**Evaluating the Impacts of Micro-Watershed Development Project on Agriculture in Bardhhaman, West Bengal**

**Abstract**

Watershed development forms an integral part of developing rain fed agriculture in India. Despite significant resources being spent on watershed development, studies on evaluation of impacts are by and large qualitative and mostly unstructured. The present paper addresses the issue of evaluation of impacts of watershed development projects using well structured survey and methodology that reduces dependence on modelling assumptions for controlling of potential confounders. The study finds that while moderate improvements have been achieved in terms of improvement in farm income, financial constraints can adversely impact intensive utilisation of soil and water resources as well diversification into other cropping activities.

**Keywords**: Watershed, Impact Evaluation, Matching, Coarsened Exact Matching (CEM), Estimands, SATT.

*Introduction*

Watershed development has been the mainstay of development programmes for rain fed and dry land agriculture by central as well as various state governments for quite some time now. Watershed is typically a catchment area from where the water flows to a particular drainage system such as a river, ranging from a few hectares to several thousands of hectares of surface area. Watershed development refers to “conservation, regeneration, and the judicious use of human and natural (like land, water, plants, animals) resources within a particular watershed” (NABARD, 2006)**.**  As the boundaries of a single watershed do not align with those of the administrative boundaries, for the purpose of treatment, it is divided into several smaller micro-watersheds to make them overlap as much as possible with the administrative boundaries. This makes the task of managing the development programme much easier as it facilitates resolving of conflict of interests among various groups much easier as well as faster and more efficient means of developing the watershed segments independent of one another. Development of micro-watersheds has been instrumental in raising agricultural productivity and employment opportunities in the rain fed and dry regions of the country, where resource degradation is a serious problem (Kerr et al. 2002, Hope 2007). In fact, the report on agriculture prepared for the 11th Five Year Plan published by the Planning Commission of India has underscored the need to raise the expenditure for accelerating the development of rain fed areas through treatment of watersheds.

Since 1970s, there has been heavy investment by the central government as well as various state governments in watershed development (Joshi et al., 2005). Given the focus of the state agencies on using watershed development as an important tool in accelerating development of rain fed regions of the country, it becomes essential to assess the impact as well as the distribution of such impacts among the targeted population (Hope, 2007).

 Estimation of different agricultural impacts of watershed development requires measurement of well defined indicators such as cropping intensity, crop diversity, net returns as well as revenue generated from cultivation activities, input usage such as fertilizers, pesticides, water, machinery and labour and others measured in terms of costs of cultivation etc. To assess the impact properly, it is necessary to measure the above mentioned indicators both in the presence as well in the absence of the treatment by collecting data from both the treated and control micro-watersheds within the same macro watershed. Though the literature on watershed impact assessment in India is quite large, most of them are qualitative in nature and also suffer from the drawbacks of lack of structure for study as well as data availability for both the treated as well as control villages and households (Kerr et al., 2000). According to the author’s knowledge, two papers that have attempted to analyse the impact of watershed development using well established quantitative techniques are Kerr et al., 2002 and Hope, 2007. Kerr et al., 2002 uses an instrumental variable model to determine the factors responsible for selection of the villages under different watershed development programs in Maharashtra and Andhra Pradesh. The paper then used the predicted values of participation of villages under different projects in other regressions to determine the factors for outcomes based on different indicators such as net returns to cultivation in the programme villages, extent of erosion in the drainage lines, investments in land improvement etc. However, almost all the indicators as well the treatment status are analysed at the village level. Hope (2007) used household data from both the treated as well as the control micro-watersheds in Madhya Pradesh and matched the treated households with the control ones using propensity scores calculated from the predicted probabilities. The predicted probabilities were obtained from the logistic regression for estimating the probabilities of access to land and threshold time taken to collect drinking water regressed on several socio-economic variables. After matching the treatment with control households on estimated propensity scores, impact of watershed development on farm income in the Rabi and Kharif seasons and time taken to collect drinking water were estimated. Though these papers have facilitated the understanding of the impacts of watershed development to a significant extent, they did not capture effects on other outcomes such as costs of cultivation, total revenue, cropping intensity and crop diversity that are very important from the view point of the planners who implement these projects and also indicate the intensity of resource use as well as diversification of crop portfolio important in reducing weather induced shocks. These studies also suffer from the drawbacks of dependence on modelling assumptions being made for the analysis of the raw data when the true model through which the data have been generated is unknown (Ho et al. 2007). The present study attempts to address all these issues. The following sections discuss in brief about the study area, information gathered through open ended discussions with the project officers, members of the villages watershed committee as well as select villagers about the impacts of the project at the village level followed by information on data collected for the study and the methodology to analyse the same. The remaining sections discuss the results of the analysis concluding finally with policy implications.

 *Brief Description of the Study Area*

The area of study, Bhalki Gram Panchayat, is located in Ausgram-II block of Burdwan district, predominantly a backward area with semi-arid climatic conditions and red lateritic sandy soils. The average annual rainfall is around 1200 mm most of which is received during the monsoons (personal communication with block officials, 2011-12). Around two-thirds of the total population in the area belong to the backward classes. The project village, Bhalki as well as the control villages are located on the upper parts of the drainage basin of Ajay-Kunnur river system, tributaries of the Damodar river, at a distance of 45 kilometres from Burdwan, 25 kilometres from Durgapur and 20 kilometres from Bolpur. Watershed development measures have been undertaken in the village utilising the funds from NABARD’s micro-watershed development programme. The area is a bit undulated with slope less than 3 per cent. Most of the farm households are marginal land holders, with many of them working as share croppers. The project village lies on the boundary of the forested lands locally known as *Jungle Mahal*, covering around a third of the total village area. Before the commencement of the micro-watershed development project, agricultural activity in the treatment village was limited to the rainy season only. Mainly, paddy was grown having low productivity.

