Yes	Yes	Critical
>100%	No	No	Semi critical
>100%	Yes	No	Over exploited
>100%	No	Yes	Over exploited
>100%	Yes	Yes	Over exploited

Table 2. Summary Statistics

	VARIABLES	Obs	Mean	Standard deviation	Minimum	Maximum
	Electric pump owner, dummy	1,396	0.27	0.44	0	1
Need for electrification	Net cultivated area	1,396	2.0	2.4	0	20
	Productive assets index	1,396	0.00	0.73	-1.23	1.42
	Proportion of the members in agriculture	1,396	0.47	0.25	0.00	1.00
Social capital	Age head of household	1,396	53.4	11.8	17.0	95.0
	No education, *dummy*	1,396	0.01	0.08	0	1
	Primary level of education, *dummy*	1,396	0.49	0.50	0	1
	Hindu, *dummy*	1,396	0.68	0.47	0	1
	Number of household members	1,396	5.7	2.8	1	17
Economic capacity	Domestic assets index	1,396	0.00	0.86	-1.81	1.52
	Sources of income apart from agriculture, *dummy*	1,396	0.75	0.44	0	1
Environmental and technical suitability	Domestic electric connection, *dummy*	1,387	0.92	0.27	0	1
	Pre-monsoon depth of groundwater (GW)	1,396	71.7	32.0	25.0	170.0
	(Pre-monsoon depth of GW)^2	1,396	6,164.8	5630.1	625.0	28,900.0
	Post-monsoon depth of GW	1,396	47.8	21.9	10.0	100.0
	(Post-monsoon depth of GW)^2	1,396	2,763.1	2295.8	100.0	10,000.0
	Semi-critical block, *dummy*	1,396	0.46	0.50	0	1
Distance from threshold	Distance from SOD 90% cutoff	1,396	34.6	21.9	-9.7	69.4
	Distance from 20 cm GW depth threshold (pre-monsoon)	1,396	11.0	13.1	-9.0	58.0
	Distance from 20 cm GW depth threshold (post-monsoon)	1,396	1.43	5.70	-17.3	17.0
Dependent variables	Crop intensity	1,396	195.1	76.6	0.0	300.0
	Winter rice					
	Share of net cultivated area	1,396	0.43	0.44	0.0	1.00
	Yield (kg/acre)	645	1,763.4	604.3	50.5	4,848.5
	Value added (INR/acre)	644	2,992.2	12,417.1	-174,248.9	54,012.1
	Number of irrigations	649	34.1	23.1	0	99
	Duration of irrigation (hours/acre)	665	203.0	202.9	0	2,400.0
	Monsoon rice					
	Share of net cultivated area	1,396	0.73	0.40	0.00	1.00
	Yield (kg/acre)	1,093	1,418.4	494.2	30.3	4,242.4
	Value added (INR/acre)	1,092	987.4	6,414.0	-20,046.3	28,363.6
	Number of irrigations	1,074	8.7	13.2	0	90
	Duration of irrigation (hours/acre)	1,104	57.3	91.9	0	1,212.1

Table 3. Logit Model of Electric Pump Ownership (PSM)

VARIABLES			*Logit* Electric Pump owner
Need for electrification	Net cultivated area		0.136***
			(0.0389)
	Productive assets index		0.662***
			(0.126)
	Proportion of the members in agriculture		-0.364
			(0.305)
Social capital	Age head of household		-0.00447
			(0.00656)
	No education, *dummy*		0.602
			(0.865)
	Primary level of education, *dummy*		0.106
			(0.147)
	Hindu, *dummy*		-0.543**
			(0.212)
	Number of household members		-0.0221
			(0.0293)
Economic capacity	Domestic assets index		0.403***
			(0.109)
	Sources of income apart from agriculture, *dummy*		-0.291*
			(0.163)
Environmental and technical suitability	Domestic electric connection, *dummy*		0.194
			(0.328)
	Pre-monsoon depth of groundwater (GW)		0.0811***
			(0.0201)
	(Pre-monsoon depth of GW)^2		-0.000392***
			(0.000103)
	Post-monsoon depth of GW		-0.0499*
			(0.0263)
	(Post-monsoon depth of GW)^2		0.000325
			(0.000220)
	Semi-critical block, *dummy*		0.921***
			(0.216)
Distance from threshold	Distance to SOD 90% cutoff		-0.00419
			(0.00574)
	Distance to 20 cm decline in GW depth in pre-monsoon		-0.00180
			(0.00737)
	Distance to 20 cm decline in GW depth in post-monsoon		-0.00254
			(0.0164)
	Constant		-1.718**
			(0.863)
	Caste dummies	*Wald test*	3.78
		P-value	(0.436)
	District dummies	*Wald test*	31.40
		P-value	(0.000)
	Observations		1387
	Pseudo R^2		0.223

