The Continuation of Civil War by Other Means? Post-Conflict Peacebuilding in Nepal, Supplemental Materials

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Supplemental Materials

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Abstract:

This document provides a deeper description of the data and additional robustness checks on the data analysis reported in the article titled, *'The Continuation of Civil War by Other Means?: Post-Conflict Peacebuilding in Nepal,'* published in the *Journal of Peacebuilding and Development.*

Key words: peacebuilding, post-civil war governance, transitional justice, compensation, opportunism

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A. Data

Data for this research come from information on compensation claims collected by the Nepali Ministry of Peace and Reconstruction (MOPR) from all eligible victims. We downloaded the original raw data from MOPR website, which were publicly available until the ministry was dissolved in 2018. There is strong reason to believe that the compensation data collected by the MOPR are reliable. MOPR created a taskforce to oversee the overall distribution of the fund. All applications were verified at the Village Development Committee (VDC) and Ward levels by 23-member Local Peace Committees (LPCs) that had representatives from all the political parties, civil society organisations as well as victims (Sajjad 2015). To ensure credibility of the ministry records, we cross-checked our data with the Conflict Victims' Profile maintained by the Informal Sector Service Center (INSEC) a prominent human rights NGO in Nepal (http://www.inseconline.org/victim/). Comparing the aggregate VDC level INSEC data with aggregated MOPR data and focusing only on applications from relatives of those killed in the conflict, we find that the average number of members of the armed forces is similar in the two data sources, while the average number of Maoist People's Liberation Army (PLA) members is over three times higher in the INSEC versus MOPR data, possibly indicating a reluctance of victims to identify themselves as such in the Interim Relief Program (IRP) application process. To further validate the credibility of the MOPR data, the quantitative data is supplemented by qualitative interviews conducted in Nepali (by a native speaking co-author) with ministry officials, NGO workers, as well as a public opinion survey of 717 randomly selected applicants from among the MOPR list and INSEC's Victims Profile in the districts of Rolpa, Mugu and Bardiya.

B. Aggregate level analysis

In our individual level analysis in the main article, after controlling for population, the district level measure of NGOs did not affect the success of individual applications. Here we move the analysis to the district level, so that we can investigate whether third-party monitoring that NGOs may perform, along with accessibility, mitigates bias in the program (H2 in the paper). Moving to a district level analysis, we reduce the number of observations in our model from 18,093 individuals to 73 districts, since 2 of Nepal's 75 districts did not record fatalities during the conflict. The district-level dependent variable we use is the ratio of rebel to government success in compensation. For our independent variables, we use district level measures for the number of and membership in NGOs, percent literacy, elevation, roads, economic development, and population.

Model 1 in Table B1 suggests that more NGOs present in a district did improve the chances of compensation for rebels relative to those on the government side. But as Model 2 shows, that result is driven by two districts: Kathmandu and the neighbouring district of Lalitpur, two districts with the largest number of NGOs. While there is no support from this analysis of NGOs performing a 'fire alarm' across the districts, this is not grounds for dismissing the importance of monitoring. This 'capital-effect' is consistent with ease of monitoring (Easterly

2006; Deaton 2013). If the process of compensation were visible anywhere, it was likely to be in the district of the nation's capital, and the neighbouring district.

Table B1: District-level Regression Analysis of Relative Success of Rebel Applicants to Government Applicants