*Project Development*

In early 2001, some villagers along with the local block development officer (BDO) came forward to organise the inhabitants of the villages into different SHGs to undertake micro-watershed development programme. Through meetings, awareness was generated by the change agents among the inhabitants about the importance of soil and water conservation measures and the benefits that can be shared by them. People were convinced about the arguments put forth; many of them joined as members of self help groups (SHGs). During the pre-project phase, saplings of *arjun*, *akashmoni*, *sonajhuri*, *shirish*, bamboo were planted on the wastelands covering around 100 hectares. Excavation of reservoirs and ponds along with renovation of existing ones were also undertaken. The work was done basically by the members of the SHGs, many of whom were women from the backward communities. The tempo of work was such that that within a few weeks of commencement, tall and hard bushes covering vast swathes of wastelands were broken up for tree plantation. The members worked very hard right from morning till late evening with a short lunch interval. NABARD officials, impressed with the progress of work released around Rs 270000 for payment towards the completion of job in confidence build-up phase. However, the members of the SHGs did not accept the money and instead demanded it to be used for setting up a mobile microfinance institution under the auspices of the watershed committee. It was created to cater basically to the working capital needs of the small farmers. In all, NABARD sanctioned Rs 5.5 million for watershed development.

During the final implementation phase of the project, more conservation structures as well as income generating avenues were created. As the slope of the land in Bhalki is less than 3 per cent, focus was laid much on the excavation of large reservoirs and inter-connected system of ponds, laid out in a way such that when the drainage lines are carrying excess run-off, a lateral outlet would force the water inside these ponds. Apart from these, other conservation structures such as contour trenches and contour bunds were also created in the afforested areas. To prevent erosion of bunds, trees such as Burma teak, sal, *shirish*, *arjun*, guava were planted that also provided long term assets based source of income to the members of SHGs that maintain these structures. Pisciculture has been promoted in the area; training has been provided to members of different self help groups. Currently, three to four large ponds that have been excavated under watershed development are being utilised for pisciculture. Orchards of mango, cashew, guava, and jackfruit covering several hectares of land have also been developed. One of these orchards, developed on an abandoned garbage dump was nurtured carefully with pitcher-based irrigation, plant by plant. In these orchards, during the gestation period, vegetables and sunflower are being grown for sustaining the SHG members looking after them. Beside these, social afforestation and nursery development has also been taken up on a massive scale.

*Impact of Micro-Watershed Development on the Villagers*

Micro-watershed development programme has brought tremendous changes in the lives of the households in Bhalki. The social forestry project has created a huge asset base to the tune of at least Rs 25-30 million for the SHG members. In the first phase of tree-clearing, 10 SHGs have earned Rs 4 million from sale of trees. Previously, owners of lands in the upper parts did not bother about using their lands for any productive use. Success of afforestation project has encouraged them to seek saplings from the nurseries run by the SHGs for planting by themselves.

Development and renovation of water bodies for water storage as well percolation into the ground as well as conserving of soil moisture have brought a huge change in the agricultural potential in the area. Though Bhalki is a backward area, it is located close to Burdwan, Durgapur and Bolpur which apart from being administrative centres are also important centres of trade, commerce and industry. Relatively easy access to these nearby wholesale markets have ensured good price discovery for the farmers, raising their income levels substantially. Development of fisheries, providing means of livelihood to around 20 families have also benefitted from easy market accessibility with annual turnover of Rs 1.5-2 millions from each pond. The orchards are being looked after properly. They are expected to yield on a commercial basis within the next two years.

Due to sandy soil, the rate of percolation from the water bodies is quite high leading to drying up within 2-3 months after the withdrawal of monsoons. It has however, resulted in steep rise in the level of the water table from 300 feet to 100-120 feet on an average.

Though the farmers of Bhalki have been able to exploit the local markets for their produce quite successfully, expansion of that opportunity to regions such as Kolkata and beyond still remains to be achieved. There have been attempts on behalf of the watershed committee to contact the big retail chains in Kolkata and Durgapur to market their produce but in vain as these chains procure things through brokers only.

*Data*

For the purpose of present study, a census was conducted of all the farm households in the treatment and the contiguous nine control villages during November-December after the end of Kharif season and during April towards the end of Rabi season. The census has information on 226 households from the treatment village and 439 households from the control villages, thereby totalling 665 respondents. Information was collected on socio-economic variables such as caste, religion, education status of the household members, employment patterns, area under cultivation, access to credit, participation in NREGA and common farm household assets. Agricultural information collected included those on the crops cultivated in Kharif and Rabi seasons, yield, marketing information, costs under different input heads including seeds, fertilizers, pesticides, traction, irrigation and different categories of labour required for cultivation on a crop-by-crop basis.

