

The Evaluation of the cash voucher programme

Background

The consortium implemented a cash-voucher assistance (CVA) programme across project locations. The assistance through cash vouchers is a humanitarian aid approach where cash or vouchers are provided directly to people in need rather than traditional forms of aid, such as food or in-kind goods. The consortium hoped to attain different outcomes at the level of the individual as well as the household. Amongst others, it was hoped to improve the income situation of households.

Through the evaluation commissioned, the consortium expected to obtain insights into the level of additional incomes households attain through the CVA programme. The evaluation comprised of an endline survey, a cross-sectional data-collection exercise that was carried out upon completion of the project interventions. The data covered both households that benefitted from the CVA programme as well as households that did not receive any CVA's. Thus, the data was observational. Furthermore, households studied had not been randomly assigned to the CVA programme or the comparison group. The consortium reported of community-based selection procedures that had helped identify those households that were given CVA's.

To estimate treatment effects, the observational endline survey was analysed using a quasi-experimental design. Propensity score matching was performed to identify an appropriate comparison group that match the group of CVA programme beneficiaries (i.e., the treatment group) in terms of observable characteristics. Propensity Score Matching (PSM) is a statistical technique used to estimate the causal effect of a treatment, intervention, or exposure in observational studies where random assignment is not possible. It helps reduce bias due to confounding variables by creating a "matched" sample of treated and untreated units that are similar based on their propensity scores. Since the comparison group is matched up to the treatment group in terms of observable characteristics exhibited by the latter, the PSM method provides an estimate of the average treatment effect on the treated (ATT). Thus, results presented below are an estimate of the average treatment effect only for those households who actually had received the treatment.

To estimate the ATT of the CVA programme, the analysis of the endline survey proceeded as follows: First, propensity scores were estimated that were eventually used to identify the comparison group. Second, the recipient and non-recipient households were then matched up using propensity scores. Third, balancing diagnostics were performed. Finally, the ATT was estimated based on the matched-up dataset. This report is an abridged summary. Its main purpose is to highlight the steps performed to carry out a quasi-experimental approach to evaluation of programme effects. Next, the data used in the analysis is briefly outlined.

The data

The consortium endline was carried out in March and April 2023 across all project locations. Data was collected using Kobo Toolbox. The data collected was then retrieved from Kobo Toolbox using a rest API. Data collection was carried out by local consultants coordinated by the global evaluation consultant. As table 1 highlights, the endline data completed comprised of 3105 observations. 1140 received cash vouchers while 1965 did not receive cash vouchers. Also, implementing partners varied in terms of the total number of observations included into the study as well as in terms of the proportion of observations that received cash vouchers.

Table 1: Sample size by treatment status and implementing partners (n = 3105)

Cash voucher status	Implementing partner					Total
	A	B	C	D	E	
not received	574	333	349	493	216	1965
received	221	65	370	275	209	1140
Total	795	398	719	768	425	3105

Table 2 on the next page presents key characteristics of the endline sample. At the global level (see rows on total), households that did not receive CVA's are more likely to be host households rather than IDP or refugee households compared to those households that were supported through CVA's. They were also less likely to have disabilities and not to be married. Non-recipients also reported to have fewer children than recipient households. Most notably, heads of households that did not receive CVA's appeared to be slightly better educated than the heads of those households that received CVA's. For example, around 21 per cent of the heads of non-recipient households reported having completed secondary education whereas it was only 9 per cent for the heads of recipient households.

There was also significant variance between groups associated with specific implementing partners. For example, the heads of non-beneficiary households associated with implementing partner B were more likely to be female than heads of beneficiary households. Also, non-beneficiary households associated with implementing partner A reported having significantly less children on average than beneficiary households. Thus, there appear to be significant differences between the beneficiary and the non-beneficiary groups globally as well as at the level of implementing partners.

These differences may also explain why the average income between CVA beneficiaries and non-beneficiaries varied. A t-test revealed a significant difference in income between non-recipient households ($m = 471.45$, $sd = 233.2$) and recipient households ($m = 377.12$, $sd = 149.71$) at the global level ($p < .000$).

Table 2: Sample means of characteristics of endline sample (n = 3105)

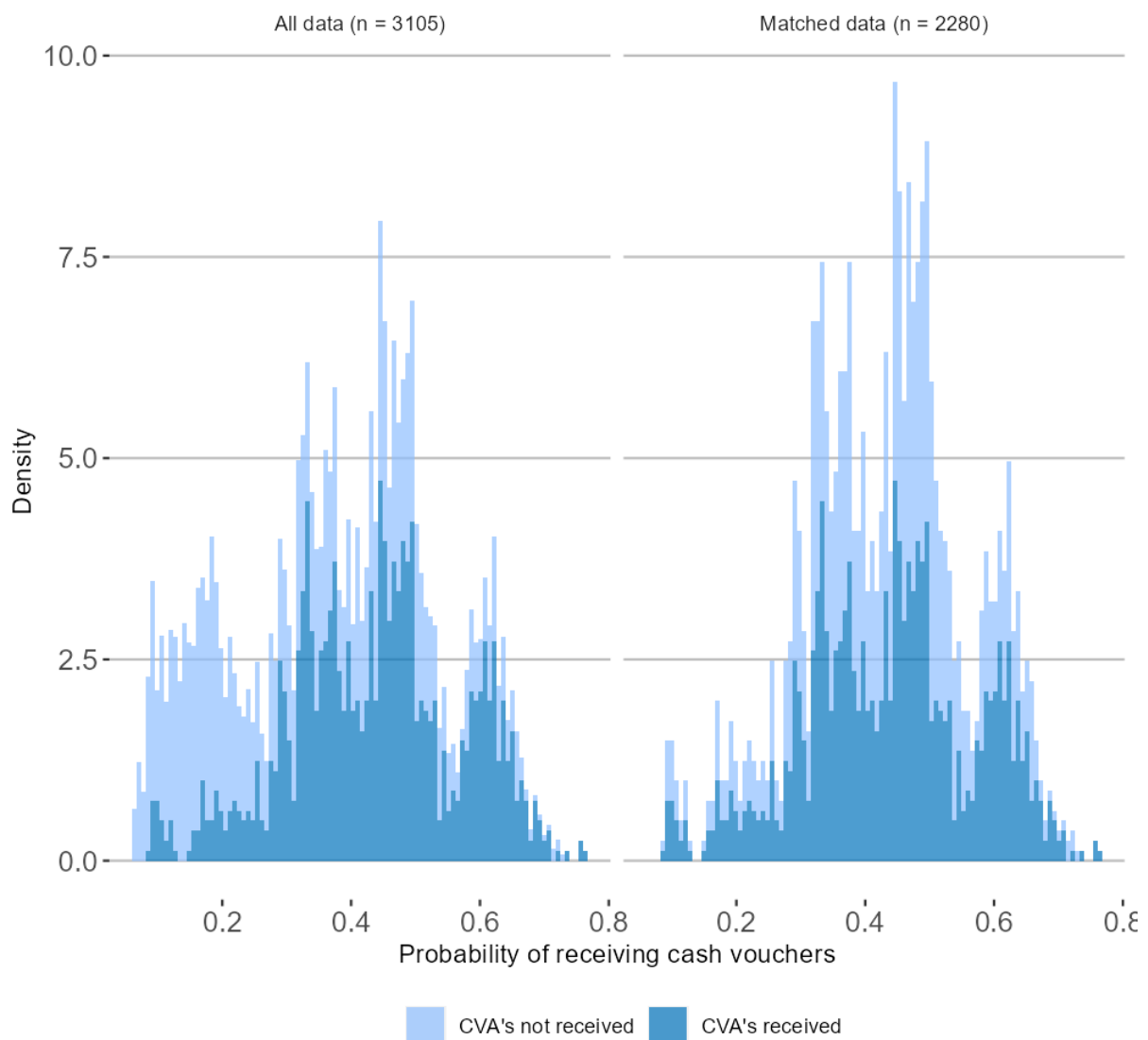
Beneficiary of partner	Cash voucher status	Being host household (in %)	Being IDP (in %)	Being refugee (in %)	Age (in year)	Being female (in %)	Being disabled (in %)	Being married (in %)	# of children	Having no education (in %)	Having no degree (in %)	Primary completed (in %)	Secondary completed (in %)	Average income (XYZ)
A	not received	0.74 (0.44)	0.26 (0.44)	0 (0.06)	40.36 (11.79)	0.23 (0.42)	0.08 (0.27)	0.7 (0.46)	2.23 (1.98)	0.36 (0.48)	0.07 (0.26)	0.25 (0.43)	0.26 (0.44)	528.64 (220.07)
	received	0.48 (0.5)	0.52 (0.5)	0 (0)	45.59 (12.42)	0.24 (0.43)	0.1 (0.29)	0.68 (0.47)	3.13 (1.65)	0.79 (0.41)	0.1 (0.31)	0.1 (0.31)	0 (0.07)	365.06 (78.83)
B	not received	0.81 (0.39)	0.09 (0.29)	0.1 (0.3)	37.61 (9.92)	0.29 (0.45)	0.06 (0.24)	0.92 (0.28)	1.81 (1.81)	0.18 (0.39)	0.07 (0.26)	0.31 (0.46)	0.32 (0.47)	619.87 (230.45)
	received	0.68 (0.47)	0 (0)	0.32 (0.47)	38.28 (7.7)	0.18 (0.39)	0.14 (0.35)	0.94 (0.24)	2.31 (1)	0.42 (0.5)	0.06 (0.24)	0.17 (0.38)	0.29 (0.46)	476.06 (167.54)
C	not received	0.6 (0.49)	0.4 (0.49)	0 (0)	36.61 (9.43)	0.24 (0.43)	0.1 (0.3)	0.11 (0.32)	1.87 (1.2)	0.33 (0.47)	0.34 (0.47)	0.22 (0.42)	0.1 (0.3)	310.36 (129.4)
	received	0.36 (0.48)	0.64 (0.48)	0 (0)	35.81 (9.77)	0.29 (0.45)	0.17 (0.38)	0.15 (0.35)	1.94 (1.22)	0.24 (0.43)	0.42 (0.49)	0.21 (0.41)	0.12 (0.32)	324.49 (120.07)
D	not received	0.6 (0.49)	0.4 (0.49)	0 (0)	41.62 (11.57)	0.25 (0.43)	0.04 (0.2)	0.75 (0.43)	1.78 (1.35)	0.58 (0.49)	0.07 (0.26)	0.12 (0.32)	0.17 (0.37)	449.35 (233.85)
	received	0.49 (0.5)	0.51 (0.5)	0 (0)	44.85 (11.1)	0.25 (0.43)	0.03 (0.18)	0.67 (0.47)	1.73 (0.95)	0.72 (0.45)	0.12 (0.33)	0.06 (0.24)	0.03 (0.18)	397.18 (172.39)
E	not received	0.7 (0.46)	0.3 (0.46)	0 (0)	37.64 (13.26)	0.49 (0.5)	0.25 (0.43)	0.69 (0.46)	2.86 (1.78)	0.42 (0.49)	0.25 (0.43)	0.14 (0.35)	0.13 (0.34)	401.35 (206.01)
	received	0.74 (0.44)	0.26 (0.44)	0 (0)	37.3 (12.37)	0.44 (0.5)	0.2 (0.4)	0.71 (0.46)	2.88 (1.82)	0.37 (0.48)	0.28 (0.45)	0.15 (0.36)	0.14 (0.35)	425.9 (178.12)
Total	not received	0.69 (0.46)	0.3 (0.46)	0.02 (0.13)	39.24 (11.38)	0.28 (0.45)	0.09 (0.28)	0.64 (0.48)	2.05 (1.69)	0.39 (0.49)	0.14 (0.34)	0.21 (0.41)	0.21 (0.4)	471.45 (233.2)
	received	0.5 (0.5)	0.48 (0.5)	0.02 (0.13)	40.3 (11.85)	0.29 (0.45)	0.13 (0.33)	0.52 (0.5)	2.31 (1.48)	0.5 (0.5)	0.24 (0.43)	0.14 (0.35)	0.09 (0.29)	377.12 (149.71)

Note: standard errors are in parentheses.