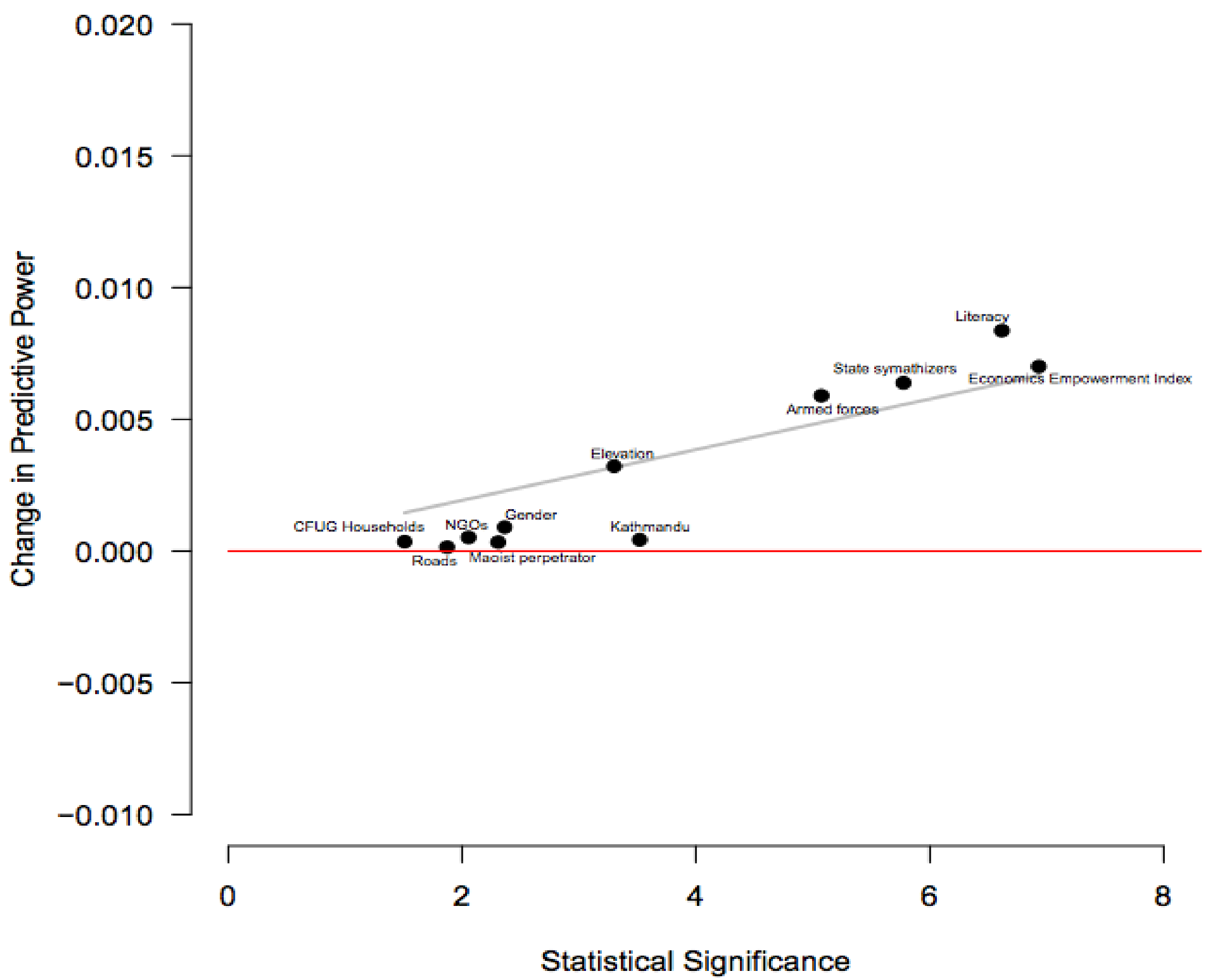
Independent Variables	**Model 1** Coefficient (SE)	**Model 2** Coefficient (SE)
NGOs (logged)	.08* (.04)	.01 (.04)
CFUG Households (100,000s)	.03 (.16)	.23 (.16)
Literacy (percent)	.004* (.002)	.002 (.002)
Elevation (Meters-Logged)	-.05 (.03)	-.10* (.03)
Roads (Kilometres-Logged)	-.003 (.016)	-.002 (.015)
Economic Empowerment Index	-.06* (.03)	-.05* (.03)
Population (logged)	-.06 (.07)	-.09 (.06)
Lalitpur (dummy)		.42* (.17)
Kathmandu (dummy)		.63* (.21)
Constant	1.61+ (.83)	2.61* (.84)
N	*73*	*73*
Adjusted R-Square	.03	.15