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4. Effects of Electricity Connections on Cropping Patterns

A. Sample = electric, diesel & water buyers		Crop intensity		Share of net cultivated area allocated to… Monsoon rice		Winter rice	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		17.2 ***	25.7 ***	0.077 ***	0.031 ***	0.210 ***	0.330 ***
		(5.41)	(3.3)	(0.026)	(0.013)	(0.033)	(0.018)
Common support sample	*Non treated*	1,010		1,010		1,010	
	Treated	353		353		353	
Sample size		1,363	1,387	1,363	1,387	1,363	1,387
Adjusted R^2			0.16		0.36		0.44

B. Sample = electric & diesel		Crop intensity		Share of net cultivated area allocated to… Monsoon rice		Winter rice	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		13.5 *	17.2 ***	0.130 ***	0.081 ***	0.255 ***	0.398 ***
		(8.7)	(4.8)	(0.047)	(0.019)	(0.049)	(0.024)
Common support sample	*Non treated*	384		384		384	
	Treated	307		307		307	
Sample size		691	765	691	765	691	765
Adjusted R^2			0.29		0.48		0.50

C. Sample = electric & water buyers		Crop intensity		Share of net cultivated area allocated to… Monsoon rice		Winter rice	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		27.0 ***	37.5 ***	0.012	-0.005	0.212 ***	0.336 ***
		(10.6)	(3.7)	(0.056)	(0.015)	(0.037)	(0.021)
Common support sample	*Non treated*	538		538		538	
	Treated	327		327		327	
Sample size		865	990	865	990	865	990
Adjusted R^2			0.25		0.30		0.48

Note: ATE = Average Treatment Effect, OLS = Ordinary Least Squares. Figures in parentheses are analytical standard errors for the ATE and standard errors for the weighted OLS. The entire list of control variables was included in the weighted OLS regressions but results are omitted here. *** stands for 1% of significance, ** for 5% and * for 10%.

Table 5. Effects of Electricity Connections on Rice Yields and Value-Added

A. Sample = electric, diesel & water buyers		Monsoon Rice				Winter Rice			
		Yield (kg/acre)		**Value Added (INR/acre)**		**Yield (kg/acre)**		**Value Added (INR/acre)**	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		82.4 *	61.8 **	1,273.0 **	629.1 *	179.3 **	44.4	2,659.0 **	380.4
		(55.9)	(29.7)	(622.5)	(369.4)	(101.0)	(51.7)	(1344.296)	(1,185.0)
Common support sample	*Non treated*	751		750		387		386	
	Treated	320		320		255		255	
Sample size		1,071	1,090	1,070	1,089	642	642	641	641
Adjusted R^2			0.09		0.21		0.11		0.06

B. Sample = electric & diesel		Monsoon Rice				Winter Rice			
		Yield (kg/acre)		**Value Added (INR/acre)**		**Yield (kg/acre)**		**Value Added (INR/acre)**	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		126.8 *	110.0 ***	2,045.0 **	1,515.0 ***	56.7	97.5	2,744.0 *	2,503.0
		(93.3)	(39.0)	(1004.1)	(537.5)	(312.6)	(86.2)	(2104.2)	(1,962.0)
Common support sample	*Non treated*	264		264		108		107	
	Treated	277		277		255		136	
Sample size		541	609	541	609	383	383	243	382
Adjusted R^2			0.09		0.17		0.11		0.05

C. Sample = electric & water buyers		Monsoon Rice				Winter Rice			
		Yield (kg/acre)		**Value Added (INR/acre)**		**Yield (kg/acre)**		**Value Added (INR/acre)**	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		47.9	11.0	932.4 *	183.9	143.5	-68.0	1,074.0	-1,586.0
		(78.2)	(35.3)	(650.5)	(416.0)	(154.7)	(54.3)	(1,501.1)	(1,249.0)
Common support sample	*Non treated*	481		481		209		209	
	Treated	296		296		176		176	
Sample size		717	816	717	815	385	514	385	514
Adjusted R^2			0.09		0.27		0.12		0.07

Note: ATE = Average Treatment Effect, OLS = Ordinary Least Squares. Figures in parentheses are analytical standard errors for the ATE and standard errors for the weighted OLS. The entire list of control variables was included in the weighted OLS regressions but results are omitted here. *** stands for 1% of significance, ** for 5% and * for 10%.