*Methodology*

For estimating the effect of treatment we assume that it is ignorable conditioned on observed confounders and that every treated unit receives the same treatment. A fixed causal effect is a function of potential outcome defined as:

$$Y\_{i}\left(1\right)- Y\_{i}(0)$$

which is the difference in the potential outcomes under treatment and control for unit i that are not necessarily observed (Ho et al. 2007). To estimate the causal effect due to treatment, we require for the treated unit under question, the value of the potential outcome both under the treatment as well under control status for evaluation. But an individual can only be in either of these two groups at the same point of time. So for every unit under study one of these potential outcomes will always be unobserved known as the fundamental problem of causal inference (Holland 1986).

For the purpose of estimation of causal effect for the treated, commonly used matching methods estimates the counterfactual corresponding to each observed treated unit i with the outcome of a control unit k that is close to i on observed vector of confounders X thereby reducing the covariate imbalance and making the treatment assignment and potential confounding variables independent. (Iacus et al., 2011)

 In conventional observational studies, quantitative assessment of impacts of treatment effect usually requires modelling assumptions and specifications. However, there is no well established method to deduce the correct functional form (Ho et al., 2007). The reasoning is equally applicable for matching methods that use estimated propensity score as a matching variable whereby the true propensity score generating model is unknown and hence there is no benchmark against which to compare the estimated models.

To reduce the dependence of the estimands of interest on modelling assumptions and empirical specifications and hence to obtain less biased and more reliable estimates, the present study first pre-processes the raw census data through reduction in imbalance in covariates among the treated and control units by balancing of the empirical distribution of the covariates defined by the following metric:

$L\_{1 }\left(f, g;H\right)= \frac{1 }{2}$ $\sum\_{l\_{1,l\_{2,………….l\_{k}ε H(X)}}}^{}|f\_{l\_{1,l\_{2…………l\_{k}}}}- g\_{l\_{1l\_{2…..l\_{k}}}}| $ (King et al., 2011, Iacus et al., 2011)

where

*L1*= multivariate imbalance measure

$H(X)= \prod\_{i=1}^{k}H(X\_{i})$, multidimensional histogram constructed from the set of cells generated by the Cartesian product of H (Xi) s that are the sets of intervals into which the supports of the variables Xi s have been cut or coarsened (the length of which is less than or equal to the range of the values for Xi,) . This is the maximum level of imbalance set ex ante for matching.

*f* and *g* are the empirical frequency distributions for the treated and control units respectively and $f\_{l\_{1,l;\_{2……l\_{k}}}} $and $g\_{l\_{1,l\_{2…….l\_{k}}}}$are the relative frequency for observations belonging to the cells with coordinates *l1,l2,................lk.*

Compared to other matching methods, the method above not only reduces imbalance in means of the covariates between and treated and control units but also imbalances in higher moments of the empirical distributions and other non-linearities and interactions due to better overlapping (Iacus et al., 2011). The remaining imbalances within the matched strata in the values between the matched treated and control units are then controlled through parametric modelling with reduced model dependence.

This method is known as coarsened exact matching (CEM) method as it coarsens the values of covariates into different well defined intervals based on substantive knowledge of the problem, for better overlapping between the treated and control groups. It satisfies the monotonic imbalance bounding principle as discussed in Iacus et al., 2011 whereby the level of imbalance chosen ex ante for one variable will not alter the maximum level of imbalance chosen for the other variables thus reducing the uncertainty regarding the level of imbalance on other variables. It meets congruence principle between the data and analysis spaces.

Coarsened exact matching also eliminates the pre-matching requirement of many matching methods of restricting the data set to the common empirical support for both the treated and control groups as the observations within a coarsened stratum containing a treated unit and a control unit no extrapolation beyond the data is involved. It is also invariant to measurement error for the variables provided the maximum error is less than or equal to the maximum width of the coarsened intervals for the particular variable and respects the resulting strata boundaries. By choosing the level of imbalance ex ante the researcher bounds the degree of model dependence as well as estimation error for the treatment effect (Iacus et al., 2011, King et al., 2011).

*Estimands of Interest*

The estimands for causal effects on indicators of interest to be estimated are net income, revenue and costs of cultivation all measured in terms of per unit of land which is bigha (40 decimals of land area), cropping intensity measured as ratio of gross cropped to net cropped area as well diversity in cropping in different seasons is defined as

$\{1-\sum\_{i=1}^{n}(^{C\_{it}}/\_{\sum\_{}^{}C\_{it}})^{2}\}$

 where Cit= area under crop i in season t.

The estimands for the causal effects on indicators can be defined as:

$$SATT= \frac{1}{n\_{T}} \sum\_{i εT}^{}TE\_{i}$$

where TEi = Yi (1) – Ŷi (0) |Xi

 nT = number of treated units

 The above estimand is applicable only when all the treated units are matched. As in our case when all treated units are not matched then SATT changes to LSATT or local sample average treatment for the treated and the estimands consequently changes to:

$$LSATT= \frac{1}{m\_{T}} \sum\_{i εT^{m}}^{}TE\_{i}$$

where mT = number of matched treated units

Tm = set of matched treated units

For the unmatched treated units we extrapolate via some model estimands on the matched units to obtain virtual control units and obtain an estimate of the estimands. The overall SATT is then calculated as the weighted average of the two estimates for matched and unmatched treated units (Iacus et al., 2011)

*Results*

*Summary Statistics of Raw Data*

Tables 1 and 2 shows the summary statistics for interval scale and categorical variables for the treated and control villages respectively. On an average, the number of household members engaged in agriculture varies from a little over 2 in case of control villages to a little over 2.5 in case of treated villages. Household members engaged in education have average highest education of 5.89 years in treated villages to 7.42 years in control villages. Average highest experience of household members currently engaged in agriculture varies very little among the treated and control villages, being around 28 years. Farm households on an average cultivate 5.70 bighas and 6.53 bighas of land in treated and control villages respectively and hence are mostly marginal farmers as per land size classification. In terms of formal sources of credit, lower proportion of farm households in treated village have access compared to those of control villages. Also, greater proportion of households belongs to backward classes in treated village than in control villages.

