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Impact of Soil and Water Conservation Improvement on the Welfare of Smallholder Farmers in Southern Malawi

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Abstract
This study employed full Mahalanobis matching and a variety of propensity score matching methods to adjust for pre-treatment observable differences between treated and untreated groups for measuring the impact of technologies. Data were collected from 619 smallholder farmers in the districts of Nsanje and Balaka in southern Malawi during 2014-2015 cropping season. There was a 27% reduction in per capita income because of farmer's involvement in soil and water conservation technologies. The impact is significant at 5% level. Similarly, there is an 8% reduction in per capita expenditure because of farmer's involvement in soil and water conservation technologies. Although households practicing the technologies under study realized nominally higher yields, the yield differences between them and those not practicing were not as significant. The study concluded that adoption of soil and water conservation technologies did not improve the incomes of small-scale farmers in the areas. These results were surprising, but several feasible explanations were made for the incongruity in the findings.
Keywords: propensity score matching, incomes, impact, smallholder farmers

1.0 Introduction

Soil and water conservation is important for alleviating water shortages, worsening soil conditions, and other negative effects of climate variability (Kurukulasuriya and Mendelsohn 2006). Soil and water conservation has changed from an initial emphasis on structures to reverse soil erosion to an important part of sustainable land management (Spielman et al., 2009). Reviewed studies has shown that farmers do apply soil and water conservation approaches for various reasons, including adaptation to environmental change and at local level to maintain or enhance the productive capacity of the land in areas prone to degradation.

For farmers to make investment decisions in agricultural practice that will improve their welfare and livelihood, there is a need to evaluate impacts between adopters and non-adopters of the technology. This paper explores the impact of soil & water conservation on smallholder farmers' income and expenditure patterns. A counterfactual analysis was built, and comparisons between the expected per capita income and expenditure under the actual and counterfactual cases between adopters and non-adopters analysed. In addition, treatment and heterogeneity effects were calculated to understand the differences in per capita income and expenditure between farm households that adopted and those that did not adopt. The study has taken into account if the differences in per capita income and expenditure between farming households that did adopt and those that did not adopt might have been perhaps due to unobserved heterogeneity.

2.0 Study Areas

This study was carried out in two districts of Balaka and Nsanje in Malawi. The districts were purposively chosen because of being prone to climate variability of droughts and flooding. Balaka District is located in the southern region of Malawi, positioned at 150 00'S latitude and 350 00'E longitude. It is on the eastern edge of the Great Rift Valley, hence has a varied topography ranging from an elevation of about 350 to 800 meters above sea level (Balaka SEP, 2010). Whereas Nsanje District is situated at the southern tip of the country within the Lower Shire valley, located 160 45'S latitude and 350 10'E longitude (Nsanje SEP, 2010).

3.0 Sampling design, instruments and data needs

This study used a mixed methods approach; both qualitative and quantities techniques involving focus group discussions and a cross-sectional survey were used. Multi-stage stratified random sampling was applied, with 619 respondents interviewed. Data was collected on the explanatory variables as adapted from the concept by Yohe and Tol (2002) and Chambers (1989). Data were analysed through the generation of descriptive statistics, and through the incorporation of a psmatch2, which implements full Mahalanobis matching and a variety of propensity score matching methods.

3.1 Propensity Score Matching (PSM) approach

As it was shown by Rosenbaum and Rubin (1983) in their work, if we can match on variable (x), then we can as well match on probability of (x). Therefore, in estimating the impact of adopting a technology on per capita income and expenditure, two groups are identified, those adopting a technology (denoted as T_i =1 for household i and those without (T_i = 0). Those adopting a technology (treated) are matched to those not adopting the technology in

question (control group) on the basis of the propensity score, given as

$$P(X_i) = Prob\ (T_i = 1|X_i) \qquad (0 < p(X_i) < 1) \tag{1}$$

Where X_i is a vector of pre adoption of technology control variables. If the T_i's are independent over all (i), and the outcomes are independent of technology adoption given (X_i) then outcomes are also independent of technology adoption given p (X_i), just as they would be if technology adoption was done randomly. Rosenbaum and Rubin (1983) established some conditions in order to be able to estimate Average Treatment on the Treated (ATT) effect based on the propensity score. The first condition is the balancing hypothesis where