* indicates $p < .05$ or better, + indicates $p < .1$

C. Predictive Power of Our Models

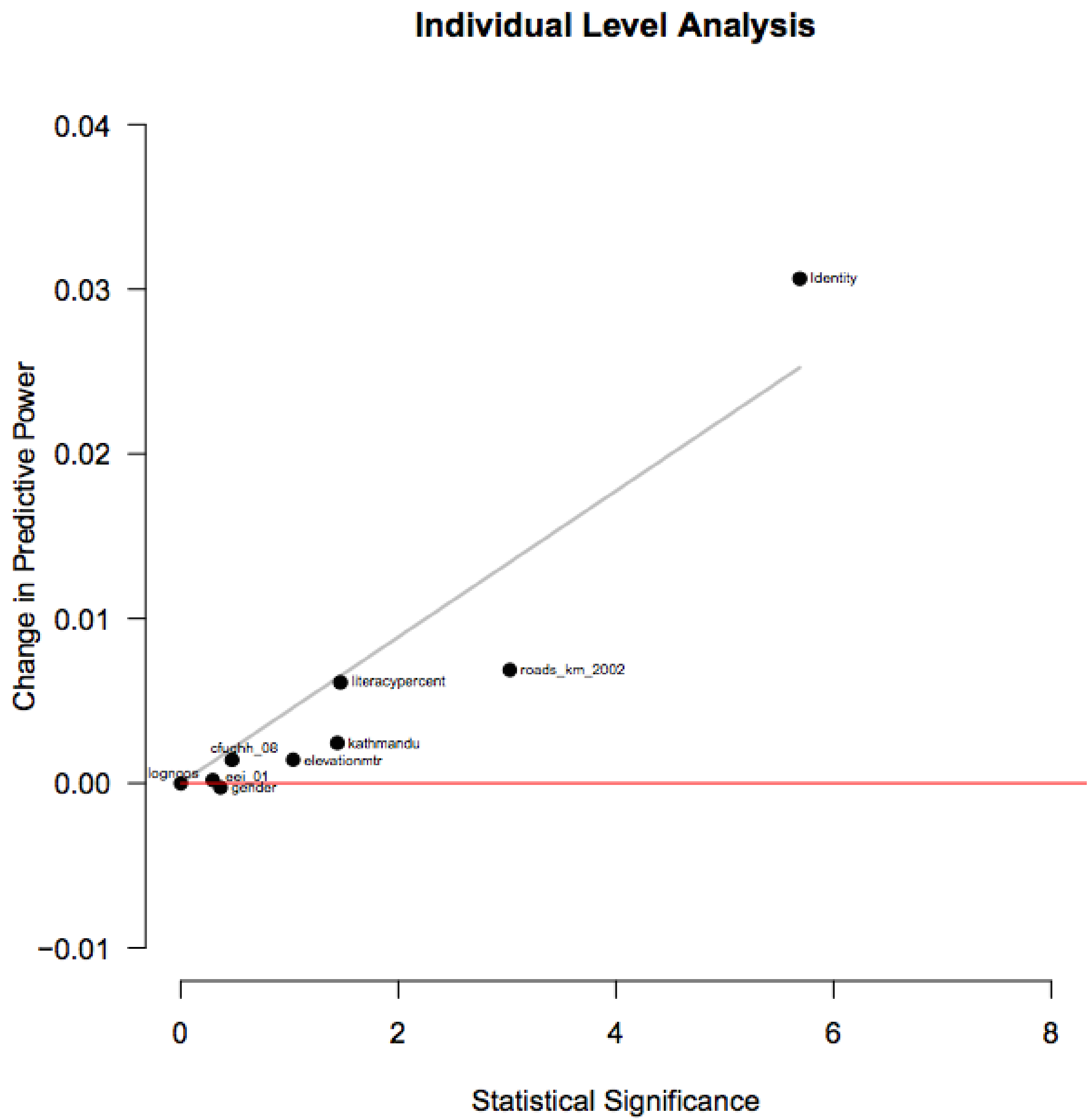
In Figure C1, following Ward et.al. (2010), we analyse the predictive power associated with each of the independent variables. As Ward et.al. argue, showing statistical significance does not always imply that a variable significantly improves a model's predictive power. They use Receiver Operator Characteristic (ROC) plots to capture the relationship between the rate of false positives and the rate of true positives. The predictive power of each independent variable is measured by comparing the area under the ROC curve with each variable removed one at a time, with that of the area of the original model. The x-axis represents the variables' statistical significance in terms of the absolute value of its t-score, while the position on the y-axis represents the marginal contribution that the variable makes to the original model's overall predictive power. The grey line shows the relationship between statistical significance and predictive power using OLS regression with no intercept. The horizontal line at y=0 represents the predictive power of the original model. Variables that lie above the zero line indicate a positive contribution to the overall predictive power, while points below the zero line would indicate a negative contribution. No variables result in a negative contribution. But the control for the number of kilometres of roads makes no contribution to the model's predictive power, while literacy rate in the district makes the greatest contribution, followed by the economic development, whether or not the victim was a member of an ethnic group that sympathized with the state, and whether or not the victim was a member of the state armed forces. This analysis again suggests that after controlling for educational, economic and remoteness differences, civil war allegiance influenced the compensation program.