Estimating propensity scores

To estimate propensity scores for both the beneficiary and the non-beneficiary group, a logistic regression was performed. Within the model, treatment status (0 = no CVA received; 1 = CVA received) was regressed on a set of variables. Observable matching variables included dummies for each of the implementing partner, household status (e.g., refugee status or hist status), as well as personal characteristics of the head of household, including age, gender, disability status, marital status, the number of his/her children, and educational outcomes.

Figure 1: Distribution of propensity scores across beneficiary groups



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Figures 1 (left panel) exhibits the diagnostic value of the propensity score across beneficiary groups using all data. They reveal that there is significant overlap in terms

of observable matching characteristics across both groups. Had there been no comparison units overlapping with a broad range of the beneficiary households, then it would not have been possible to estimate the average treatment effect on income of the CVA programme. Annex A presents the diagnostic value of the propensity score across beneficiary groups for each implementing partner. There appears to be a substantial common support across beneficiary groups for each implementing partner. Only in case of implementing partner B, the distribution appears to be sparse. It may be predominantly due to the relatively small sample size that was accumulated for implementing partner B. Especially when compared with implementing partner A, C, and D, it was rather small with just 398 observations. Nonetheless, given the general substantial overlap between beneficiary and non-beneficiary groups in terms of propensity scores, one can proceed estimating the ATT for the CVA programme.

Table 3: summary of balance across beneficiary groups (all data; n = 3105)

Matching variables	Means (CVA received)	Means (CVA not received)	Std. Mean. Diff.	Var. Ratio	eCDF. Mean	eCDF. Max	Std. Pair. Dist.
P score	0.44	0.33	0.81	0.66	0.18	0.32	NA
beneficiary of partner B	0.06	0.17	-0.48	NA	0.11	0.11	NA
beneficiary of partner C	0.32	0.18	0.31	NA	0.15	0.15	NA
beneficiary of partner D	0.24	0.25	-0.02	NA	0.01	0.01	NA
beneficiary of partner E	0.18	0.11	0.19	NA	0.07	0.07	NA
being IDP	0.48	0.3	0.36	NA	0.18	0.18	NA
being a refugee	0.02	0.02	0.01	NA	0	0	NA
age	40.3	39.24	0.09	1.08	0.02	0.05	NA
being female	0.29	0.28	0.04	NA	0.02	0.02	NA
having disabilities	0.13	0.09	0.11	NA	0.04	0.04	NA
being married	0.52	0.64	-0.24	NA	0.12	0.12	NA
# of children	2.31	2.05	0.18	0.77	0.02	0.1	NA
no education	0.5	0.39	0.22	NA	0.11	0.11	NA
no degree	0.24	0.14	0.24	NA	0.1	0.1	NA
primary completed	0.14	0.21	-0.19	NA	0.07	0.07	NA
secondary completed	0.09	0.21	-0.41	NA	0.12	0.12	NA
university completed	0.02	0.05	-0.27	NA	0.04	0.04	NA
other degrees	0.01	0.01	0.06	NA	0.01	0.01	NA

Note: Due to the dummy-data setup of the model to estimate propensity score, some variables (i.e., being beneficiary of partner A, being a host household etc.) are not included into the tables. However, a closer look into those variables suggested substantial imbalances between the beneficiary and the non-beneficiary group before matching.

The right panel of figure 1 depicts the distribution of both the beneficiary and the non-beneficiary groups across propensity scores. Matching up both groups clearly lines up the common support of both groups in terms of propensity scores. By and large both distributions are now overlapping. Table 3 and 4 provide further insights into the level

of balance across the beneficiary and the non-beneficiary group before (table 3) and after matching *table 4). Matching did not result in the exclusion of many data points. Given a beneficiary group comprising of 1140 observations, matching up data resulted in the omission of 825 non-beneficiary households. Comparing the means of both the beneficiary and the non-beneficiary group before and after matching highlights that systematic differences between both subsets were substantially reduced (columns 2 and 3 of respective tables). As a consequence, both groups hardly differed in terms of the propensity score (p score).

Table 4: summary of balance across beneficiary groups (matched data; n = 2280)

Matching variables	Means (CVA received)	Means (CVA not received)	Std. mean. diff.	Var. ratio	eCDF. mean	eCDF. max	Std. pair. dist.
P score	0.44	0.43	0.06	1.12	0.01	0.06	0.06
beneficiary of partner B	0.06	0.05	0.01	NA	0	0	0.23
beneficiary of partner C	0.32	0.29	0.08	NA	0.04	0.04	0.67
beneficiary of partner D	0.24	0.29	-0.1	NA	0.04	0.04	0.71
beneficiary of partner E	0.18	0.17	0.02	NA	0.01	0.01	0.7
being IDP	0.48	0.43	0.11	NA	0.05	0.05	0.6
being a refugee	0.02	0.02	-0.02	NA	0	0	0.25
age	40.3	40.79	-0.04	1.01	0.01	0.04	1.07
being female	0.29	0.28	0.03	NA	0.01	0.01	0.85
having disabilities	0.13	0.11	0.03	NA	0.01	0.01	0.6
being married	0.52	0.54	-0.04	NA	0.02	0.02	0.84
# of children	2.31	2.32	-0.01	0.92	0.01	0.02	0.97
no education	0.5	0.56	-0.14	NA	0.07	0.07	0.87
no degree	0.24	0.2	0.09	NA	0.04	0.04	0.65
primary completed	0.14	0.14	0	NA	0	0	0.61
secondary completed	0.09	0.07	0.07	NA	0.02	0.02	0.37
university completed	0.02	0.01	0.03	NA	0	0	0.19
other degrees	0.01	0.01	0.03	NA	0	0	0.16

Note: Due to the dummy-data setup of the model to estimate propensity score, some variables (i.e., being beneficiary of partner A, being a hist household etc,) are not included into the tables. However, a closer look into those variables did not suggest substantial imbalances between the beneficiary and the non-beneficiary group after matching.

The acceptable balancing performance is also expressed amongst others by the standardized mean difference (Std. mean. diff.). The standardized mean difference (SMD) is a metric used to assess the balance of covariates between evaluation groups before and after matching. It quantifies the difference in means of a covariate between the groups, standardized by the pooled standard deviation, making it unitless and comparable across covariates. Any std. mean. diff. below 0.1 indicates acceptable balance. This threshold has been taken by almost all matching variables. Both groups may only somewhat differ in terms of extent to which observations has not attained

any education (i.e., no education). Here, the std. mean. diff. is between 0.1 and 0.2. This result could indicate potential imbalance between both groups and thus bias the estimation of programme effects.

Annex B presents exploratory graphs on the relationship between matching variables and propensity scores within the matched dataset. By and large, the relationship between propensity scores on the one side as well as the individual matching variables on the other side appear to be congruent across both the beneficiary and non-beneficiary group. It is again bears testimony of the balance across both groups attained through the matching.

Table 4 presents the results of the regression modelling performed on both the full dataset (columns 1 and 2) as well as the matched data (columns 3 and 4). Columns 1 and 3 present the result of a simple bivariate regression of income on treatment status. Columns 2 and 4 present the result of the full regression of income on treatment status controlling for the different covariates amongst others listed in table 3 or 4.

As one would expect, the differences between estimated effects of beneficiary status on income are the starkest in case of the bivariate regression model. However, controlling for the different covariates reduces the differences. In case of the full data, the effect is around $\beta_{income;full}$ 13.32 (1.83; $p < .001$). This is equal to an effect size of around 0.06 standard deviation associated with income expressed in XYZ. In case of the matched data, the effect is higher with about $\beta_{income;matched}$ 22.45 (1.86; $p < .001$). This is equal to an effect size of around 0.1 standard deviation. Thus, using the quasi-experimental estimation approach of propensity score matching results in an estimation of the effect size, which is about 70 per cent higher compared to the unadjusted regression model.

By matching beneficiary and non-beneficiary households on propensity scores, a quasi-randomized sample was created where the distribution of covariates is similar between treated and untreated groups. This enhances the interpretability of the treatment effect of the CVA programme as causal. Of course, an effect size or just around 0.1 standard deviation is a rather small effect. However, it appears to be a realistic estimate given the small scope of the programme implemented by the consortium.