Table 6. Impact on Water Uses

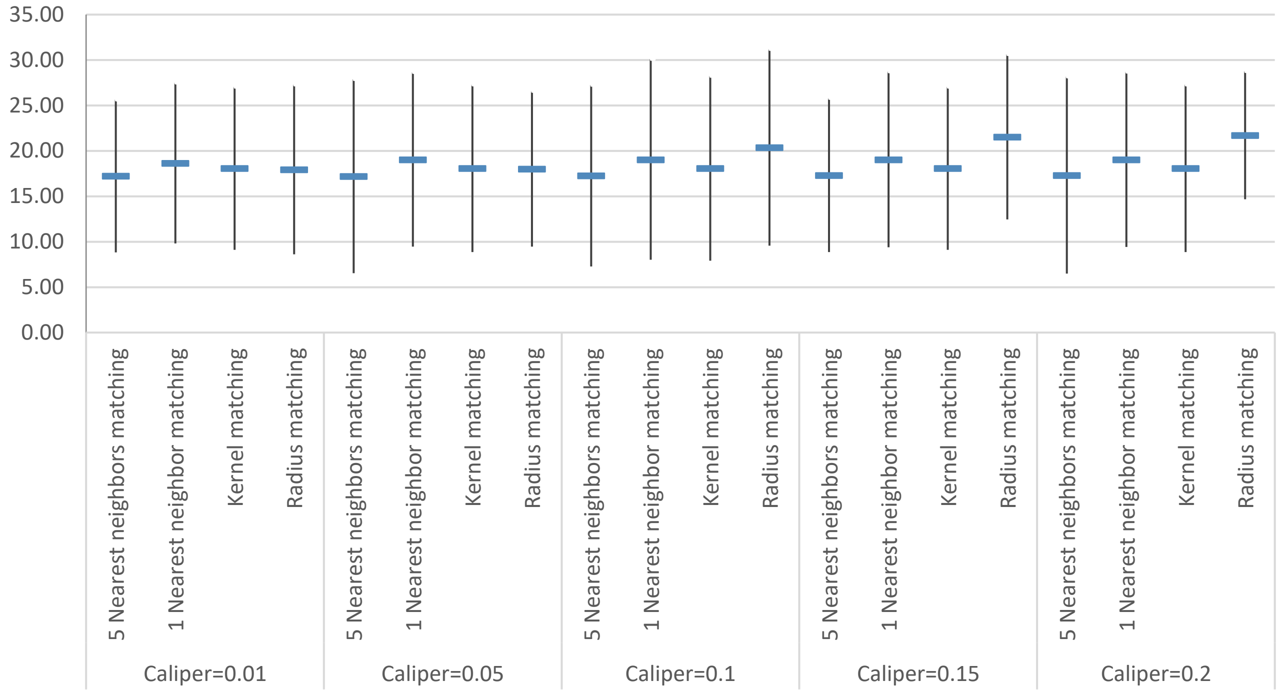
A. Sample = electric, diesel & water buyers		Monsoon Rice: Total Irrigations (number/crop)		Monsoon Rice: Hours (hours/acre/crop)		Winter Rice: Total Irrigations (number/crop)		Winter Rice: Hours (hours/acre/crop)	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		4.8 ***	3.6 ***	33.8 ***	27.9 ***	7.7 ***	9.2 ***	45.8 **	66.1 ***
		(1.5)	(0.8)	(10.8)	(5.3)	(3.4)	(1.9)	(23.5)	(17.5)
Common support sample	*Non treated*	734		760		364		377	
	Treated	319		322		223		228	
Sample size		1,053	1,070	1,082	1,101	587	646	605	662
Adjusted R^2			0.48		0.44		0.76		0.52