Figure C1: Change in Predictive Power of Each Independent Variable



The impact is also clear in Figure C2 where the three key characteristics that impact who received compensation are replaced with a count variable, which captures the number of identity characteristics. This measure has the largest impact on the change in predicting the power of receiving compensation, over three times that of the next important factors, literacy and the number of kilometers of roads.

Figure C2: Change in Predictive Power of Using a Count of "Identity" Characteristics



D. Additional Models and Robustness Tests

We took numerous additional steps to test the robustness of our results. In addition to the Ministry data on conflict fatalities, we make use of the information gathered by INSEC. While compensation in other conflicts is a function of Truth Commissions, the INSEC data, which are relied on by the international community and by researchers (OHCHR 2012; Gilligan et al. 2014; Holtermann, 2014; Bohara et al. 2006; Murshed & Gates 2005; Do and Iyer 2010; Adhikari and Samford 2013), provides 'truth' to benchmark the 'politicized' delivery of compensation as described in the Ministry data. The Victims Profile maintained by INSEC provides fatality information that can be matched to the Ministry data at the local (VDC) level.

We use the INSEC number of fatalities at the VDC level as an additional independent control variable to account for the actual number of victims. Results reported in Table D1 are very similar to the model in Table 3 of our article, with the aggregate number killed by VDC according to INSEC significant at the .02 level. This additional control helps to account for actual victim demand in predicting successful applications. The results support our main findings.

Table D1: Individual level Logit Analysis of who Received Compensation using INSEC Data on Number Killed as a Control for the Level of VDC Violence

Independent Variable	**Coefficient (SE)**	**Marginal Effect**
Maoist Perpetrator	.10* (.04)	.02*
State Sympathizer	.20* (.04)	.04*
Member of the Armed Forces	.29* (.06)	.06*
CFUG Households (1000s)	-.002+ (.001)	-.0004+
NGOs (logged)	.10* (.04)	.02*
Male	.13* (.05)	.03*
Literacy	.02* (.002)	.003*
Elevation (Meters)	-.0001* (.00003)	-.00002*
Roads (Kilometers)	-.0003* (.0002)	-.00007*
Economic Empowerment Index	-.18* (.03)	-.04*
Kathmandu (dummy)	-.10* (.26)	-.23*
INSEC Killed	.004* (.002)	.0009*
Constant	.14 (.22)	
N	18,093	
LLR (chi2)	250.25*	
Percent Correctly Predicted	68%	

* indicates $p < .05$ or better, + indicates $p < .1$

Additionally, we test whether or not we should be using a multilevel or hierarchical model given that individuals are nested in VDCs, and VDCs are nested in districts, giving the data a hierarchical structure. In the random intercept model, including both VDC and district, the intraclass correlation coefficient (ICC) indicates that only 5% of the variance can be attributed to district specific effects and only 7% to VDC specific effects. These are both sufficiently small to be nothing more than random error. Research suggests that variance into the double digits (at least 10% and some suggest 20%) is needed to warrant the use of a hierarchical model.

Finally, we use various matching techniques to test the robustness of our results. Before subjecting our models to matching, we use inverse probability weighting on the data since we know that the treatment assignment is not likely to be random. Inverse probability weighting models the treatment assignment process in the case of non-random treatment assignment. Let's assume, for example, that the *Maoist Perpetrator* treatment is not random. There are two different kinds of weights, un-stabilized and stabilized weights. Sometimes, large weights emerge in un-stabilized weighting, which often increases the variance of the estimates. To counter these negative effects, stabilized weights are used. Table D2 shows the logistic regression results using un-stabilized weights (column 1), stabilized weights (column 2), and general logistic regression results (column 3).

Table D2: Results using Un-Stabilized Weights, Stabilized Weights, and Normal Logistic Regression

Independent Variable	Model (1)	Model (2)	Model (3)
	Un-stabilized	**Stabilized**	**Normal**
Maoist Perpetrator	.13*** (.05)	.13** (.05)	.10** (.04)
State Sympathizer	.25*** (.06)	.23*** (.07)	.20*** (.04)
Member of the Armed Forces	.07 (.11)	.02 (.13)	.29*** (.06)
NGOs (logged)	-.03 (.08)	-.02 (.09)	.09** (.04)
CFUG Households	.0000019 (.0000022)	.0000010 (.0000025)	-.0000020 (.0000013)
Male	.25*** (.08)	.19*** (.06)	.13** (.05)
Literacy	.01 (.004)	.01 (.005)	.02*** (.002)
Elevation (Meters)	-.00013** (.000054)	-.00014** (.000057)	-.0001*** (.000031)
Roads (Kilometres)	-.000053 (.0003)	-.0001 (.0003)	-.0003* (.0002)
Economic Empowerment Index	-1.26*** (.41)	-1.37*** (.45)	-1.85*** (.27)
Kathmandu (dummy control)	-.03 (.54)	.0003 (.66)	-.89*** (.25)
Constant	.72* (.42)	.81* (.48)	.26 (.22)
N	18,093	18,093	18,093