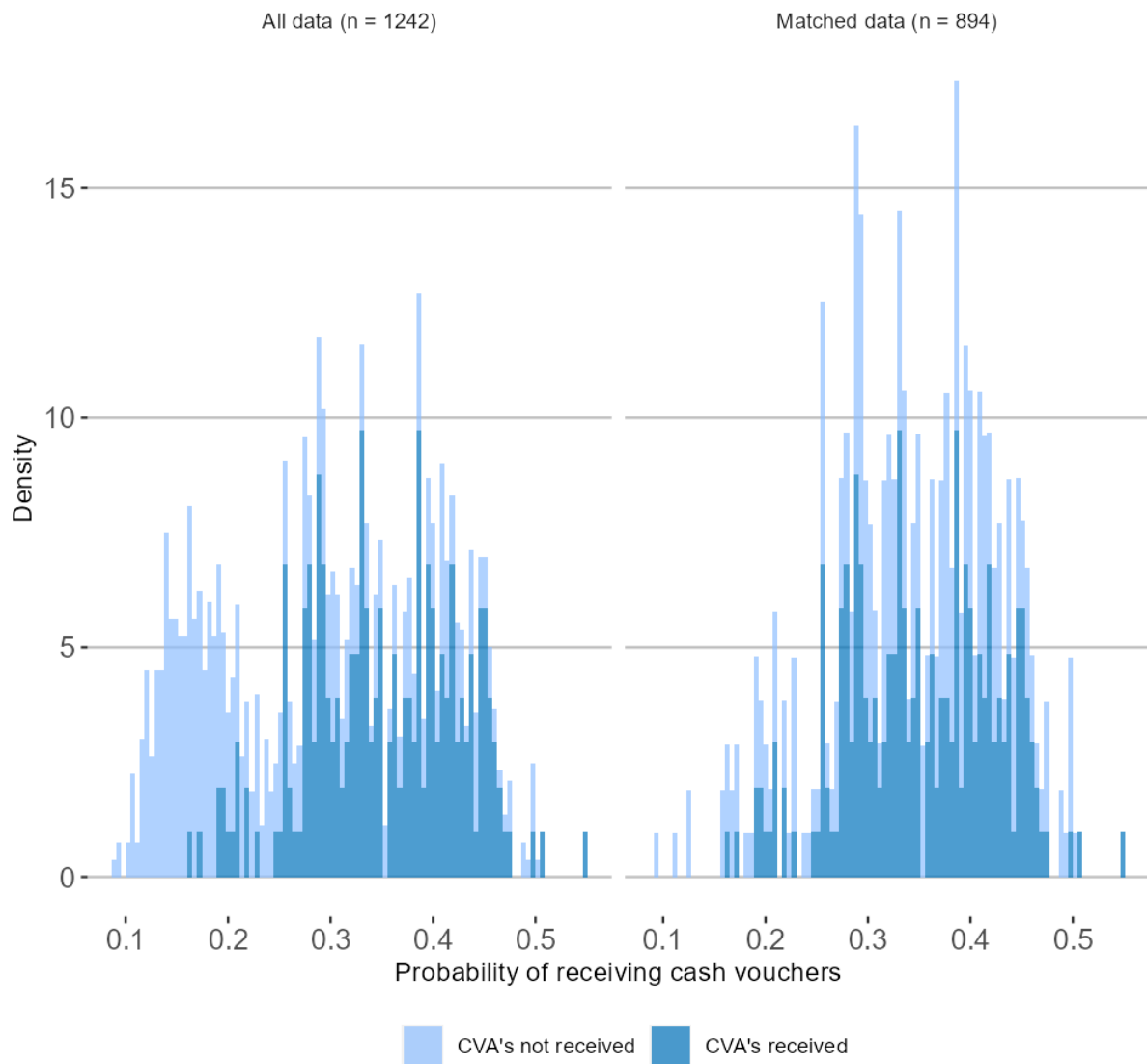
Table 4: Estimated CVA effects on income

	<i>Dependent variable:</i>			
	Average income attained			
	1	2	3	4
Cash vouchers received	-94.32*** (7.69)	13.32*** (1.83)	25.03*** (6.28)	22.45*** (1.86)
Beneficiary of partner B		14.01*** (3.13)		6.13 (5.65)
Beneficiary of partner C		-66.55*** (2.87)		-47.86*** (3.25)
Beneficiary of partner D		-26.97*** (2.43)		-17.50*** (2.91)
Beneficiary of partner E		-40.18*** (2.94)		-21.31*** (3.25)
Being an IDP		-82.22*** (1.89)		-77.88*** (1.96)
Being a refugee		-137.24*** (6.80)		-118.37*** (8.26)
Age (standardized)		26.49*** (0.90)		28.43*** (1.00)
Being female		-18.08*** (2.04)		-20.56*** (2.36)
Being disabled		-37.40*** (2.85)		-36.88*** (2.95)
Being married		58.79*** (2.19)		56.19*** (2.48)
# of children		-6.05*** (0.54)		-4.34*** (0.67)
Having no education		-202.29*** (8.49)		-210.58*** (8.26)
Having no degree		-182.56*** (8.64)		-196.75*** (8.43)
Primary education completed		-43.69*** (8.63)		-69.01*** (8.53)
Secondary education completed		106.29*** (8.66)		76.21*** (8.74)
University completed		563.41*** (9.37)		529.07*** (11.02)
Constant	471.45*** (4.66)	562.90*** (8.97)	352.10*** (4.44)	552.36*** (9.12)
Observations	3,105	3,105	2,280	2,280
Log Likelihood	-20,956.60	-16,313.54	-14,657.56	-11,857.19
Akaike Inf. Crit.	41,917.19	32,663.07	29,319.12	23,750.37

Note: *p<0.1; **p<0.05; ***p<0.01

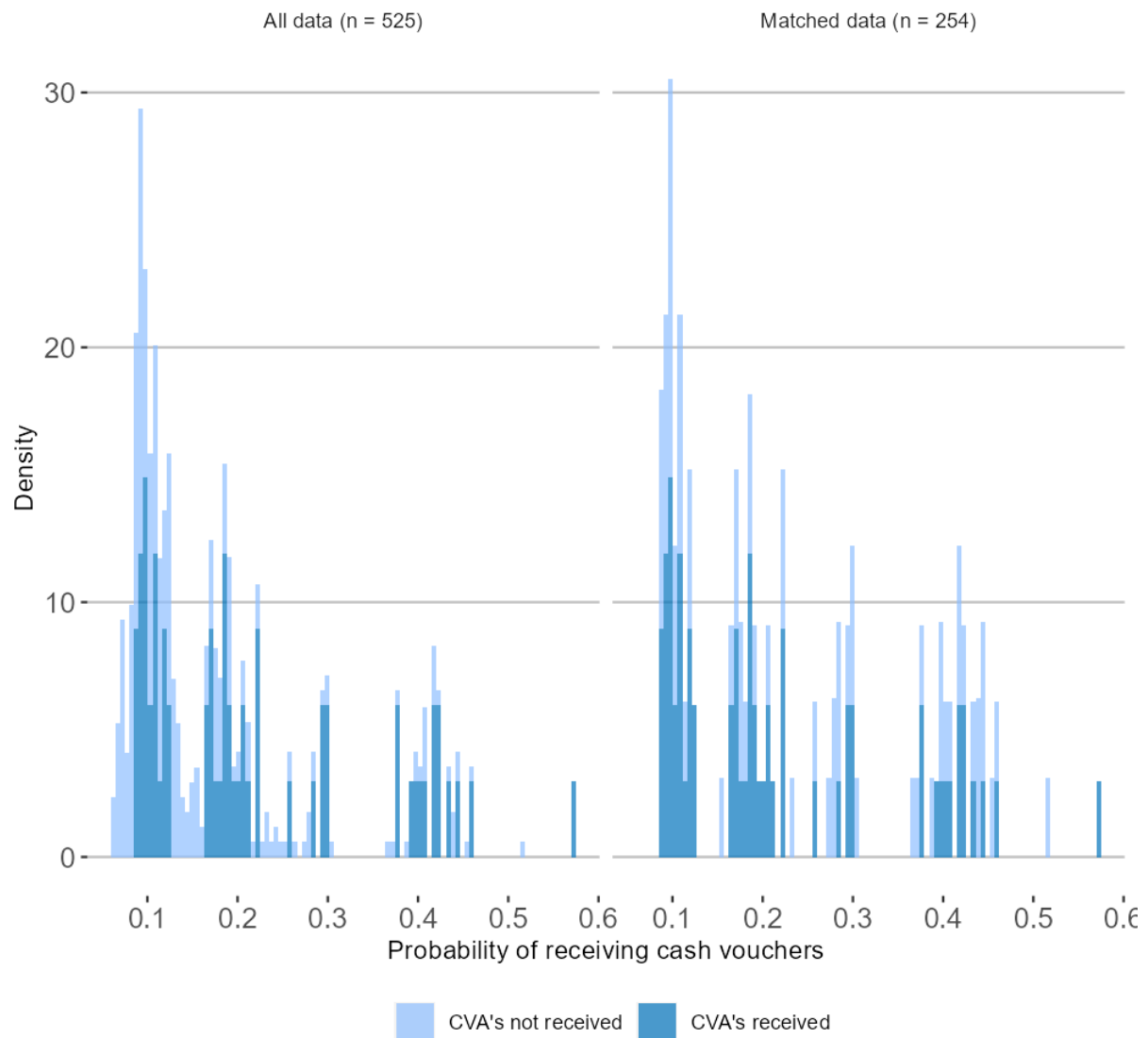
Annex A: Partner-specific distribution of propensity scores across beneficiary groups

Figure A1: Distribution of propensity scores across beneficiary groups (implementing partner A only)



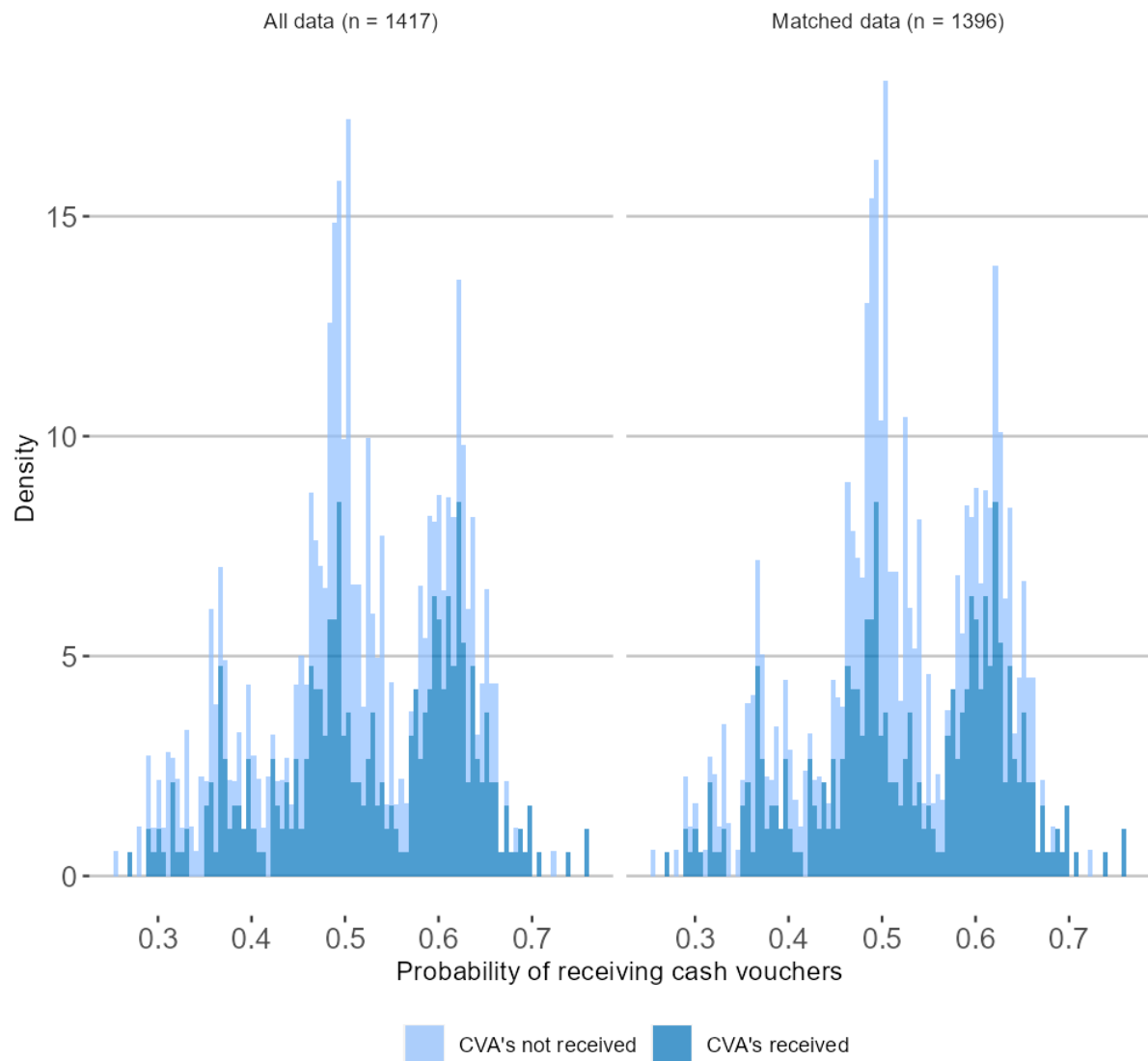
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**Figure A2: Distribution of propensity scores across beneficiary groups
(implementing partner B only)**