B. Sample = electric & diesel		Monsoon Rice: Total Irrigations (number/crop)		Monsoon Rice: Hours (hours/acre/crop)		Winter Rice: Total Irrigations (number/crop)		Winter Rice: Hours (hours/acre/crop)	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		3.7 **	2.4 **	39.1 ***	28.5 ***	-1.2	2.8	45.4	43.1
		(2.1)	(1.2)	(14.02)	(7.2)	(8.6)	(3.2)	(40.4)	(31.7)
Common support sample	*Non treated*	248		278		108		112	
	Treated	269		337		142		148	
Sample size		517	602	615	615	250	389	260	397
Adjusted R^2			0.49		0.48		0.79		0.51

C. Sample = electric & water buyers		Monsoon Rice: Total Irrigations (number/crop)		Monsoon Rice: Hours (hours/acre/crop)		Winter Rice: Total Irrigations (number/crop)		Winter Rice: Hours (hours/acre/crop)	
		ATE	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*	*ATE*	*Weighted OLS*
Electric pump owner		4.6 ***	4.7 ***	27.4 **	19.9 ***	10.9 ***	11.1 ***	41.1 *	31.2
		(1.2)	(0.9)	(10.5)	(6.4)	(3.5)	(2.0)	(28.6)	(19.1)
Common support sample	*Non treated*	409		426		209		214	
	Treated	288		298		180		183	
Sample size		697	803	724	823	389	520	397	529
Adjusted R^2			0.47		0.41		0.77		0.56

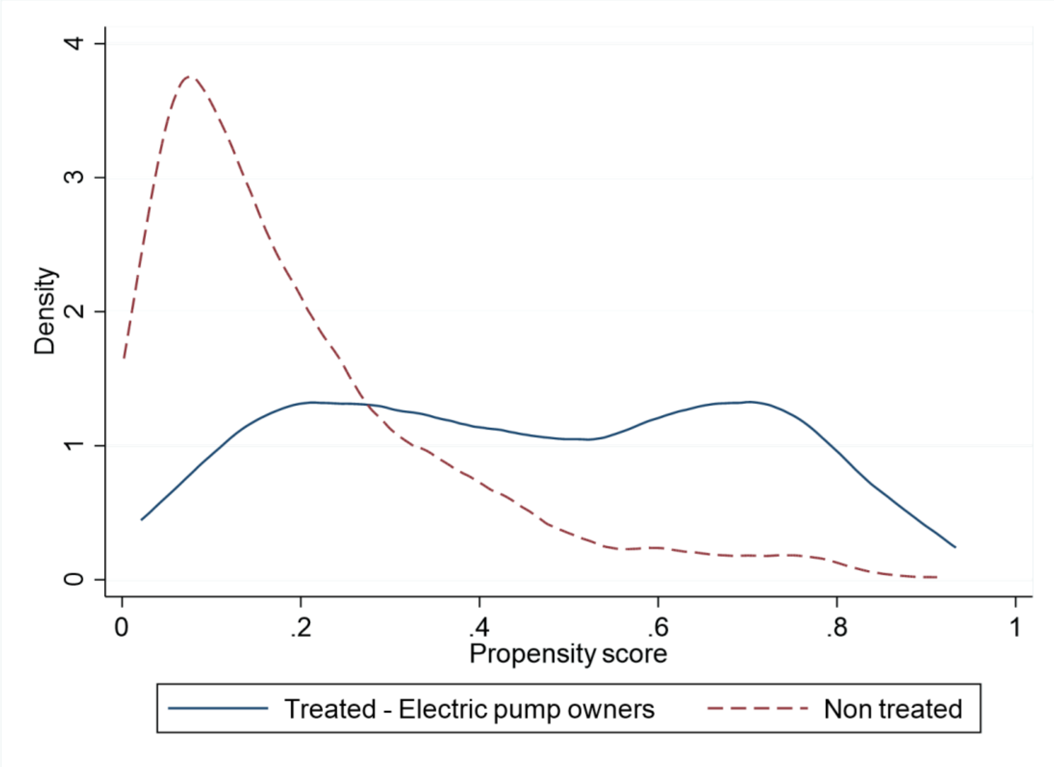
Note: ATE = Average Treatment Effect, OLS = Ordinary Least Squares. Figures in parentheses are analytical standard errors for the ATE and standard errors for the weighted OLS. The entire list of control variables was included in the weighted OLS regressions but results are omitted here. *** stands for 1% of significance, ** for 5% and * for 10%.