$$T \perp X \,|\, P(x) \tag{2}$$

This means that for observations with the same propensity score, the distribution of pre-treatment characteristics must be the same across control and treated groups (Appendix 1). That is, conditional on the propensity score, each individual has the same probability of assignment to treatment, as in a randomized experiment. We also tested the "balancing properties" of the data by testing that treatment and comparison observations had the same distribution (mean) of propensity scores and of control variables within groupings (roughly quantiles) of the propensity score. The second condition is on un-confoundedness or Conditional Independence Assumption (CIA) given the propensity score

$$Y_1, Y_0 \perp T \,|\, X \Rightarrow Y_1, Y_0, \perp T \,|\, P(X) \tag{3}$$

If assignment to treatment is un-confounded conditional on the variables pre-treatment, then assignment to treatment is un-confounded given the propensity score. The performance difference between treatment and control groups was estimated by the average treatment effect on the treated (ATT), as a second step (Appendix 2). After computing the propensity score, the ATT (τ) effect was estimated as follows:

$$\tau = E(Y_{1i} - Y_{0i}|D_i = 1) \tag{4}$$

$$\tau = E\{E(Y_{1i} - Y_{0i}|D_i = 1,\ P(X))\} \tag{5}$$

$$\tau = E\{E(Y_{1i} - Y_{0i}|D_i = 1,\ P(X)) - E\ \{Y_{0i}|D_i = 0,\ P(X_i)\}\ |\ D_i = 1\} \tag{6}$$

where: Y_{1i} is the potential outcome if the individual is treated.
Y_{0i} is the potential outcome if the individual is not treated.

After running the propensity score matching test on the technologies, we were able to isolate the untreated group, treated group on support and the treated group but of support (Appendix 3).

The strength of these matching approaches is that they can provide reliable estimates of program impact provided that (1) a comparable group of non-beneficiary households is available, and (2) there is access to carefully collected household survey data with many variables that are correlated with program participation and the outcome variables.

These approaches relies on two assumptions about the data and the model. The first assumption is that, after controlling for all pre-adoption observable household and community characteristics that are correlated with technology participation and the outcome variable, non-beneficiaries have the same average outcome as beneficiaries would have had if they did not adopt the technology. The second assumption is that for each beneficiary household and for all observable characteristics, a comparison group of non-beneficiaries with similar propensity scores exists. Heckman et al., (1997) emphasised that the quality of the match can be improved by ensuring that matches are formed only where the distribution of the density of the propensity scores overlap between treatment and comparison observations, or where the propensity score densities have common support (Appendix 4).

Common support was then improved by dropping treatment observations whose estimated propensity score is greater than the maximum or less than the minimum of the comparison group propensity scores. Similarly, comparison group observations with a propensity score below the minimum or above the maximum of the treatment observations can be dropped. All results presented below are based on specifications that passed the balancing tests (Appendix 5) conducted.

The true ATT indicates the mean difference between those adopting a technology and non-adopters, who are identical in observable characteristics and adequately weighted by a balanced probability of participation. An adequate match of a participant with his/her counterfactual is achieved, as long as they are identical in their observable characteristics. In order to obtain such matched pairs, this study applied three different matching methods that vary in terms of bias and efficiency as applied by Caliendo and Kopeinig (2005). Nearest neighbour matching, stratification matching, and kernel matching were the three matching techniques used.

3.2 Sensitivity Analysis

Lastly we had to do a sensitivity analysis to examine how strong the influence of γ on the participation process needs to be, in order to attenuate the impact of participation on potential outcomes (Rosenbaum, 2002). For the sake of simplicity, it is assumed that the unobservable variable is a binary variable taking values zero or one (Rosenbaum, 2002). The following bounds on the odds ratio of the participation probability of both individuals were applied as

$$\frac{1}{e^{\gamma}} \leq \frac{P(X_m)(1-P(X_n))}{P(X_n)(1-P(X_m))} \leq e^{\gamma} \quad (7)$$

In this case individuals had the same probability of participation in soil & water technology adoption, provided that they were identical in X, only if $e^{\gamma} = 1$ (Rosenbaum, 2002). If e^{γ} is close to one and changes the inference about the treatment effect, the impact of participation on potential outcomes is said to be sensitive to hidden bias. In contrast, insensitive treatment effects would be obtained if a large value of e^{γ} does not alter the inference about treatment effects (Rosenbaum, 2002). In this sense, e^{γ} could be interpreted as a measure of the degree of departure from a study that is free of unobservable selection bias (Rosenbaum, 2002).