*Matching Results*

For the purpose of our analysis, we first try to reduce the imbalance in the values of six covariates: land, farm hands per household, experience of the oldest farm hand, highest educated farm hand access to formal source of credit and membership in backward community between treated and control groups. Table 3 shows the initial level of multivariate imbalance for the overall raw data and for the individual covariates.

For a starting point of reference, the matching algorithm automatically coarsens the values covariates to match the treated and the control units. Table 4 shows the results of automated matching method. There are now 98 treated units matched to 113 control units with a reduction in measure of post matching multivariate imbalance of 0.642 compared to 0.872 for the original data. The region of common support for covariates between matched treated and control units is 23.3% of the data space compared to just 7.3% for the original data.

In order to get more number of matched treated as well as control units, we now coarsen the *Highest Education* variable by grouping values into different categories as per classification of different levels of education: uneducated(0), primary (1-4), middle high school (5-8), high school (9-12) and university (13 and above). We next coarsen the *Area Cultivated* variable by first grouping the values as per farmer type-land size classification: a) Marginal (>0<=6.25), b) Small (>6.25<=12.50), c) Medium (>12.5<=25) and d) Medium -Large (>25<=62.5) and then in intervals of 6.25 bighas each from 2 bighas to 25 bighas and the last interval of 25.01 bighas to 50 bighas. We then carry two different matching exercises using the CEM algorithm with same level of coarsening for *Highest Education* variable but two different levels of coarsening for *Area Cultivated* variable thereby yielding different levels of multivariate imbalance as well as number of matched treated and control units. Tables 5 and 6 respectively show the outcomes of the different matching exercises

In Table 5 corresponding to a multivariate imbalance measure of 0.699 post matching, we obtain 164 control and 125 treated units whereas in Table 6, for a multivariate imbalance measure of 0.583, we obtain 106 treated and 119 control units. While in the Table 5, the region of common support for the covariates between matched treated and control units is 19.2% of the data space, it 25.4% in Table 6.

From Table5 and Table 6 it is clear that the level of imbalance as measured by difference in means of values of the covariates between matched treated and control units within the matched strata for *Highest Education* as well as *Area Cultivated* is several times lower than that fixed ex ante. In fact the level of imbalance post matching has improved in case of *Area Cultivated* variable under the user chosen coarsening levels compared to that of automated coarsening where the level of coarsening is much less.

In case of *Highest Education* variable the level of imbalance is lesser in the case where multivariate imbalance measure is 0.699 compared to the case of automated coarsening induced multivariate imbalance measure of 0.642; it is however larger in case where multivariate imbalance measure is 0.583. But the imbalance achieved is much lower than that set ex ante. The logic applies equally to other matched covariates that are automatically coarsened (stratum intervals are not shown).

*Estimation of Treatment Effects*

We now use the matched data obtained from different matching exercises with different levels of coarsening of covariates to arrive at the estimates of local sample average treatment effect(SATT) for the treated that utilises only the matched subsamples and global sample average treatment effect for the treated by including the unmatched treated units in the analysis. We estimate both homogeneous as well as non-homogeneous treatment effects i.e. random effects within the matched strata, using linear and linear random effects models respectively for quantities of interest as explained in section above. Tables 7-12 shows the estimates of different treatment effects for unit net returns, unit sales, unit cost, cropping intensity, crop diversity during Kharif and crop diversity during Rabi seasons respectively. Apart from the matched data set *Automated* where the covariate values have been automatically coarsened with a post matching multivariate imbalance measure of 0.642, we have two other matched data sets *Match I* with a post matching imbalance measure of 0.583 and *Match II* with a post matching imbalance measure of 0.699.

From Table 7 containing the local SATT estimates on Unit Net Returns, under the assumption constant treatment effect across matched strata, it ranges from Rs. 757.96 in *Automated* to Rs. 1179.66 in *Match I* to Rs. 918.14 in *Match II*. The global estimates for the respective data sets are Rs. 1148.22, Rs. 1323.34 and Rs. 1309.83. Relaxing the implicit constant treatment effect assumption of regression approach, un-weighted random effects models are estimated within each stratum and then results are averaged across stratum with appropriate weights to arrive at the non-homogenous local SATT effects which stand at Rs. 733.44 for *Automated*, Rs. 1110.10 for *Match I* and Rs. 887.65 for *Match II*. In case of global SATT, the estimates for the respective data sets are Rs. 1528.33, Rs. 1544.13, Rs. 1535.52. From the estimates it can be clearly seen that for both linear and linear random effects model, the difference between the local and global SATT estimates varies across the matched data sets with different numbers of matched treated units and post matching imbalance measures and region of common support. From the differences it is clear that the discrepancies are the lowest in case of *Match I* for both the models.