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Finally, we apply different packages in R to get matched data and use Stata to run logistic regression analysis. Table D3 shows results from different matching techniques using only the perpetrator as the treatment. The number of observations varies because after matching only the matched observations remain in the dataset. We used two methods of matching:

- *Exact Matching* matches each treated unit to all possible control units with the same values on all the covariates.
- *Nearest Neighbour Matching* selects the best control individual for each treated individual. There are different kinds of nearest neighbour matching, such as one to one, one to many, and so on. We use one to one.

Figure D1 shows that our data balance after matching. The distribution of the propensity scores for treated and control units are almost the same. Table D3 shows results from logistic models on the matched data. The results are similar for the two techniques of matching, and similar to our main findings without matching. Notably, the identity characteristics are all strongly significant in the expected direction, along with many of the control variables.

Figure D1: Distribution of Propensity Scores

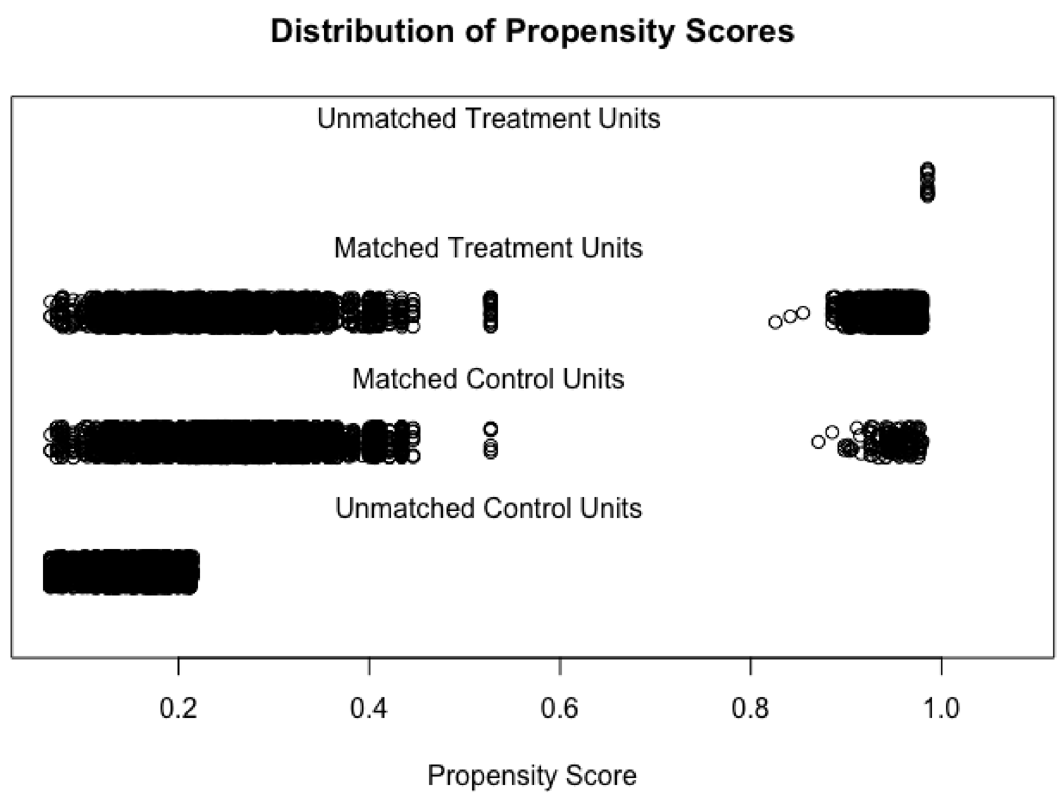


Table D3: Results using Exact Matching and Nearest Neighbour Matching on Perpetrator