We also checked the quality of the matching estimators by standardizing the differences in observables' means between participants and non-participants. The standardized difference in percent after matching represents, for a given independent covariate X, the difference in sample means in the participating (X_1) and matched non-participating (X_0) sub-samples as a percentage of the square root of the average sample variances (S_1^2 and S_0^2) (Rosenbaum and Rubin, 1985), given as

$$SD = \left[100 \frac{(\bar{X}_i - \overline{X_0})}{(0.5(S_1^2 + S_0^2))^{0.5}}\right] \quad (8)$$

Although there exists no clear threshold of successful or failed matching, a remaining bias below 5% after matching is accepted as an indication that the balance among the different observable characteristics between the matched groups is sufficient (Caliendo and Kopeinig, 2005).

Our results of sensitivity analysis (Appendix 6) show that the inference for the effect of the two technologies is not changing though the participants and non-participant households have been allowed to differ in their odds of being treated up to ($e^{\gamma} = 3$) in terms of unobserved covariates. This means that for all outcome variables estimated, at various level of critical value of e^{γ}, the p-critical values are significant which further indicate that we have considered important covariates that affected both participation and outcome variables. We couldn't get the critical value e^{γ} where the estimated ATT is questioned even if we had set largely up to 3. Thus, we can conclude that our impact estimates (ATT) are insensitive to unobserved selection bias and are a pure effect of the technologies.

4.0 Results and Discussion

Our data shows that about 41% of the farmers use soil and water conservation practices. Farmers did practice a range of soil and water conservation strategies such as vertiver grass planting (42.4%), agroforestry (14.0%), box ridges (27.6%) and gulley check (4.4%). When mean crop yields, revenue and expenditure comparisons are made between adopters and non-adopters using t-statistics analysis. There are some statistical significant mean differences in the mean increase of maize and tobacco yields for those practicing soil and water conservation (Table 1). Our findings do concur to those by Asfaw et al., (2014) who found that adoption of soil water conservation strategies consistently improved overall maize yields.

TABLE 1: COMPARISON OF HOUSEHOLD AVERAGE CROP YIELD, REVENUE AND EXPENDITURE

	Non adopters	Adopters
Crop yield (kg)		
Maize	659 (54)	906***(78)
Millet	90 (14)	94(13)
Tobacco	19 (4)***	61***(13)
Revenue (MK)		
Crop revenue	29374 (2864)**	41635(4229)
Livestock revenue	15963 (2835)	15814 (2458)
Total agric. Revenue	45337 (4117)**	57449 (4814)
Non-farm revenue	144160 (10230)*	183130*(15923)
Total revenue	189498 (11354)**	240580**(16623)
Expenditure (MK)		
Agriculture cost	15312(2460)***	30325**(4052)
Capital expenditure	1229 (404)*	2599 (759)
Clothing expenditure	19534 (1707)***	26593 (2624)
Other expenditures	26564 (2154)***	39236*** (3592)
Total expenditure	137056 (8839)***	193295** (11753)

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

The mean income from non-farm sources was statistically different for adopters and non-adopters. We note with interest that on the expenditure, the mean agriculture cost and other expenses was also t- statistically different, this could signify that technologies implemented do come at a cost despite them improving farmer's livelihood.

The difference between net value of crop production and their associated costs using t-test, shows that adopters were better off than non-adopters. These findings are similar to Muzari et al., (2013), who found that smallholder households practicing conservation agriculture in Zimbabwe's Makonde region had significantly higher mean maize output per household of 7.31 ton. Those not practicing conservation agriculture had a significantly lower mean crop output per household of 1.04 ton. (Muzari et al., 2013). However, because adoption is endogenous, a simple comparison of the outcome indicators of adopter and non-adopters has no causal interpretation (Asfaw et al., 2013). Hence this results, must be interpreted with caution because crop productivity may also be influenced by plot and household characteristics, apart from adoption of technologies.

4.1 Propensity score matching result

The estimated results appears to perform well for the intended matching exercise and impact assessment, as the pseudo-R2 values (pseudo R2 = 0.091 for soil & water conservation) shows that the competing households do not have many distinct characteristics in per capita income, so that finding a good match between the treated and non-treated households becomes easier in the different technologies under study.