From Table 8 containing the local SATT estimates on Unit Sales, under the assumption constant treatment effect across matched strata, it ranges from Rs. 2122.00 in *Automated* to Rs. 2256.78 in *Match I* to Rs2294.36 in *Match II*. The global estimates for the respective data sets are Rs. 2238.40, Rs. 2372.32 and Rs. 2626.66. Corresponding non-homogenous local SATT effects are Rs. 2152.24 for *Automated*, Rs. 2256.78 for *Match I* and Rs. 2294.36 for *Match II*. For global SATT, the estimates for the respective data sets are Rs. 2773.67, Rs. 2760.94, and Rs. 2775.08. From the estimates it can be clearly seen that for both linear and linear random effects model, the difference between the local and global SATT estimates varies across the matched data sets with different numbers of matched treated units and post matching imbalance measures and region of common support, though much lesser than in case of Unit Net Returns. From the differences it is clear that the discrepancies are the lowest in case of *Match I* for linear model and *Match II* in case of linear random effects model. While *Match II* has the highest level of post matching level of imbalance and lowest region of common support, it has the lowest level of imbalance for the *Area Cultivated* amongst all the three data sets, indicating sensitivity of linear random effects model to level of imbalance in *Area Cultivated* which is quite plausible given the indicator of interest in question as well as the nature of estimation strategy for random effects.

From Table 9 containing the local SATT estimates on Unit Cost, under the assumption of constant treatment effect across matched strata, it ranges from Rs. 1364.24 in *Automated* to Rs. 1308.25 in *Match I* to Rs. 1529.24 in *Match II*. The global estimates for the respective data sets are Rs. 1090.18, Rs. 1048.98 and Rs. 1316.83. Corresponding non-homogenous local SATT effects are Rs. 1362.73 for *Automated*, Rs. 1283.75 for *Match I* and Rs. 1462.23 for *Match II*. For global SATT, the estimates for the respective data sets are Rs. 1206.05, Rs. 1185.64, and Rs. 1193.92. In this case, the global SATT is less than the local SATT for all the matched data sets across different modelling assumptions. Again, it can be clearly seen that for both linear and linear random effects model, the difference between the local and global SATT estimates varies across the matched data sets with different numbers of matched treated units and post matching imbalance measures and region of common support. From the differences it is clear that the discrepancies are the lowest in case of *Match II* for linear model and *Automated* in case of linear random effects model. The variation in difference between local and global SATT across modelling assumptions for the same data set clearly shows the sensitivity of modelling assumptions to imbalance in covariates between treated and control groups.

From Table 10 for Cropping Intensity, under the assumption of constant treatment effect across matched strata, local SATT are 1.61% in *Automated* to 2.26% in *Match I* to -0.12% in *Match II*. The global estimates for the respective data sets are -0.26%, -0.14% and -0.74%. Corresponding non-homogenous local SATT effects are 0.29% for *Automated*, 0.94% for *Match I* -1.58% for *Match II*. For global SATT, the estimates for the respective data sets are -3.66%, -4.11, and -3.77%. In most of the cases for estimation of treatment effect on cropping intensity we find that the effect changes in sign from positive to negative when one moves from local to global SATT except in case of *Match II* for both the models. This clearly shows that extrapolating the results far from the region of common support not only leads to more discrepancy in estimates it also makes them less robust especially in this case when the effect to be measured has to be very precise in terms of difference. For the effect on Crop Diversity for the Kharif season as displayed in Table 11, there is minute increase in diversity ranging from 0.04 to 0.06 under constant treatment effect assumption across strata and 0.06 under non-homogeneous treatment effect assumption in case of local SATT. For global SATT, it is 0.06 for both the treatment effects. Unlike other indicators, the variation in estimates for crop diversity in Kharif are almost absent across modelling assumptions and data sets showing insensitivity to data imbalance.

Finally as shown in Table 12, for crop diversity in rabi season while it is negative for global SATT for all the treatment effect assumptions and data sets, in case of local SATT it is positive for *Automated* and *Match I* and negative for *Match II* under constant treatment effect assumption, it is positive for *Automated* and negative for *Match I* and *Match II* under non-constant treatment effects assumption. Again similar to that for cropping intensity, there is a change of sign from positive to negative for *Automated* and *Match I* under constant treatment effect assumption and for *Automated* under non-constant treatment assumption.

*Discussion*

The present study on impact assessment of micro-watershed project has shown that dependence on modelling assumptions for estimating the impacts of treatment from imbalanced observational data can adversely affect the informing of the process of policy making. Varying levels of multivariate as well as univariate imbalance among the treated and control units will have varying degrees of discrepancy in estimated effects across different modelling assumptions. Hence reliance on or sticking to a specific modelling assumption can bias decision making which is a matter of serious concern when the question of allocation of scarce resources to different types of development projects is involved.