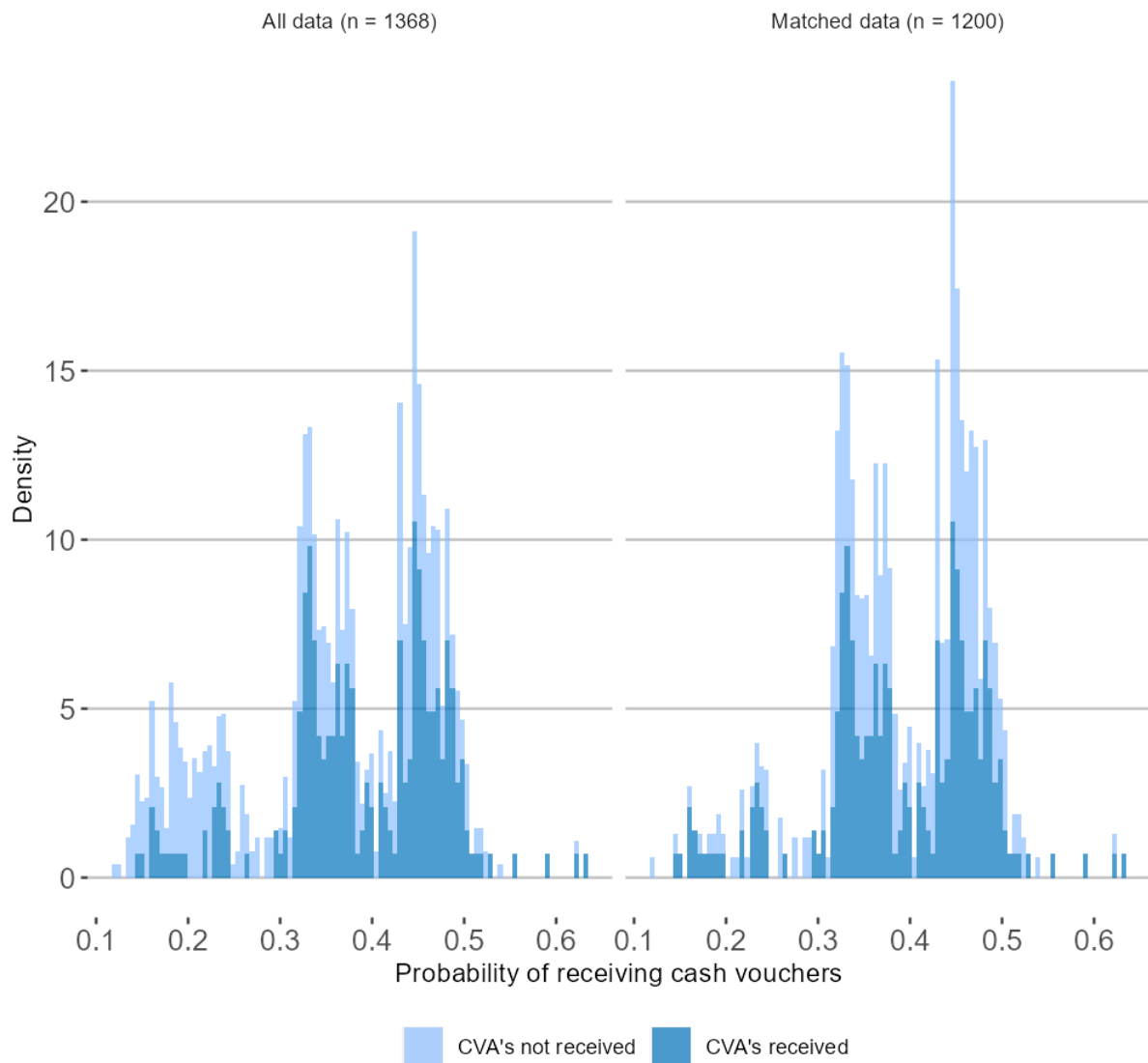
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Figure A3: Distribution of propensity scores across beneficiary groups (implementing partner C only)



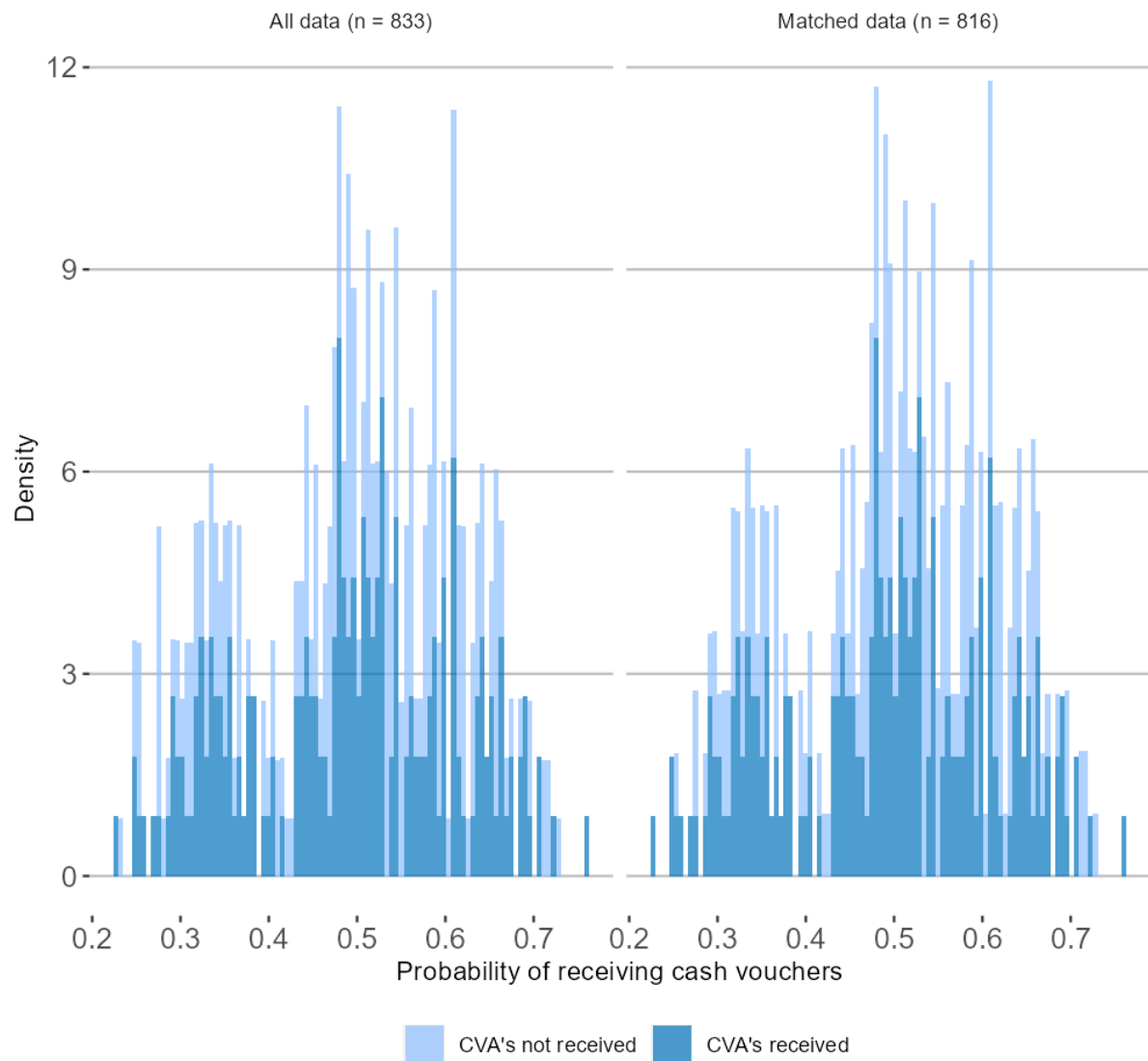
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**Figure A4: Distribution of propensity scores across beneficiary groups
(implementing partner D only)**