Independent Variables	Model (1)	Model (2)
	Exact Matching	**Nearest Neighbour Matching**
Maoist Perpetrator	.11** (.04)	.15*** (.05)
State Sympathizer	.21*** (.04)	.27*** (.04)
Member of the Armed Forces	.32*** (.06)	.30*** (.06)
NGOs (logged)	.14*** (.05)	.17*** (.05)
CFUG Households	-.000003** (.0000014)	-.000004*** (.0000016)
Male	.18*** (.06)	.20** (.09)
Literacy	.02*** (.002)	.01*** (.003)
Elevation (Meters)	-.0001*** (.000032)	-.00001** (.00004)
Roads (Kilometres)	-.00033** (.0002)	-.0005*** (.0002)
Economic Empowerment Index	-2.20*** (.28)	-2.01*** (0.32)
Kathmandu (dummy control)	-1.02*** (.26)	-1.03*** (.27)
Constant	-.14 (.25)	-.34 (.33)
N	16,850	11,950

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

We perform similar matching techniques to test our models using different combinations of the identity characteristics. First, we use a strict definition of an identity applicant where the applicant possesses all three identity characteristics that made applicants more likely to receive compensation—identifies as victim of the Maoists, identifies with an ethnic group that supported the state, and identifies as a member of the state armed forces. Here we matched with applicants that have none of these identity characteristics using a strict definition on non-identity applicants. Figure D2 shows the data balance after matching and Table D4 shows the results of the logistic regressions using the two different matching methods.

Figure D2: Nearest Neighbour Match Balance with Applicants with All Three Identity Characteristics

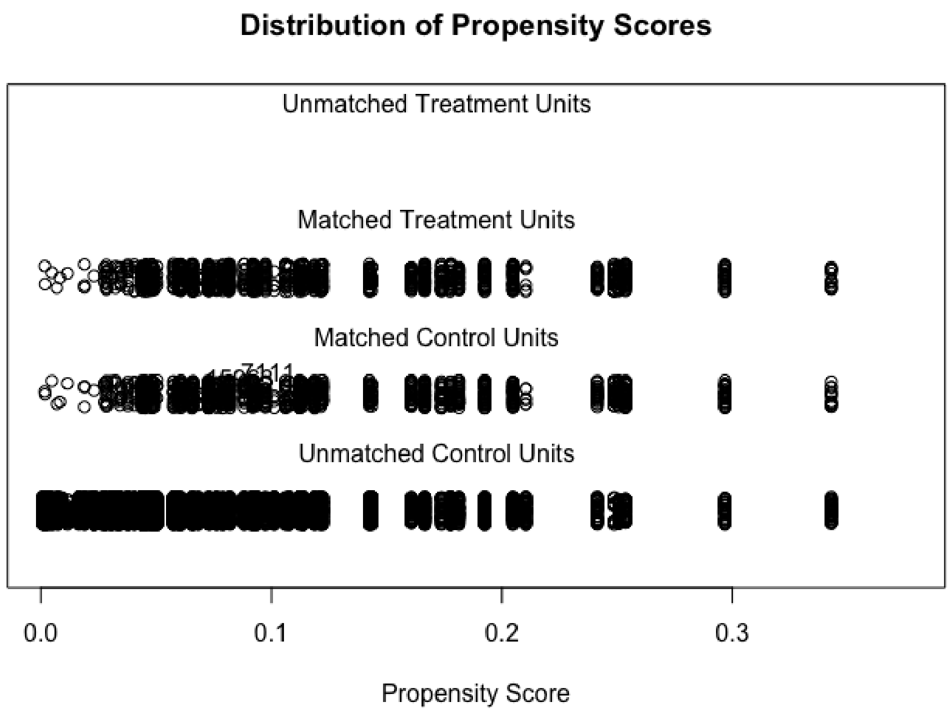


Table D4: Results using Exact Matching and Nearest Neighbour Matching—Strict Matching of Applicants with All Three Identity Characteristics to Applicants with None of the Characteristics

Independent Variables	Model (1)	Model (2)
	Exact Matching, Strict Identity, Strict Non-Identity	**Nearest Neighbour Matching, Strict Identity, Strict Non-Identity**
All Three Identity Characteristics	.37*** (.07)	.43*** (.09)
NGOs (logged)	.11** (.05)	.10 (.11)
CFUG Households	-.0000023 (.0000014)	.0000014 (.0000037)
Male	-.01 (.15)	-.26 (.67)
Literacy	.02*** (.0025)	.01** (.01)
Elevation (Meters)	-.0001*** (.000033)	-.00024*** (.000081)
Roads (Kilometres)	-.0003* (.0002)	-.0014*** (.0004)
Economic Empowerment Index	-2.09*** (.28)	-.55 (.64)
Kathmandu (dummy control)	-.87*** (.26)	-.44 (.44)
Constant	.41 (.40)	.91 (1.47)
N	16,130	2,768

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Next, we maintain the strict definition of an identity applicant where the applicant possesses all three identity characteristics, but relax the condition on the non-identity applicants using an “or” condition, so any one or more of the identity characteristics can be absent. Figure D3 shows the results of the matching and the results of the models are reported on Table D5.