Appendix Figure A.1. Sensitivity analysis - Propensity score matching method and caliper

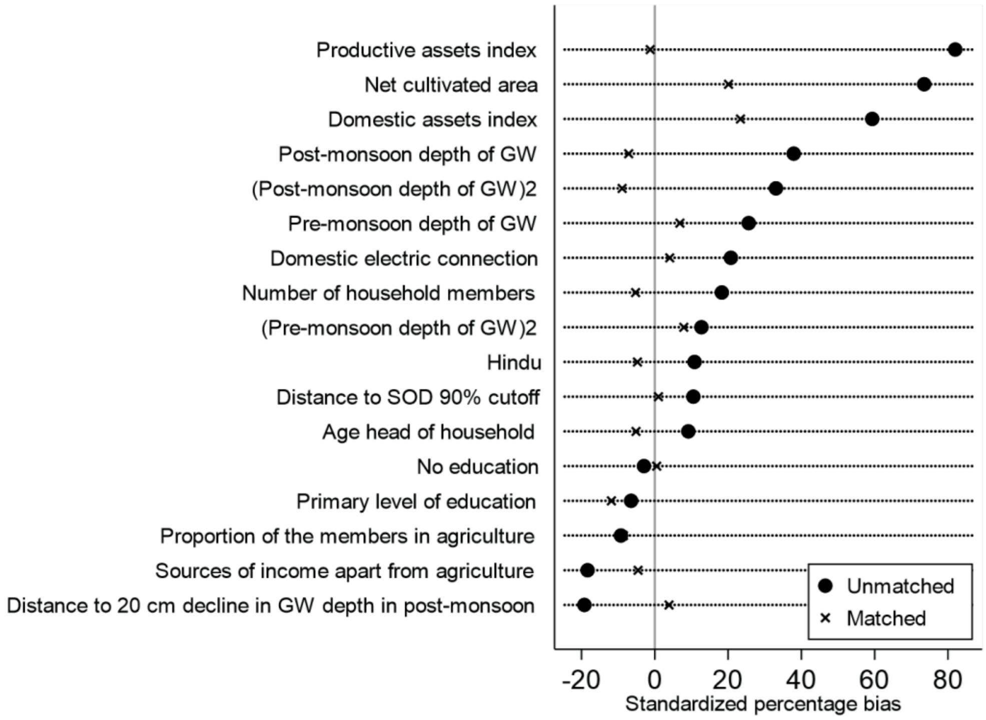


Note: The blue segments are the values of the estimated ATE by the different matching methods and the vertical lines are the 95% confidence intervals.

Appendix Figure A.2. Kernel distributions of propensity scores, common support



Appendix Figure A.3. Standardized percentage bias across covariates



Appendix Table A.1. Hausman-Wu-Rubin test, conditional inference

VARIABLES	(1) Crop intensity	(2) Share of net cultivated area - monsoon rice	(3) Share of net cultivated area - winter rice	(4) Yield (kg/acre) - winter rice	(5) Value added (INR/acre) - winter rice	(6) Yield (kg/acre) - monsoon rice	(7) Value added (INR/acre) - monsoon rice	(8) Number of irrigations - winter rice	(9) Number of irrigations - monsoon rice
Propensity score	17.93	0.477***	0.414***	-178.4	3,402	363.3***	6,130***	-42.69*	-7.310
	(11.12)	(0.0552)	(0.0675)	(128.3)	(2,855)	(82.13)	(1,037)	(22.70)	(7.541)
Residuals from logit regression	-28.71	-0.229*	-0.600***	-161.7	3,673	91.65	6,080**	-25.41	8.526
	(25.29)	(0.126)	(0.154)	(295.8)	(6,564)	(192.4)	(2,429)	(52.86)	(17.64)
Constant	203.8***	0.702***	0.573***	1,887***	708.7	1,277***	-3,103***	124.1***	23.19***
	(11.21)	(0.0557)	(0.0681)	(133.2)	(2,958)	(85.04)	(1,073)	(23.74)	(7.789)
Observations	910	910	910	468	467	749	749	477	754
R-squared	0.005	0.090	0.069	0.004	0.003	0.026	0.047	0.007	0.002

Note: Figures in parentheses are standard errors. *** stands for 1% of significance, ** for 5% and * for 10%.