While moderate improvements have been accomplished in terms of economic parameters such as unit net returns to cultivation, unit sales for the farm households in the treated micro-watershed, improvements in terms of ecologically as sustainability wise critical agronomic parameters have been marginal at the best. While there has been a significant but small increase in cropping diversity during the Kharif season in the treated micro-watershed, over the control ones, there has been deterioration for the same during the Rabi season. In case of cropping diversity, while the local SATT estimates show small but positive changes for all but one data set across different types of treatment effect assumptions, they all turn out to be negative for global SATT. Even accounting for model dependent nature of global SATT estimates, this is indeed a matter of concern for the planner as increase in crop diversity and cropping intensity are desirable mission objectives. Why this is happening is not clear from the cross-sectional data collected per se but an attempt can always be made for an intuitive explanation based on the circumstances that prevailed in the area during the period of study as well as the pre-existing economic conditions. Though not reported here, treatment effect on unit cost for the Kharif season shows that there has been a substantial increase in expenditure in treated area over that of control areas that fully accounts for overall increase in expenditure for the treated households in the entire season. As paddy is grown mainly during the Kharif season in these areas, this change in terms of expenditure can be interpreted as the intention of the households in the treated areas to concentrate their resources on paddy cultivation that requires much less of attention compared to other crops such as vegetables and also less susceptible to pests and diseases. Since paddy has got a wider market than those of other crops in these areas and as the soil moisture has increased due to watershed treatment in these areas, for a given level of expenditure, the yield will be more. During the season under study, the wholesale market for paddy have been down due to bumper harvest as well as large inventory accumulated from preceding two seasons During the first round of survey, when the rabi season was about to commence, farmers were unable to sell their harvest. After government intervention, they were able to sell their produce to the farmers’ cooperatives but the payment was delayed by few months. Combining this fact with the increased expenditure made by the treated households than those of non-treated ones may have discouraged the farmers in the treated areas to undertake expenditure for Rabi cultivation. Discussions with the farmers from the treated areas somewhat point towards this. This is indeed a matter of concern as inability to diversify as well as intensifying the cropping activities due to financial constraints can prove to be more costly from risk and vulnerability point of view that can altogether undermine the very basis behind the undertaking of implementation such resource conservation measures.

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*Appendix*

Table 1: Summary Statistics for Interval Variables

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *Variable* | *Unit of Measurement* | *Treatment Status* | *Number of Observations* | *Mean Value* |
| *Farm Hands* | No. of Household Members  | *Treated* | 226 | 2.52(1.40) |
| *Control* | 439 | 2.15(1.35) |
| *Highest Educated Farm Hand* | Years of Education | *Treated* | 226 | 5.89(4.65) |
| *Control* | 439 | 7.42(4.56) |
| *Experience of Oldest Farm Hand* | Years of Farming Experience | *Treated* | 226 | 27.88(14.36) |
| *Control* | 439 | 27.92(14.12) |
| *Land*  | Area Cultivated by Farm Household | *Treated* | 226 | 5.70(6.24) |
| *Control* | 439 | 6.53(6.68) |

Figures in parentheses denote standard deviation

Table 2: Summary Statistics for categorical variables

|  |  |  |  |
| --- | --- | --- | --- |
| *Variable* | *Treatment Status* | *No. of Observations* | *Proportion of Households* |
| *Access to Formal Credit* | *Treated* | 226 | 18.58 |
| *Control* | 439 | 24.37 |
| *Belonging to Backward Class* | *Treated* | 226 | 80.97 |
| *Control* | 439 | 69.70 |

Table 3: Measures of Imbalance for Initial Raw Data

|  |
| --- |
| Multivariate Imbalance Measure: L1=0.872 |
| Percentage of local common support: LCS=7.3% |
| Univariate Imbalance Measures: |
| Variable | **Statistic** | **Type** | **L1** | **Min** | **25%** | **50%** | **75%** | **Max** |
| *Farm Hands* | -0.3696353 | *(diff)* | 0.1582035 | 1 | 0 | 0 | 0 | 1 |
| *Highest Education* | 1.5230512 | *(diff)* | 0.1369968 | 0 | 5 | 1 | 1 | 2 |
| *Farm Experience* | 0.0351866 | *(diff)* | 0.0255408 | 1 | 3 | 0 | -2 | -7 |
| *Area Cultivated* | 0.8261934 | *(diff)* | 0.1049247 | 0 | 0 | 0.5 | 1 | -9 |
| *Formal Credit* | 0.0578951 | *(diff)* | 0.0578951 | 0 | 0 | 0 | 0 | 0 |
| *Backward* | -0.1126958 | *(diff)* | 0.1126958 | 0 | -1 | 0 | 0 | 0 |

Table 4: Matching Results for Automated Coarsening of Covariates

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
| **Treatment** | **Control** |
| All | 226 | 439 |
| Matched | 98 | 113 |
| Unmatched | 128 | 326 |
|  |  |  |
| Multivariate Imbalance Measure: L1=0.642 |
| Percentage of local common support: LCS=23.3% |
| Univariate Imbalance Measures: |
| Variable | **Statistic** | **Type** | **L1** | **Min** | **25%** | **50%** | **75%** | **Max** |
| *Farm Hands* | 0.00E+00 | *(diff)* | 4.86E-17 | 0 | 0 | 0 | 0 | 0 |
| *Highest Education* | -2.89E-02 | *(diff)* | 1.02E-02 | 0 | 0 | 0 | 0 | 0 |
| *Farm Experience* | 4.91E-01 | *(diff)* | 1.02E-02 | 0 | 0 | 0 | 0 | 5 |
| *Area Cultivated* | 3.11E-01 | *(diff)* | 6.46E-02 | 0 | 1 | 0.5 | 0 | 0 |
| *Formal Credit* | 0.00E+00 | *(diff)* | 5.90E-17 | 0 | 0 | 0 | 0 | 0 |
| *Backward* | -1.11E-16 | *(diff)* | 6.94E-17 | 0 | 0 | 0 | 0 | 0 |