The maximum likelihood estimate shows that being a lead farmer and artisan/skilled tradesman significantly influenced adoption of soil and water conservation. This pattern was similarly observed in per capita expenditure. These variables, had greater significant effect on the decisions of the farmers to adopt soil & water conservation (Table 2). Amongst the variables included in our model, education of the household head, household size, farm size and the occurrence of droughts were theorised to increase the likelihood of farm households adopting soil and water conservation. Scaled adoption of a technology requires a certain level of technical understanding of the husbandry practices associated with the given technology. Literature suggests that adoption of agricultural technologies, generally, is conditioned by socioeconomic and biophysical environment from within farmers operate and attributes of the technology in question (Feder, et al., 1985; Saha, et al., 1994; Batz, et al., 1999). Factors like gender, level of education, access to extension services and markets, proximity to main roads, household incomes as well as social capital somehow influence the adoption of agricultural technologies (Doss, 2006; Katengeza, et al., 2012).

TABLE 2: MAXIMUM LIKELIHOOD ESTIMATE TO PARTICIPATION IN THE TECHNOLOGIES

Dummy variable	Ln _ per capita income	Ln _ per capita expenditure
Lead farmer (1=yes)	0.799*** (0.273)	0.791*** (0.273)
Artisan/skilled tradesman (1=yes)	-1.234** (0.639)	-1.224** (0.638)
_cons	3.505 (4.907)	3.876 (4.898)
N	216	217
LR chi^2	26.28	26.04
P> chi^2	0.0935	0.0988
Pseudo R^2	0.091	0.0899
Log likelihood	130.73	-131.8

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

There is a 27% reduction in per capita income because of farmer's involvement in soil and water conservation. The impact is significant at 5% level. The results are consistent with stratification and kernel matching methods, as soil and water conservation technologies reduces per capita income by 12 and 7% respectively at a 5% significance level. Similarly, there is an 8% reduction in per capita expenditure because of farmer's involvement in soil and water conservation. The impact is significant at 5% level. Stratification and kernel matching methods also reduces per capita expenditure by 3 and 27.4% respectively at a 5% significance level. These results contradicts those by Kato et al., (2011), who found a significant contribution of 4% and 25% production increase, for the adopters of soil and water conservation in the low and high rainfall areas of Ethiopia using a Cobb-Douglas function. Kassie (2013) found that the adoption of minimum tillage with residue retention significantly increased maize yield of between 60 to 75%.

Literature has confirmed the controversial, mixed and sometimes conflicting results relative to expected benefits of soil and water conservation strategies (Zulu, 2016). Although adopters in this study realized nominally higher yields, the yield differences were not as significant. We expected the yield response in most crops by the adopters to be significantly higher yields for farmers employing the technology. In a study by Thierfelder et al., (2013), it is stated that conservation agriculture do increase rainwater infiltration by 24 to40%, increases maize yield up to two-fold (Thierfelder et al., 2013).

There are several feasible explanations for the incongruent in our results obtained. The first one being that for crop plants to be able to assimilate nutrients, they need water in adequate amounts. Water is not readily available in these districts because of low precipitation levels hence the root zone find it difficult absorb these nutrients. The soil biophysical conditions in the district are not suitable for the technology. Although the use of

soil and water conservation technologies has often been promoted in the study areas, several farmers lack access to complementary agricultural services, such as access to credit and information. There could be possible ways to make soil and water conservation measures more profitable, but the question, of course, is why farmers many of whom had more than 15 years' experience of farming, were not taking the technologies.

5.0 Conclusion

This study aimed to gauge the impact of soil and water conservation on the welfare of the farmers by using income and expenditure as proxies. Lack of positive impact in our findings might be a result of respondents hiding information on income earned/spent and assets available, as most of them were not willing to disclose their income/expenditure and assets owned in anticipation to receive hand outs from the researchers. The other reason per our intuition is that farmers from Nsanje, which contributed a bigger proportion of the sample size do not use soil and water conservation because they see their land to be already fertile and no need for them to adopt the technologies. This was confirmed in the focus group discussions. Nevertheless increased effort for exploring these technologies further and provide optimum plot specific productivity rate of changes is necessary for policy formulation