Appendix Table A.2. Rosenbaum bounds

Gamma	Crop intensity	Share of net cultivated area - monsoon rice	Share of net cultivated area - winter rice	Yield (kg/acre) - winter rice	Value added (INR/acre) - winter rice	Yield (kg/acre) - monsoon rice	Value added (INR/acre) - monsoon rice	Number of irrigations - winter rice	Duration of irrigation (hours/acre) - winter rice	Number of irrigations - monsoon rice	Duration of irrigation (hours/acre) - monsoon rice
1.0	0.0000	0.0035	0.0000	0.0307	0.0512	0.0021	0.0048	0.0011	0.0164	0.0863	0.0009
1.1	0.0000	0.0247	0.0000	**0.1035**	**0.1520**	0.0170	0.0318	0.0073	0.0650	**0.2652**	0.0082
1.2	0.0000	0.0966	0.0000	0.2395	0.3167	0.0732	**0.1176**	0.0295	**0.1712**	0.5173	0.0418
1.3	0.0000	**0.2441**	0.0000	0.4208	0.5116	**0.2002**	0.2828	0.0836	0.3329	0.7455	**0.1318**
1.4	0.0001	0.4479	0.0000	0.6065	0.6905	0.3913	0.4968	**0.1806**	0.5186	0.8911	0.2902
1.5	0.0008	0.6526	0.0000	0.7606	0.8249	0.5986	0.6983	0.3161	0.6888	0.9614	0.4892
1.6	0.0040	0.8111	0.0000	0.8684	0.9105	0.7709	0.8446	0.4711	0.8185	0.9884	0.6788
1.7	0.0141	0.9104	0.0000	0.9339	0.9581	0.8858	0.9303	0.6213	0.9037	0.9969	0.8229
1.8	0.0390	0.9624	0.0000	0.9693	0.9819	0.9497	0.9724	0.7481	0.9530	0.9993	0.9136
1.9	0.0877	0.9858	0.0000	0.9867	0.9927	0.9802	0.9902	0.8436	0.9787	0.9999	0.9622
2.0	**0.1662**	0.9951	0.0000	0.9946	0.9972	0.9929	0.9969	0.9088	0.9909	1.0000	0.9850

Note: Upper bounds significance level are presented for different levels of gamma.

Appendix Table A.3. Balancing tests, before and after matching

VARIABLES			Means		t-test of difference	
			Treated	Control	t-stat	p-value
	Propensity score	Unmatched	0.455	0.197	22.06	0.000
		Matched	0.437	0.437	0.00	1.000
Need for electrification	Net cultivated area (acres)	Unmatched	3.4	1.5	13.39	0.000
		Matched	3.1	3.4	-1.32	0.187
	Productive assets index	Unmatched	0.414	-0.145	13.32	0.000
		Matched	0.388	0.372	0.31	0.757
	Proportion of the members in agriculture	Unmatched	0.452	0.475	-1.51	0.132
		Matched	0.456	0.462	-0.38	0.707
Social capital	Age head of household (years)	Unmatched	54.2	53.1	1.48	0.138
		Matched	54.2	54.0	0.28	0.782
	No education, *dummy*	Unmatched	0.005	0.008	-0.47	0.639
		Matched	0.006	0.008	-0.41	0.679
	Primary level of education, *dummy*	Unmatched	0.470	0.502	-1.06	0.288
		Matched	0.476	0.422	1.45	0.148
	Hindu, *dummy*	Unmatched	0.717	0.667	1.77	0.078
		Matched	0.714	0.681	0.94	0.349
	Number of household members	Unmatched	6.1	5.6	3.08	0.002
		Matched	6.0	6.0	-0.07	0.945
Economic capacity	Domestic assets index	Unmatched	0.355	-0.121	9.41	0.000
		Matched	0.331	0.403	-1.27	0.204
	Sources of income apart from agriculture, *dummy*	Unmatched	0.685	0.766	-3.09	0.002
		Matched	0.697	0.674	0.64	0.521
Environmental and technical suitability	Domestic electric connection, *dummy*	Unmatched	0.959	0.908	3.16	0.002
		Matched	0.960	0.968	-0.57	0.571
	Pre-monsoon depth of ground water (GW)	Unmatched	77.5	69.8	3.98	0.000
		Matched	77.4	77.2	0.09	0.930
	(Pre-monsoon depth of GW)^2	Unmatched	6,687.1	6,008.6	1.98	0.048
		Matched	6,688.9	6,790.2	-0.28	0.780
	Post-monsoon depth of GW	Unmatched	53.8	45.7	6.14	0.000
		Matched	53.4	50.9	1.64	0.102
	(Post-monsoon depth of GW)^2	Unmatched	3,318.8	2,577.1	5.36	0.000
		Matched	3,277.3	3,001.4	1.72	0.085
	Semi-critical block, *dummy*	Unmatched	0.595	0.409	6.21	0.000
		Matched	0.586	0.508	2.09	0.037
Distance to threshold	Distance from SOD 90% cutoff	Unmatched	36.4	34.2	1.67	0.095
		Matched	36.2	36.3	-0.02	0.980
	Distance from 20 cm decline in GW depth (pre-monsoon)	Unmatched	12.1	10.7	1.83	0.067
		Matched	12.0	12.3	-0.35	0.724
	Distance from 20 cm decline in GW depth (post-monsoon)	Unmatched	0.7	1.7	-3.05	0.002
		Matched	0.7	1.4	-1.54	0.124