Figure D3: Nearest Neighbour Match Balance with Strict Identity Applicants

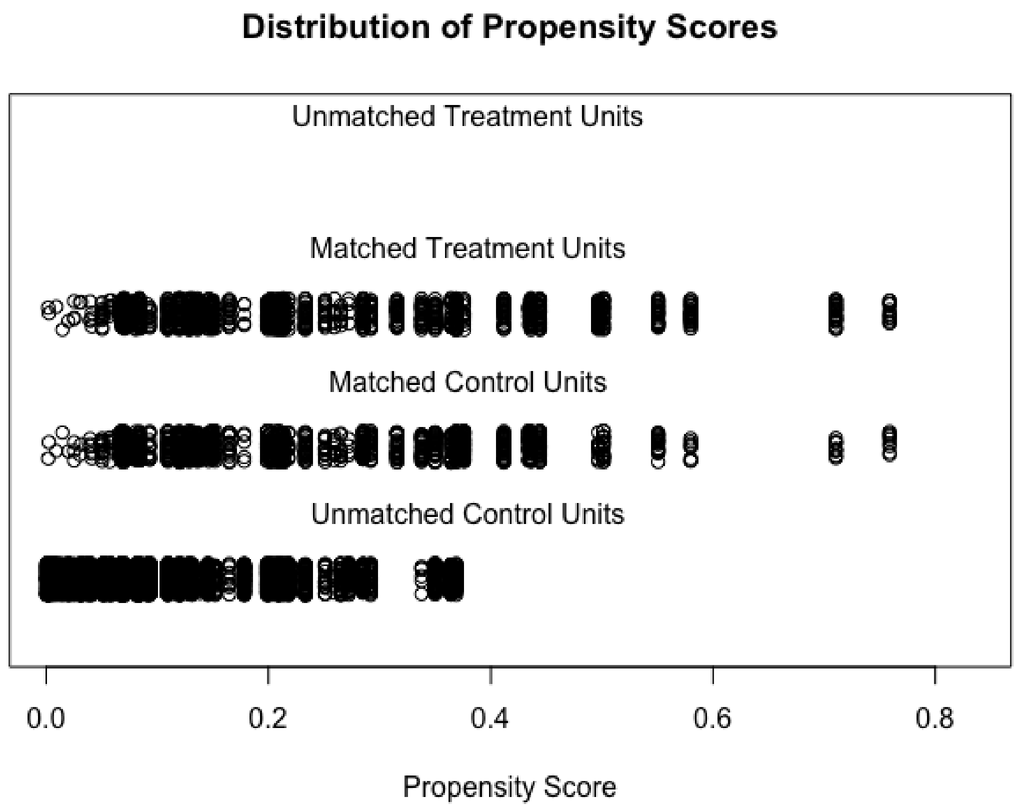


Table D5: Results using Exact Matching and Nearest Neighbour Matching with Strict Identity Applicants matched to Lenient Non-Identity Candidates

Independent Variables	**Model (1)**	**Model (2)**
	Exact Matching - Strict Identity, Lenient Non-Identity	Nearest Neighbour Matching - Strict Identity, Lenient Non-Identity
Strict Ideal Candidate	.51*** (.07)	.49*** (.09)
NGOs (logged)	.25*** (.06)	.0003 (.11)
CFUG Households	-.000007*** (.000002)	-.0000018 (.0000037)
Male	-.15 (.20)	-.25 (.69)
Literacy	.02*** (.004)	.01 (.006)
Elevation (Meters)	-.000056 (.000044)	-.000010 (.000083)
Roads (Kilometres)	-.0002 (.0002)	-.001*** (.0004)
Economic Empowerment Index	-2.88*** (.39)	-.19 (.65)
Kathmandu (dummy control)	-1.65*** (.39)	-.68 (.48)
Constant	-.02 (.55)	1.35 (1.52)
Observations	8,619	2,768

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Finally, we relax the condition on the identity variable to allow the applicant to have any one or more of the identity characteristics, rather than requiring all three. These are matched to the strict case of applicants having none of the identity characteristics. The matching results are reported in Figure D4 and the results of the models are reported on Table D6.