6.0 Acknowledgement

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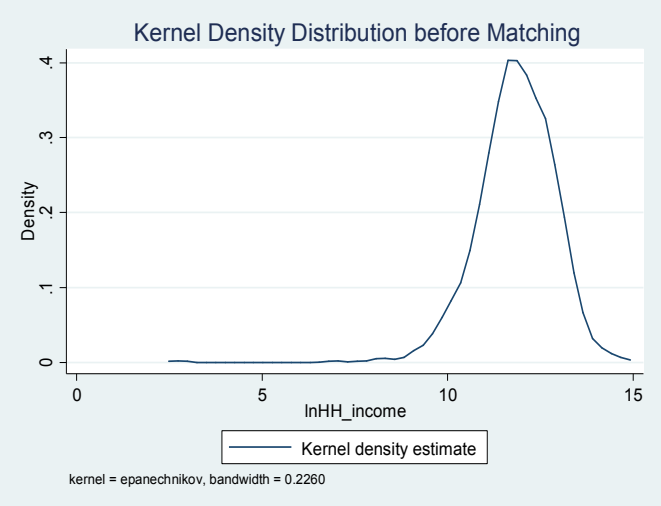
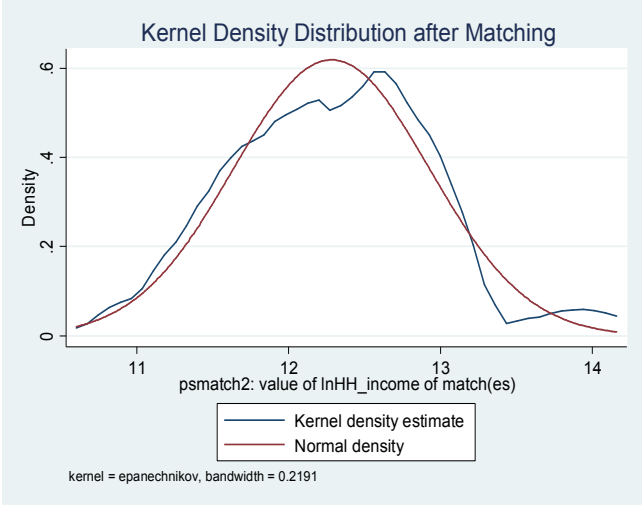
Appendix 1: Distribution in per capita income before and after transformation



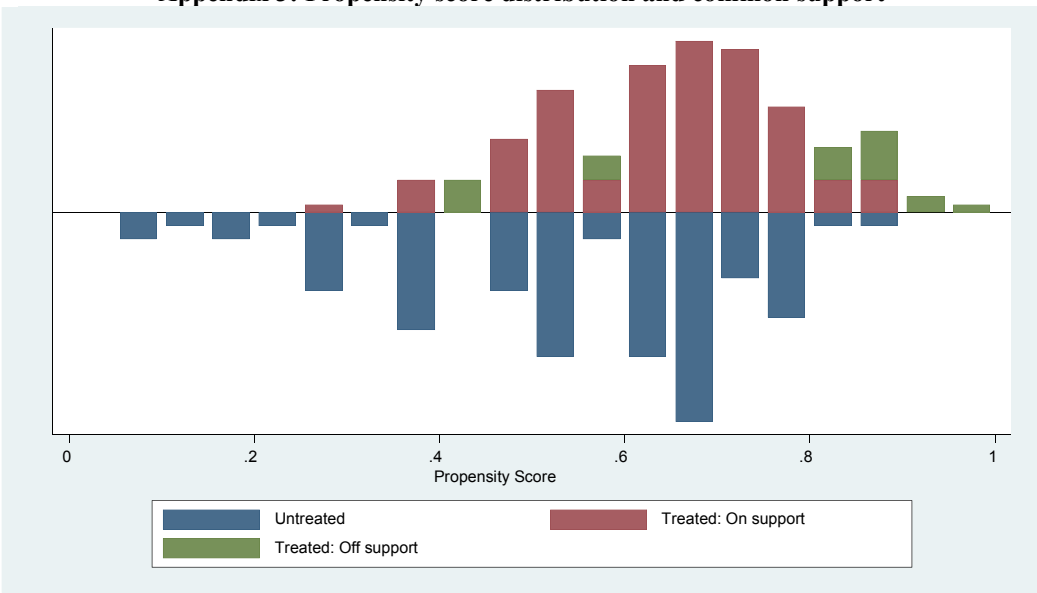


Appendix 2: Performance difference between treatment and control groups

	Treated	Controls	Difference	S.E.	T-stat
Ln_percapita Income with Soil and water technologies					
Unmatched	11.96	12.02	-0.07	0.13	-0.52*
ATT	11.98	12.08	-0.10	0.17	-0.59*
Ln_percapita Expenditure with Soil and water technologies					
Unmatched	9.82	10.06	-0.24	0.16	-1.49*
ATT	9.87	10.15	-0.28	0.17	-1.70*