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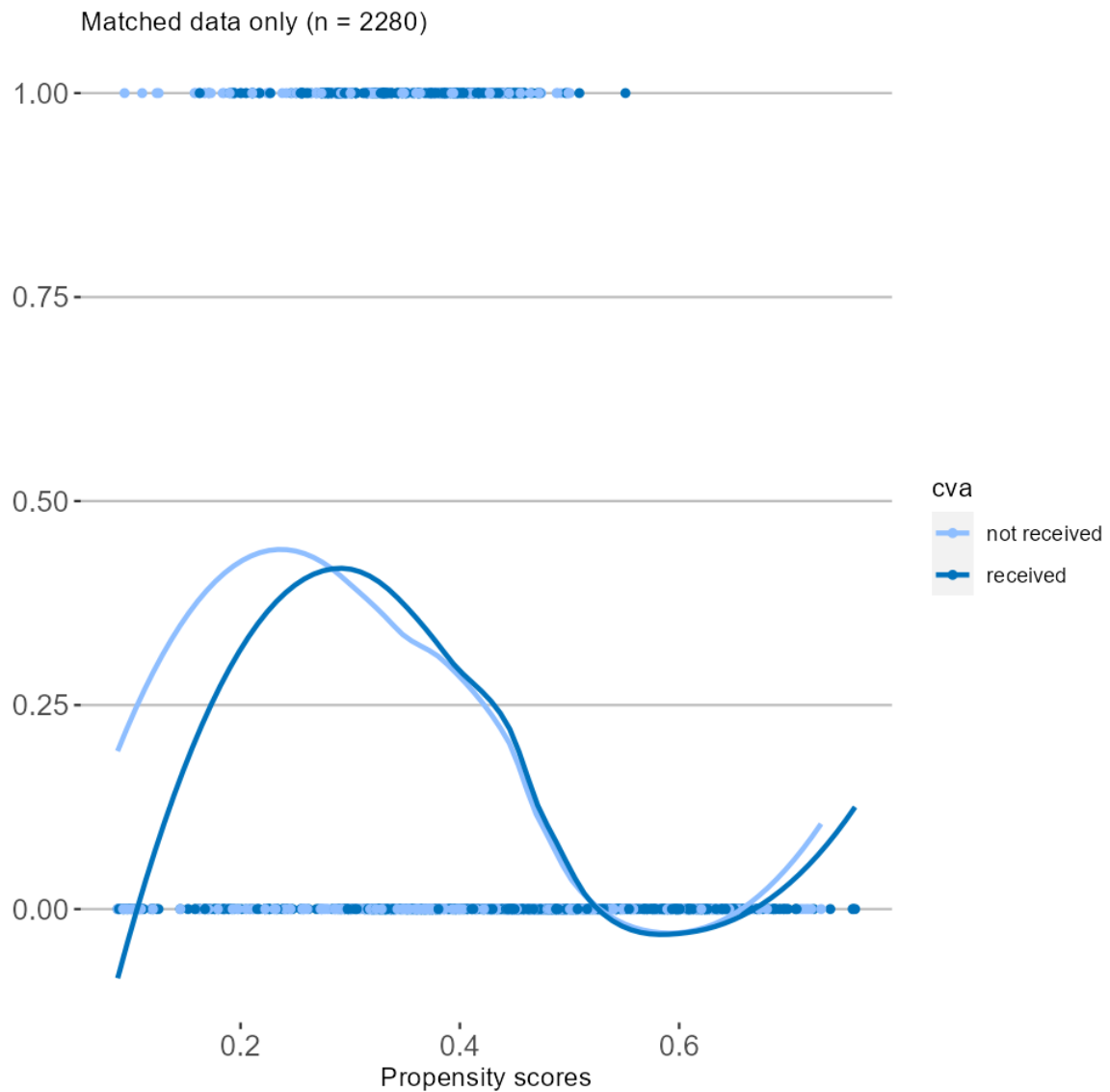
**Figure A5: Distribution of propensity scores across beneficiary groups
(implementing partner E only)**



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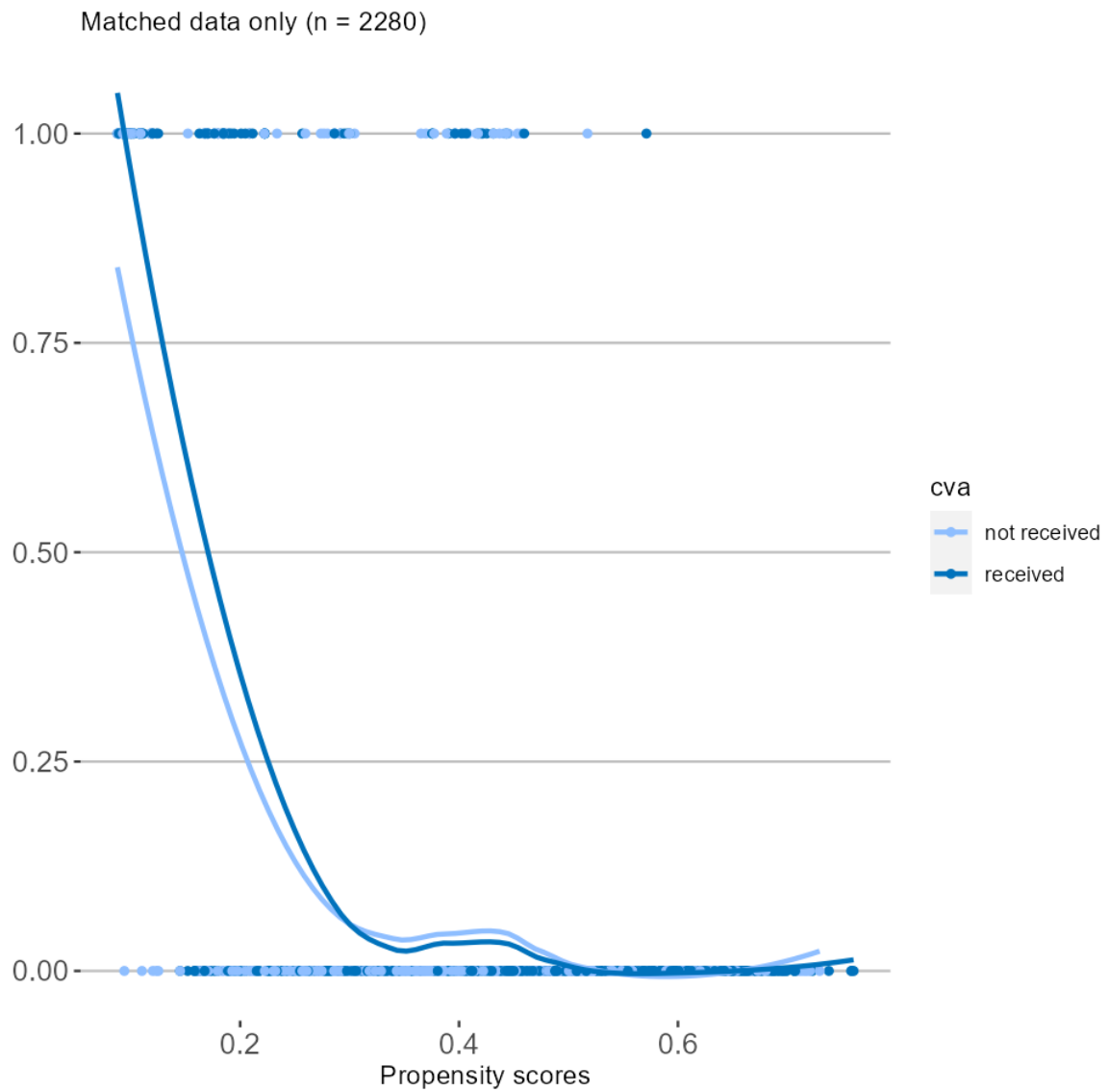
Annex B: Relationship between matching variables and propensity scores across beneficiary groups

Figure B1: Relationship between 'being beneficiary of implementing partner (A)' and propensity scores across beneficiary groups



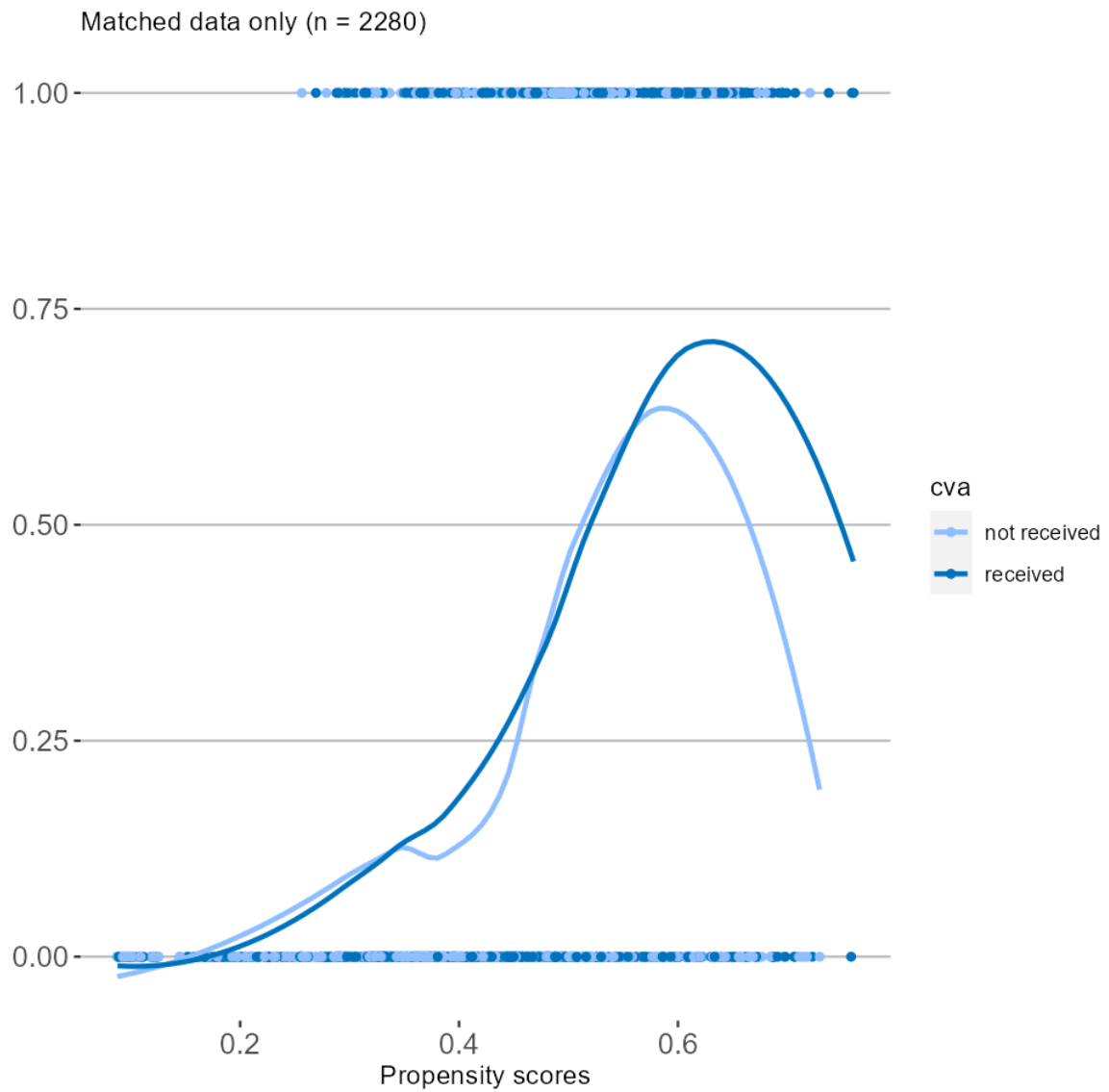
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Figure B2: Relationship between 'being beneficiary of implementing partner (B)' and propensity scores across beneficiary groups