Figure D4: Nearest Neighbour Match Balance with Lenient Identity Characteristic Definition

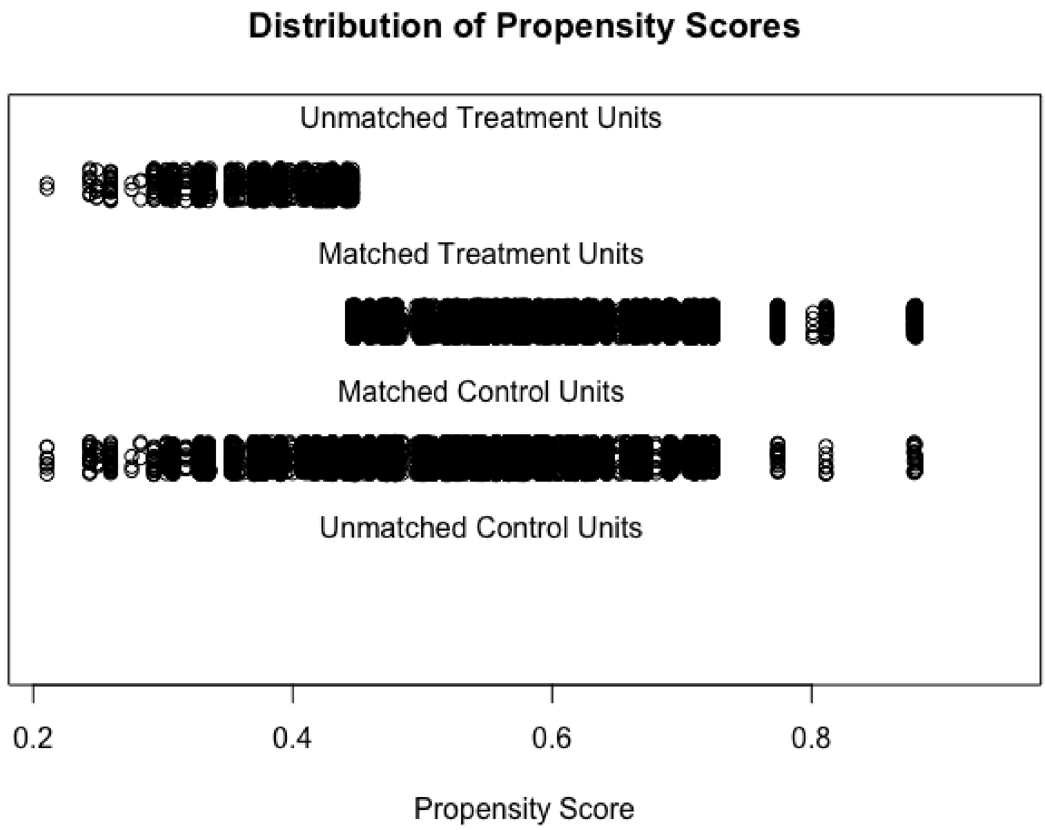


Table D6: Results using Exact Matching and Nearest Neighbour Matching with Lenient Identity Characteristic Definition

Independent Variables	**Model (1)**	**Model (2)**
	Exact Matching - Lenient Identity, Strict Non-Identity	Nearest Neighbour Matching- Lenient Identity, Strict Non-Identity
Lenient Ideal Candidate	.26*** (.03)	.28*** (.04)
NGOs (logged)	.10** (.04)	.11** (.05)
CFUG Households	-.0000018 (.0000013)	-.000002 (.0000014)
Male	.16*** (.05)	.10 (.06)
Literacy	.02*** (.002)	.02*** (.002)
Elevation (Meters)	-.0001*** (.00003)	-.0001*** (.00003)
Roads (Kilometres)	-.0004** (.0002)	-.0005*** (.0002)
Economic Empowerment Index	-1.86*** (.26)	-2.00*** (.27)
Kathmandu (dummy control)	-.87*** (.26)	-.82*** (.26)
Constant	-.05 (.24)	.06 (.26)
N	18,083	16,800

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Overall, the results from the various matching exercise are consistent with the main findings.

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