*** p<0.01, ** p<0.05, * p<0.1

Appendix 3: Propensity score distribution and common support

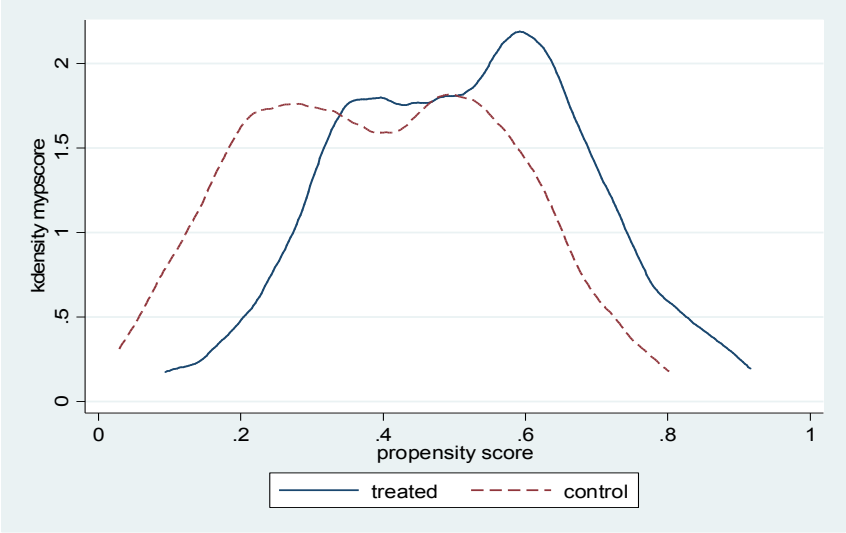


Note: Treated: on support" indicates the observations in the adoption group that have suitable comparison. "Treated: off support' "indicates that the observations in the adoption group that do not have a suitable comparison

APPENDIX 4: BALANCING PROPERTIES TEST

	Area of Common Support	Blocks	Balancing Result
ln_percapita income			
Soil and water technologies	0.24640378, 0.97168243	5	Satisfied
ln_percapita expenditure			
Soil and water technologies	0.20993335, 0.97689421	5	Satisfied

Appendix 5 Graphical output of the propensity score matching



Appendix 6: Income and expenditure sensitivity analysis

Gamma (Γ)	Income sensitivity analysis			Expenditure sensitivity analysis		
	Lower. Bound HL Est.	Upper. Bound HL Est.	Confidence interval	Lower. Bound HL Est.	Upper. Bound HL Est.	Confidence interval
1	-0.218	-0.176	-0.462, 0.163	-0.218	-0.176	-0.462, 0.163
1.2	-0.317	-0.059	-0.574, 0.261	-0.317	-0.059	-0.574, 0.261
1.4	-0.397	0.019	-0.676, 0.353	-0.397	0.019	-0.676, 0.353
1.6	-0.472	0.080	-0.735, 0.431	-0.472	0.080	-0.735, 0.431
1.8	-0.543	0.158	-0.809, 0.501	-0.543	0.158	-0.809, 0.501
2	-0.595	0.215	-0.885, 0.563	-0.595	0.215	-0.885, 0.563
2.2	-0.658	0.259	-0.944, 0.628	-0.658	0.259	-0.944, 0.628
2.4	-0.700	0.298	-0.999, 0.679	-0.700	0.298	-0.999, 0.679
2.6	-0.742	0.347	-1.062, 0.735	-0.742	0.347	-1.062, 0.735
2.8	-0.782	0.388	-1.112, 0.783	-0.782	0.388	-1.112, 0.783
3	-0.820	0.418	-1.162, 0.822	-0.820	0.418	-1.162, 0.822

Gamma (Γ): log odds of differential assignment due to unobserved factors
Lower Bound HL Est.: upper bound Hodges-Lehmann point estimate
Upper Bound HL Est.: lower bound Hodges-Lehmann point estimate
Lower and Upper confidence interval (95%)