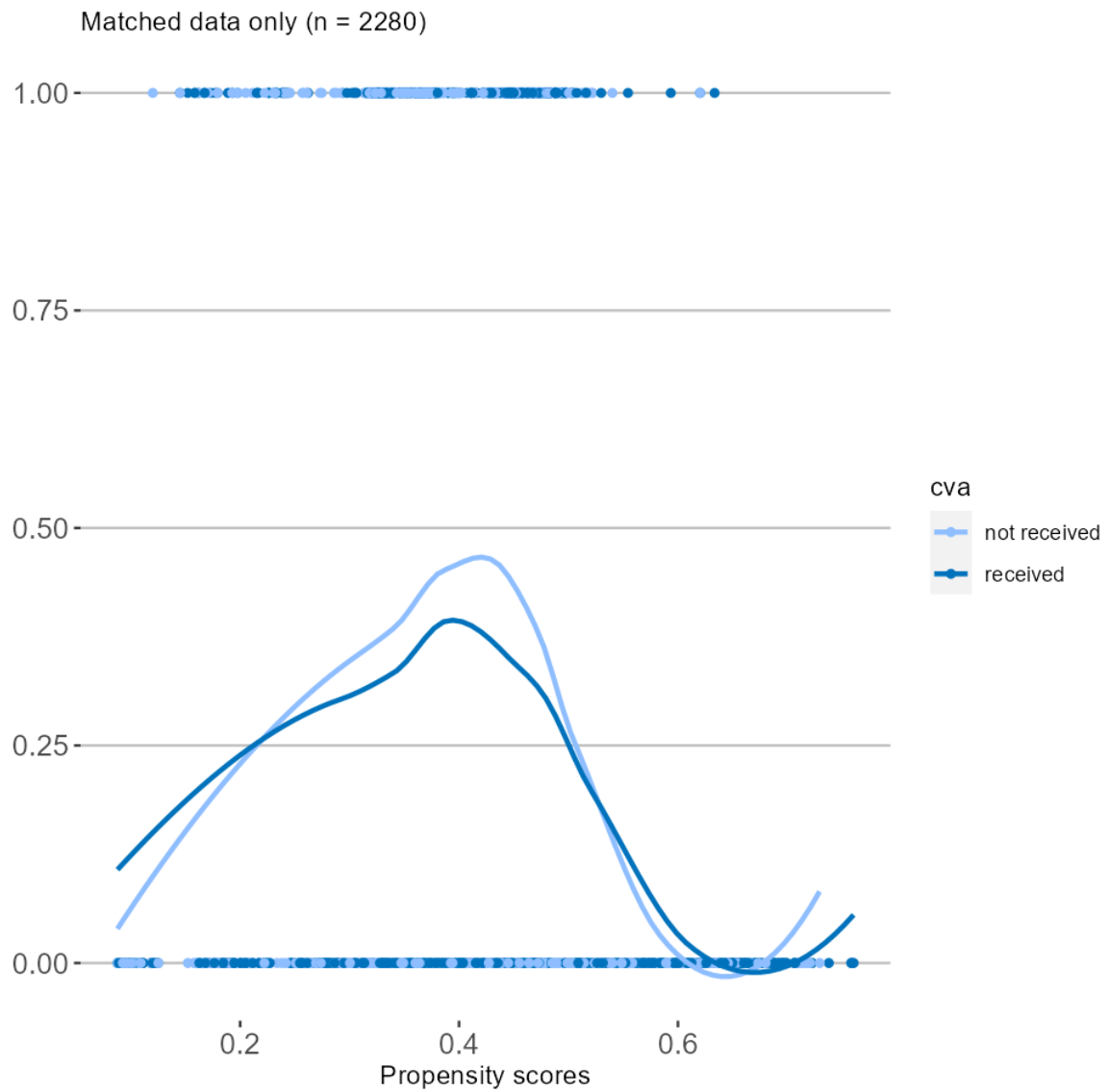
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Figure B3: Relationship between 'being beneficiary of implementing partner (C)' and propensity scores across beneficiary groups



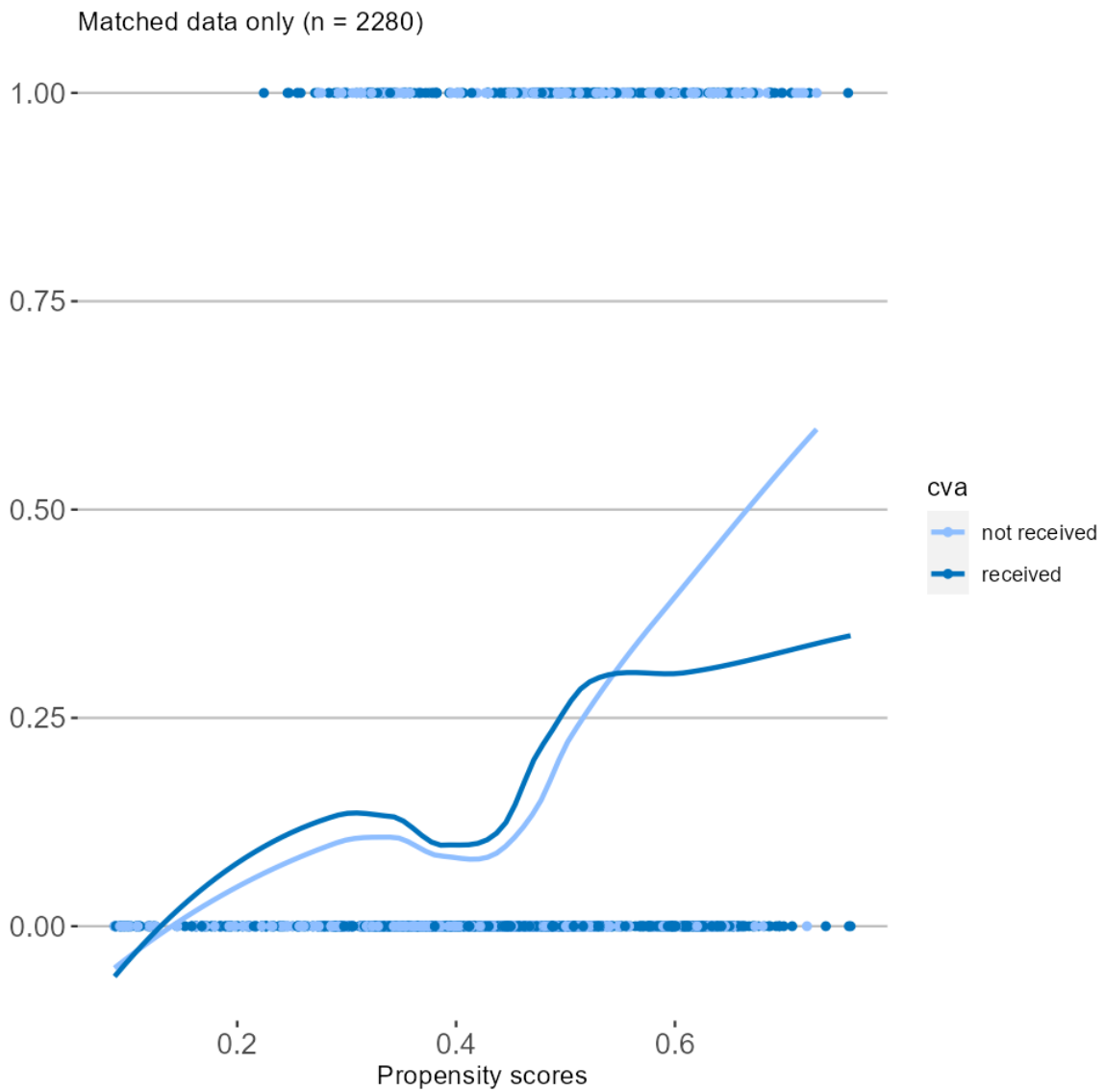
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Figure B4: Relationship between 'being beneficiary of implementing partner (D)' and propensity scores across beneficiary groups



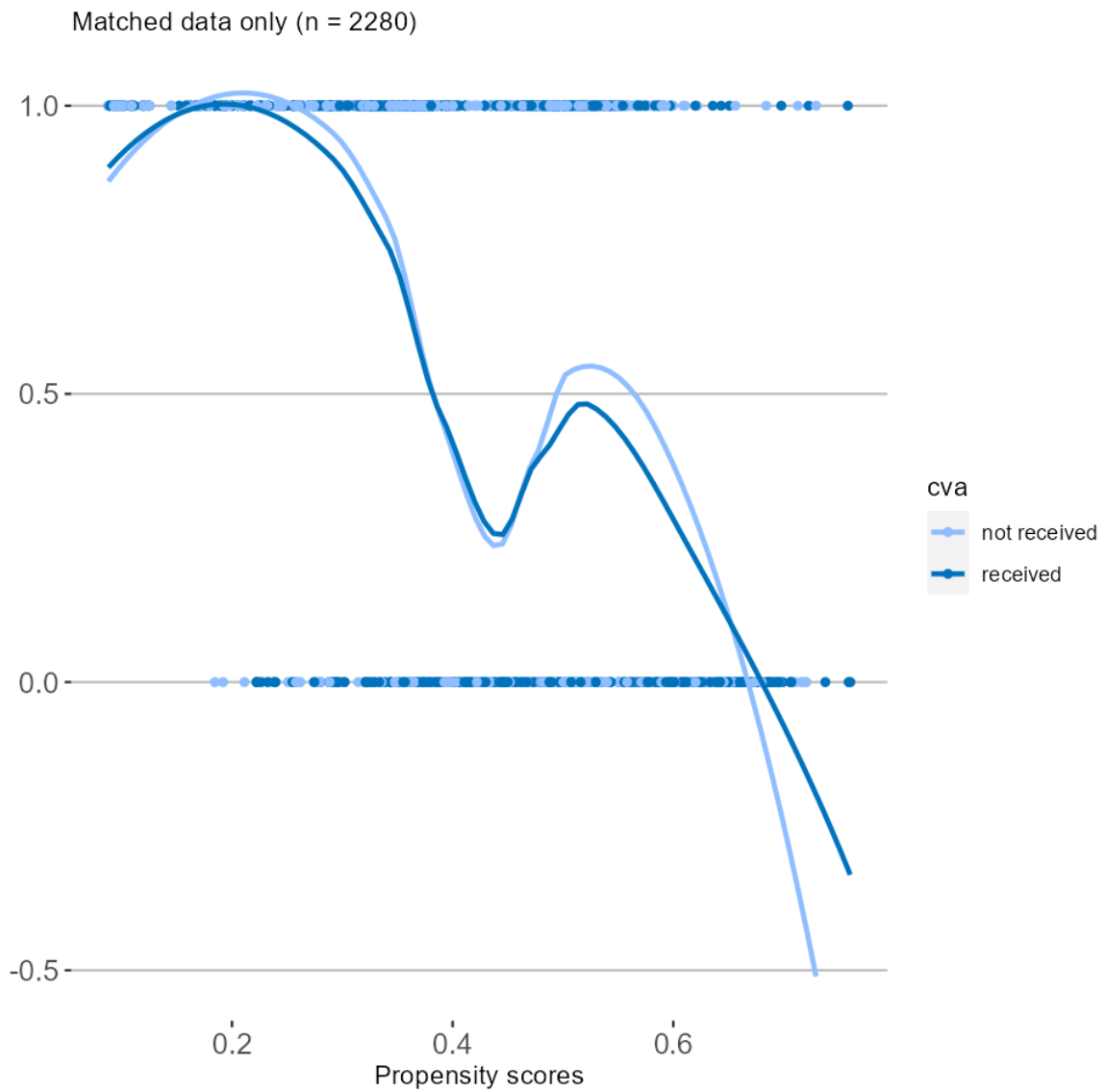
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Figure B5: Relationship between 'being beneficiary of implementing partner (E)' and propensity scores across beneficiary groups