Appendix Table A.4. Multiple hypothesis testing

Subgroup	Difference in means between treated and control	P-values			
		Unadjusted	Multiplicity adjusted		
			List, Shaikh, Xu	Bonferroni	Holm
Crop intensity	24.8	0.0003***	0.0003***	0.0036***	0.0023***
Winter rice					
Share of net cultivated area	0.339	0.0003***	0.0003***	0.0036***	0.0016***
Yield (kg/acre)	82.0	0.1003	0.1866	1.0000	0.2006
Value added (INR/acre)	2,845.5	0.0133	0.036**	0.1466	0.0400**
Number of irrigations	9.5	0.0003***	0.0003***	0.0036***	0.0026***
Duration of irrigation (hours/acre)	20.9	0.2136	0.2136	1.0000	0.2136
Monsoon rice					
Share of net cultivated area	0.176	0.0003***	0.0003***	0.0036***	0.0036***
Yield (kg/acre)	135.2	0.0003***	0.0003***	0.0036***	0.002***
Value added (INR/acre)	2,027.4	0.0003***	0.0003***	0.0036***	0.003***
Number of irrigations	4.7	0.0003***	0.0003***	0.0036***	0.0033***
Duration of irrigation (hours/acre)	21.3	0.0076***	0.0283**	0.0843*	0.0306**

Note: *** stands for 1% of significance, ** for 5% and * for 10%.

[1] 'Safe" blocks are those where groundwater has not been heavily developed and where groundwater levels recharge significantly post-monsoon. See Table 1 for thresholds used to categorize blocks.

[2] Prior to 2011, West Bengal charged a flat tariff for electricity. This was changed to metering and volumetric pricing by 2011. This change reduced the number of pumping hours in the winter season, but did not influence either the cropping patterns or the yields of the winter rice crop (Meenakshi *et al*., 2013).

[3] In West Bengal, the West Bengal State Electricity Department Corporation Limited (WBSED) applies three different tariffs over 24 hours for agricultural connections. Nights rates are much lower and are supposed to incentive farmers to irrigate during the nights to balance the power consumption.

[4] The productive assets in this index include ploughs, power tillers/tractors, spay machine, husking machine, treadle pump, manual pumps, bullocks, cows, calves, buffalos, goats, sheep, chickens, ducks, and geese.

[5] The wealth assets in this index include beds, chairs, tables, sofas, cupboards, wooden or steel boxes, radios, televisions, sewing machines, stoves, mobile phones, bicycles, motorcycles, solar panels, batteries, and water storage tanks.

[6] We describe the PSM procedure here for the full sample. We also conducted the analysis separately for two subsamples in which (1) electric-pump owners are the treated farmers and diesel-pump owners are the counterfactual farmers, and (2) electric-pump owners are the treated farmers and water buyers are the counterfactual farmers.

[7] The standardised percentage bias is the difference of the sample means in the treated and control sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (Rosenbaum and Rubin, 1985).

[8] The treatment is here defined as the ownership of an electric pump. In theory, Average Treatment Effect on Treated (ATT) could be calculated by considering the use or not of the electric pump by electric pump owners; however, only 1.08% of the owners did not use their pumps during the growing seasons for which the data was collected.

[9] We conduct propensity score matching separately for the separate sub-samples (electric- and diesel-pump owners, and electric-pump owners and water buyers). Results of the logit prediction models and tests of conditional independence, common support, and balancing for these sub-samples are similar to those for the pooled sample and are available from the authors upon request.