Table 5: Matching Results for User Defined Coarsening

|  |  |  |  |
| --- | --- | --- | --- |
|  | Treated | Control |  |
| All | 226 | 439 |
| Matched | 125 | 164 |
| Unmatched | 101 | 275 |
|  |
| Multivariate Imbalance Measure: L1=0.699 |
| Percentage of local common support: LCS=19.2% |
| Univariate Imbalance Measures: |
| Variable | **Statistic** | **Type** | **L1** | **Min** | **25%** | **50%** | **75%** | **Max** |
| *Farm Hands* | 4.44E-16 | *(diff)* | 0.00E+00 | 0 | 0 | 0 | 0 | 0 |
| *Highest Education* | -2.55E-02 | *(diff)* | 2.78E-17 | 0 | 0 | 1 | 0 | 0 |
| *Farm Experience* | 1.54E-01 | *(diff)* | 1.33E-02 | 0 | 1 | 0 | 0 | 5 |
| *Area Cultivated* | -9.85E-02 | *(diff)* | 4.92E-02 | 0 | 0.5 | 0 | -1.25 | 8 |
| *Formal Credit* | 1.39E-17 | *(diff)* | 0.00E+00 | 0 | 0 | 0 | 0 | 0 |
| *Backward* | 1.11E-16 | *(diff)* | 1.39E-17 | 0 | 0 | 0 | 0 | 0 |

Table 6: Matching Results for User Defined Coarsening

|  |  |  |  |
| --- | --- | --- | --- |
|  | Treated | Control |  |
| All | 226 | 439 |
| Matched | 106 | 119 |
| Unmatched | 120 | 320 |
|  |
| Multivariate Imbalance Measure: L1=0.583 |
| Percentage of local common support: LCS=25.4% |
| Univariate Imbalance Measures: |
| Variable | **Statistic** | **Type** | **L1** | **Min** | **25%** | **50%** | **75%** | **Max** |
| *Farm Hands* | 0 | (diff) | 3.82E-17 | 0 | 0 | 0 | 0 | 0 |
| *Highest Education* | -0.0861635 | (diff) | 8.50E-17 | 0 | 0 | 0 | 0 | 0 |
| *Farm Experience* | 0.4356469 | (diff) | 1.89E-02 | 0 | 2 | 0 | 0 | 5  |
| *Area Cultivated* | -0.0223158 | (diff) | 3.99E-02 | 0 | 0.5 | 0 | -0.5 | 8 |
| *Formal Credit* | 0 | (diff) | 6.25E-17 | 0 | 0 | 0 | 0 | 0 |
| *Backward* | 0 | (diff) | 6.94E-17 | 0 | 0 | 0 | 0 | 0 |

Table 7: Estimates of Impact on Unit Net Returns

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Matching Method | Multivariate Imbalance Measure | SATT | Effect | Point Estimate | p-value | Confidence Interval |
| Unit Net Returns | Automated | 0.642 | Local | Homogeneous | 757.96 | 0.32 | [-762.18, 2278.10] |
| Non-Homogeneous | 733.44 | 0.00 | [296.14, 1170.74] |
| Global | Homogeneous | 1148.22 | 0.05 | [225.28, 2071.17] |
| Non-Homogeneous | 1528.33 | 0.00 | [1442.70, 1614.08] |
| Match I | 0.583 | Local | Homogeneous | 1179.66 | 0.06 | [-19.23, 2378.55] |
| Non-Homogeneous | 1110.10 | 0.00 | [872.62, 1347.58] |
| Global | Homogeneous | 1323.34 | 0.03 | [467.34, 2179.33] |
| Non-Homogeneous | 1544.13 | 0.00 | [1467.11, 1621.15] |
| Match II | 0.699 | Local | Homogeneous | 918.14 | 0.07 | [-80.44, 1916.71] |
| Non-Homogeneous | 887.65 | 0.00 | [675.50, 1099.80] |
| Global | Homogeneous | 1309.83 | 0.06 | [477.59, 2142.07] |
| Non-Homogeneous | 1535.52 | 0.00 | [1441.40, 1629.63] |

Table 8: Estimates of Impact on Unit Sales

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Matching Method | Multivariate Imbalance Measure | SATT | Effect | Point Estimate | p-value | Confidence Interval |
| Unit Sales | Automated | 0.642 | Local | Homogeneous | 2122.20 | 0.01 | [470.66, 3773.75] |
| Non-Homogeneous | 2152.24 | 0.00 | [1733.22, 2571.26] |
| Global | Homogeneous | 2238.40 | 0.00 | [1246.24, 3230.56] |
| Non-Homogeneous | 2773.67 | 0.00 | [2679.47, 2867.87] |
| Match I | 0.583 | Local | Homogeneous | 2487.91 | 0.00 | [1154.65, 3821.17] |
| Non-Homogeneous | 2256.78 | 0.00 | [2032.99, 2480.56] |
| Global | Homogeneous | 2372.32 | 0.00 | [1445.25, 3299.40] |
| Non-Homogeneous | 2760.94 | 0.00 | [2679.33, 2842.54] |
| Match II | 0.699 | Local | Homogeneous | 2447.38 | 0.00 | [1337.72, 3557.05] |
| Non-Homogeneous | 2294.36 | 0.00 | [2102.89, 2485.83] |
| Global | Homogeneous | 2626.66 | 0.00 | [1720.12, 3533.20] |
| Non-Homogeneous | 2775.08 | 0.00 | [2675.23, 2875.93] |