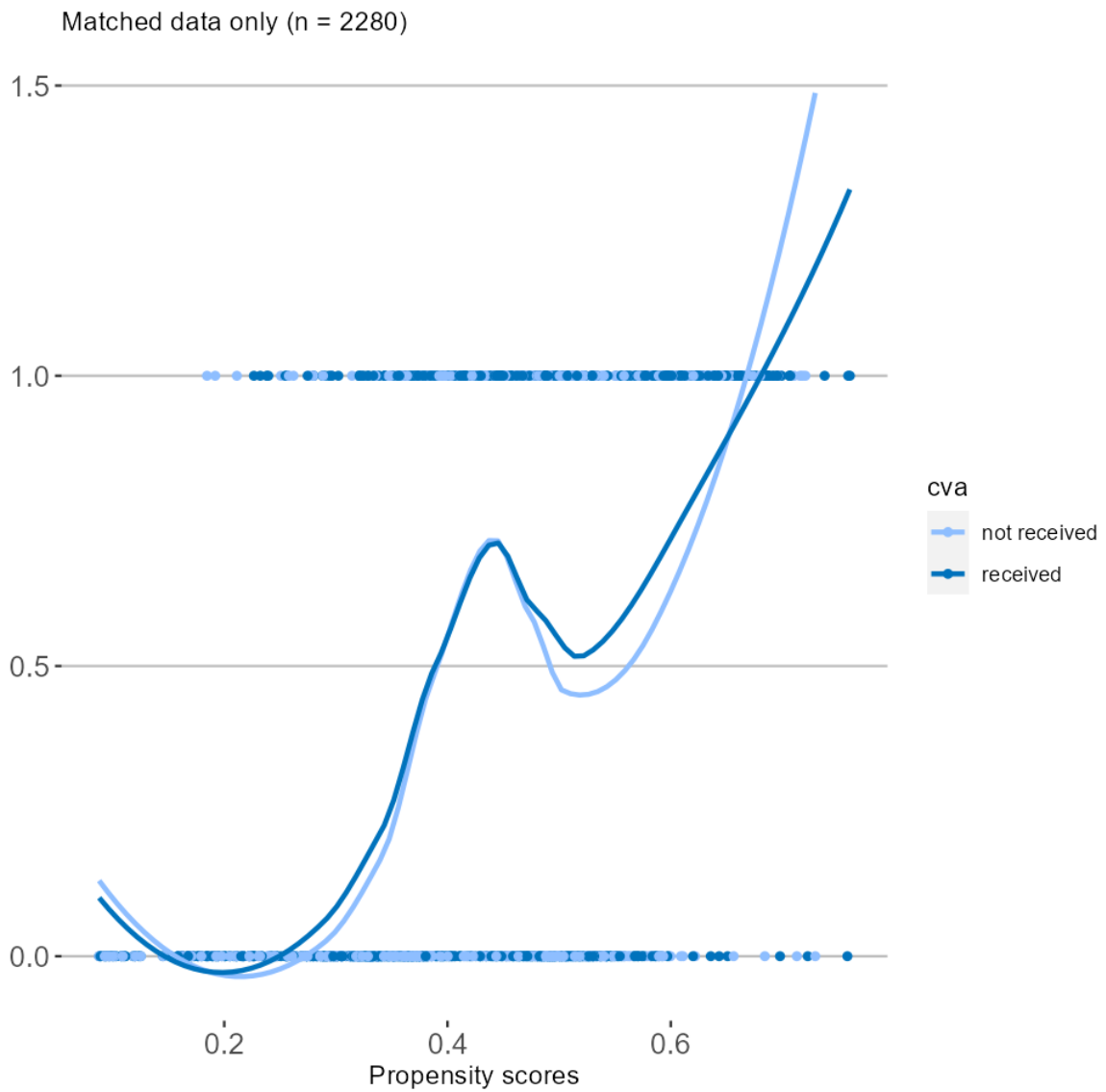
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Figure B6: Relationship between 'being host' and propensity scores across beneficiary groups



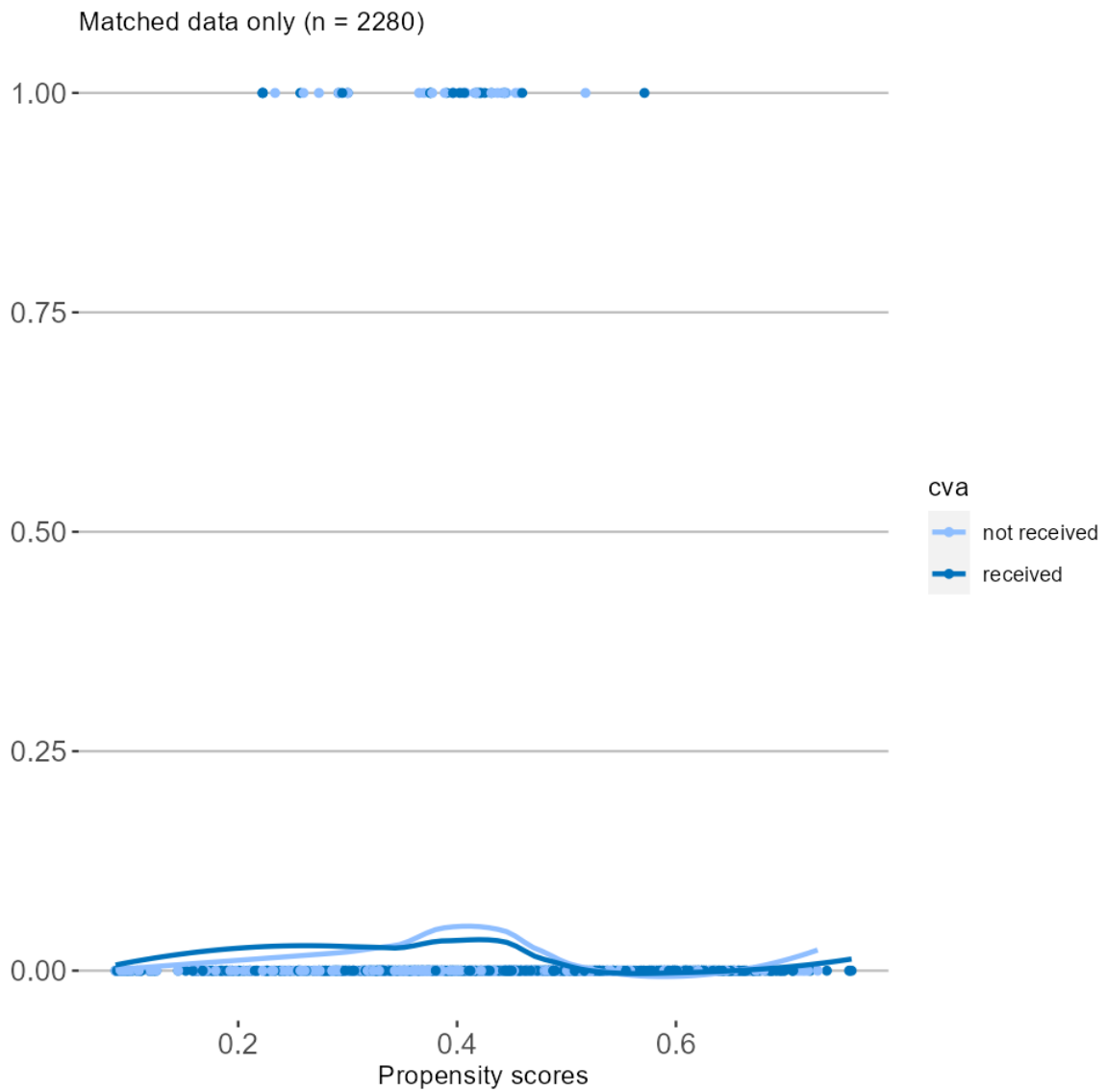
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Figure B7: Relationship between 'being IDP' and propensity scores across beneficiary groups