Table 9: Estimates of Impact on Unit Cost

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Matching Method | Multivariate Imbalance Measure | SATT | Effect | Point Estimate | p-value | Confidence Interval |
| Unit Cost | Automated | 0.642 | Local | Homogeneous | 1364.24 | 0.00 | [430.60, 2297.89] |
| Non-Homogeneous | 1362.73 | 0.00 | [1169.60, 1555.86] |
| Global | Homogeneous | 1090.18 | 0.00 | [567.28, 1613.08] |
| Non-Homogeneous | 1206.05 | 0.00 | [1155.53, 1256.56] |
| Match I | 0.583 | Local | Homogeneous | 1308.25 | 0.00 | [471.87, 2144.63] |
| Non-Homogeneous | 1283.75 | 0.00 | [ 1153.43, 1414.06] |
| Global | Homogeneous | 1048.98 | 0.00 | [524.13, 1573.84] |
| Non-Homogeneous | 1185.64 | 0.00 | [1140.22, 1231. 07] |
| Match II | 0.699 | Local | Homogeneous | 1529.24 | 0.00 | [769.58, 2288.91] |
| Non-Homogeneous | 1462.23 | 0.00 | [1328.36, 1596.09] |
| Global | Homogeneous | 1316.83 | 0.00 | [805.58, 1828.09] |
| Non-Homogeneous | 1193.92 | 0.00 | [1140.65, 1247.17] |

Table 10: Estimates of Impact on Cropping Intensity

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Matching Method | Multivariate Imbalance Measure | SATT | Effect | Point Estimate | p-value | Confidence Interval |
| Cropping Intensity | Automated | 0.642 | Local | Homogeneous | 1.61 | 0.66 | [-5.64, 8.85] |
| Non-Homogeneous | 0.29 | 0.71 | [-1.26, 1.84] |
| Global | Homogeneous | -0.26 | 0.09 | [-4.28, 3.75] |
| Non-Homogeneous | -3.66 | 1.00 | [-4.08, -3.24] |
| Match I | 0.583 | Local | Homogeneous | 2.26 | 0.48 | [-4.07, 8.60] |
| Non-Homogeneous | 0.94 | 0.07 | [-0.07, 1.95] |
| Global | Homogeneous | -0.14 | 0.04 | [-4.25, 3.97] |
| Non-Homogeneous | -4.11 | 1.00 | [-4.46, -3.76] |
| Match II | 0.699 | Local | Homogeneous | -0.12 | 0.97 | [-6.14, 5.89] |
| Non-Homogeneous | -1.58 | 0.99 | [-2.71, -0.44] |
| Global | Homogeneous | -0.74 | 0.22 | [-4.48, 3.32] |
| Non-Homogeneous | -3.77 | 1.00 | [-4.22, -3.32] |

Table 11: Estimates of Impact on Crop Diversity during Kharif season

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Matching Method | Multivariate Imbalance Measure | SATT | Effect | Point Estimate | p-value | Confidence Interval |
| Kharif Diversity  | Automated | 0.642 | Local | Homogeneous | 0.05 | 0.00 | [0.02, 0.07] |
| Non-Homogeneous | 0.05 | 0.00 | [0.04, 0.05] |
| Global | Homogeneous | 0.06 | 0.00 | [0.04, 0.09] |
| Non-Homogeneous | 0.06 | 0.00 | [0.06, 0.07] |
| Match I | 0.583 | Local | Homogeneous | 0.04 | 0.02 | [0.02, 0.07] |
| Non-Homogeneous | 0.04 | 0.00 | [0.03, 0.04] |
| Global | Homogeneous | 0.06 | 0.00 | [0.04, 0.09] |
| Non-Homogeneous | 0.06 | 0.00 | [0.06, 0.07] |
| Match II | 0.699 | Local | Homogeneous | 0.04 | 0.00 | [0.02, 0.07] |
| Non-Homogeneous | 0.04 | 0.00 | [0.04, 0.05] |
| Global | Homogeneous | 0.06 | 0.00 | [0.04, 0.09] |
| Non-Homogeneous | 0.06 | 0.00 | [0.06, 0.07] |

Table 12: Estimates of Impact on Crop Diversity during Rabi season

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Matching Method | Multivariate Imbalance Measure | SATT | Effect | Point Estimate | p-value | Confidence Interval |
| Rabi Diversity | Automated | 0.642 | Local | Homogeneous | 0.00 | 0.95 | [-0.04, 0.05] |
| Non-Homogeneous | 0.00 | 0.56 | [-0.02, 0.01] |
| Global | Homogeneous | -0.03 | 0.77 | [-0.06, 0.00] |
| Non-Homogeneous | -0.02 | 1.00 | [-0.03, -0.02] |
| Match I | 0.583 | Local | Homogeneous | 0.00 | 0.72 | [-0.05, 0.04] |
| Non-Homogeneous | -0.01 | 0.99 | [-0.02, 0.00] |
| Global | Homogeneous | -0.02 | 0.71 | [-0.06, 0.01] |
| Non-Homogeneous | -0.03 | 1.00 | [-0.03, -0.02] |
| Match II | 0.699 | Local | Homogeneous | -0.01 | 0.57 | [-0.05, 0.03] |
| Non-Homogeneous | -0.01 | 0.99 | [-0.02, -0.01] |
| Global | Homogeneous | -0.02 | 0.56 | [-0.05, 0.01] |
| Non-Homogeneous | -0.02 | 1.00 | [-0.024, -0.18] |