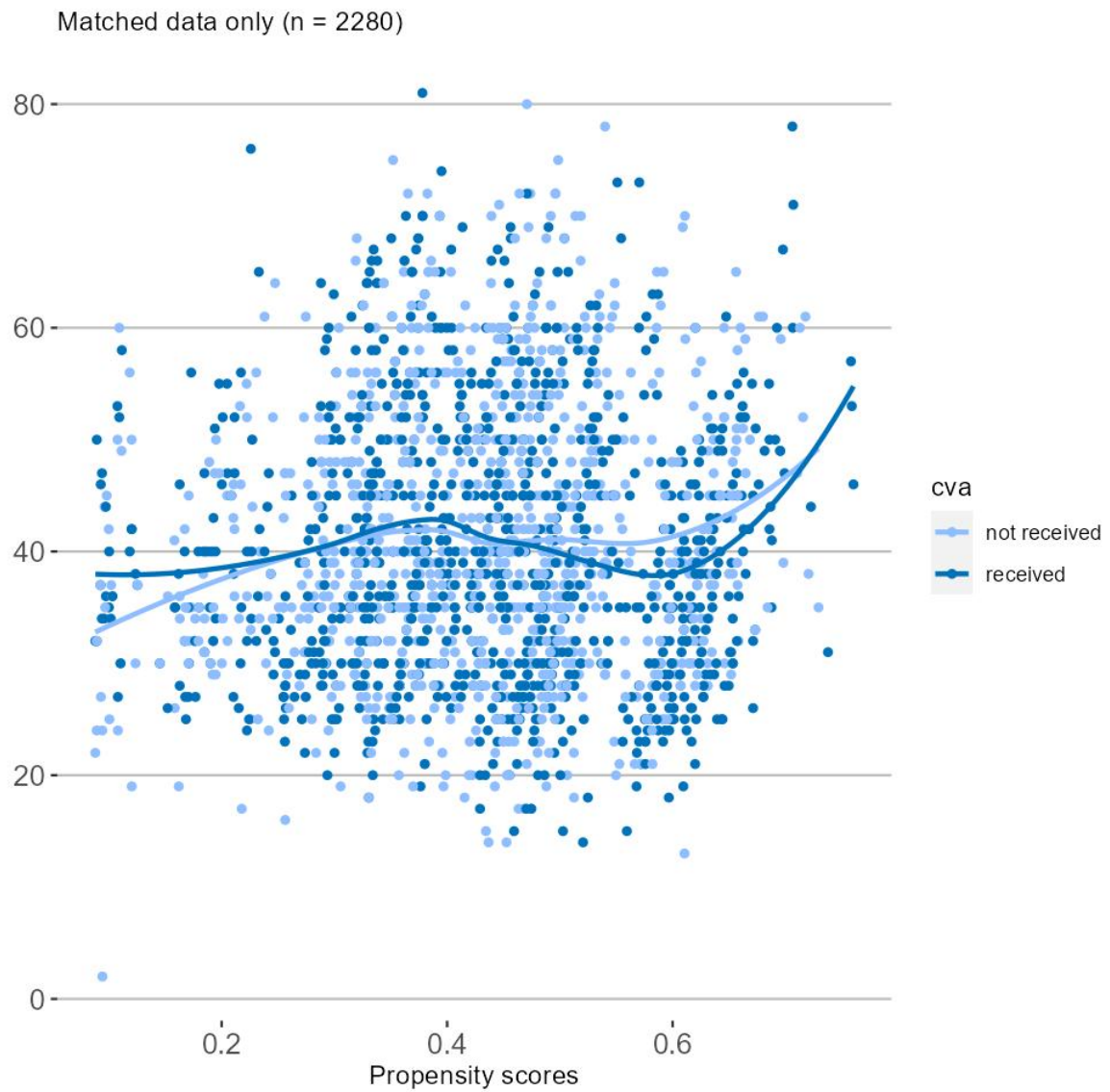
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Figure B8: Relationship between 'being refugee' and propensity scores across beneficiary groups



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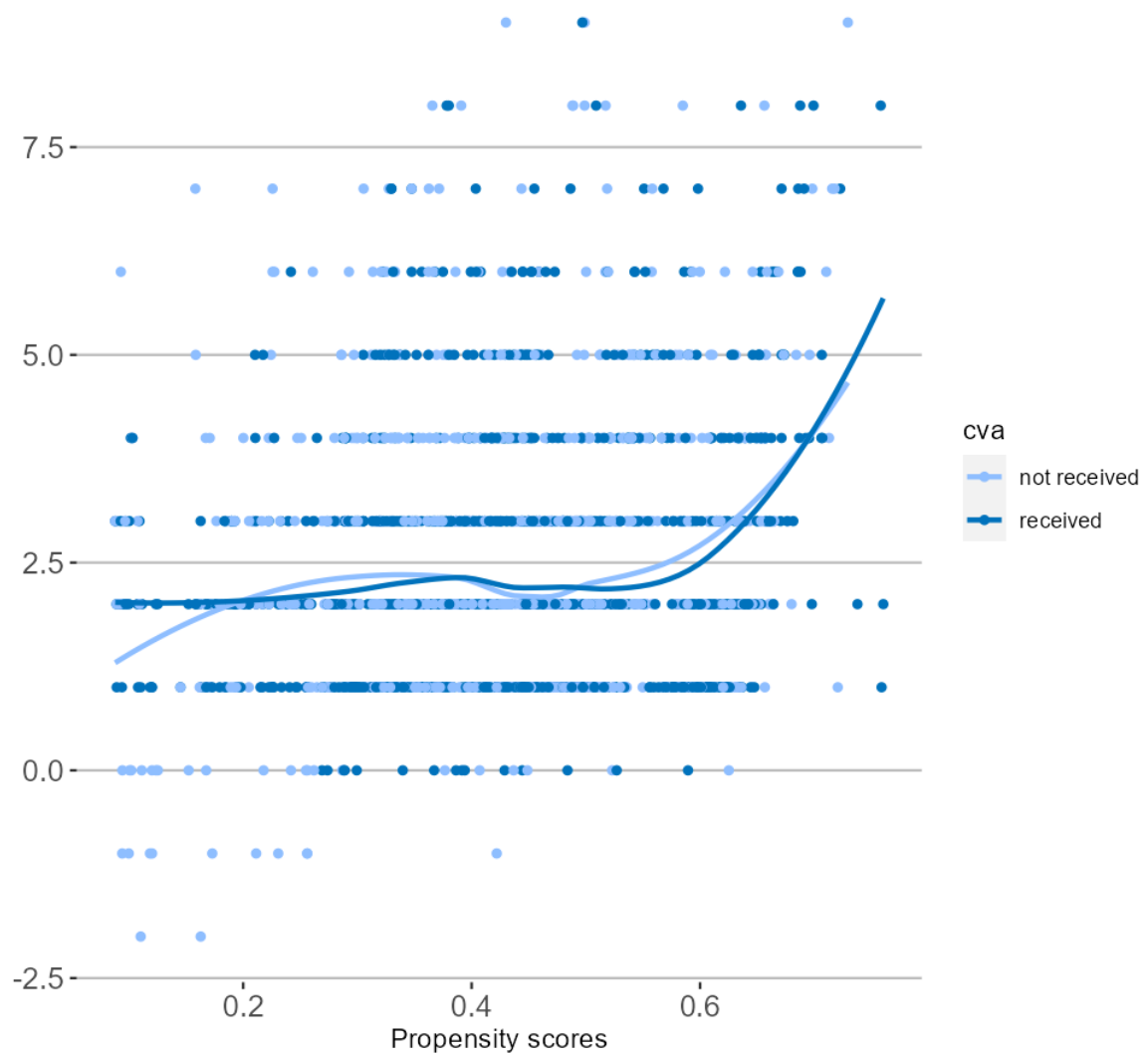
Figure B9: Relationship between 'age' and propensity scores across beneficiary groups



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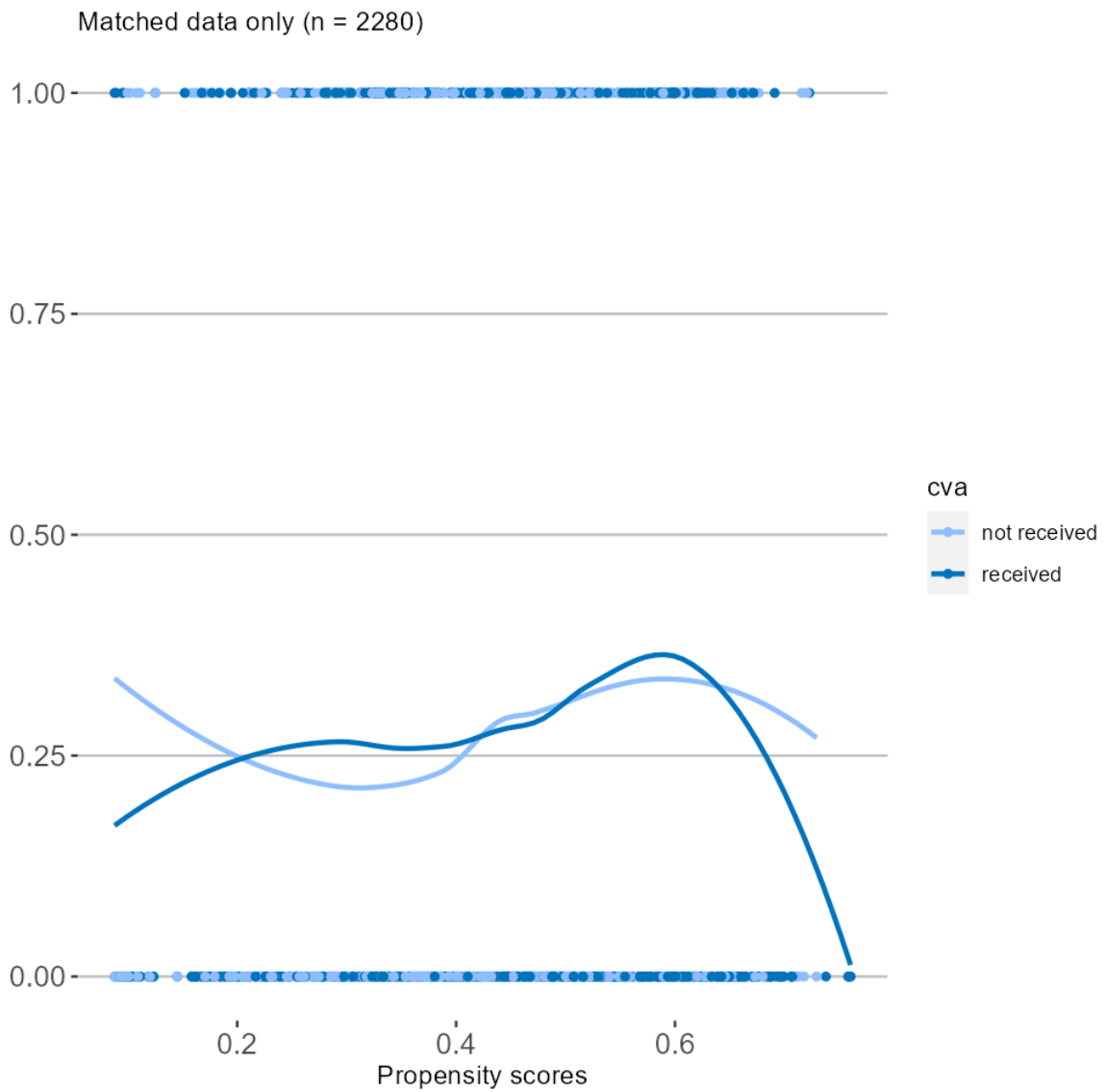
Figure B10: Relationship between ‘# of children’ and propensity scores across beneficiary groups

Matched data only (n = 2280)



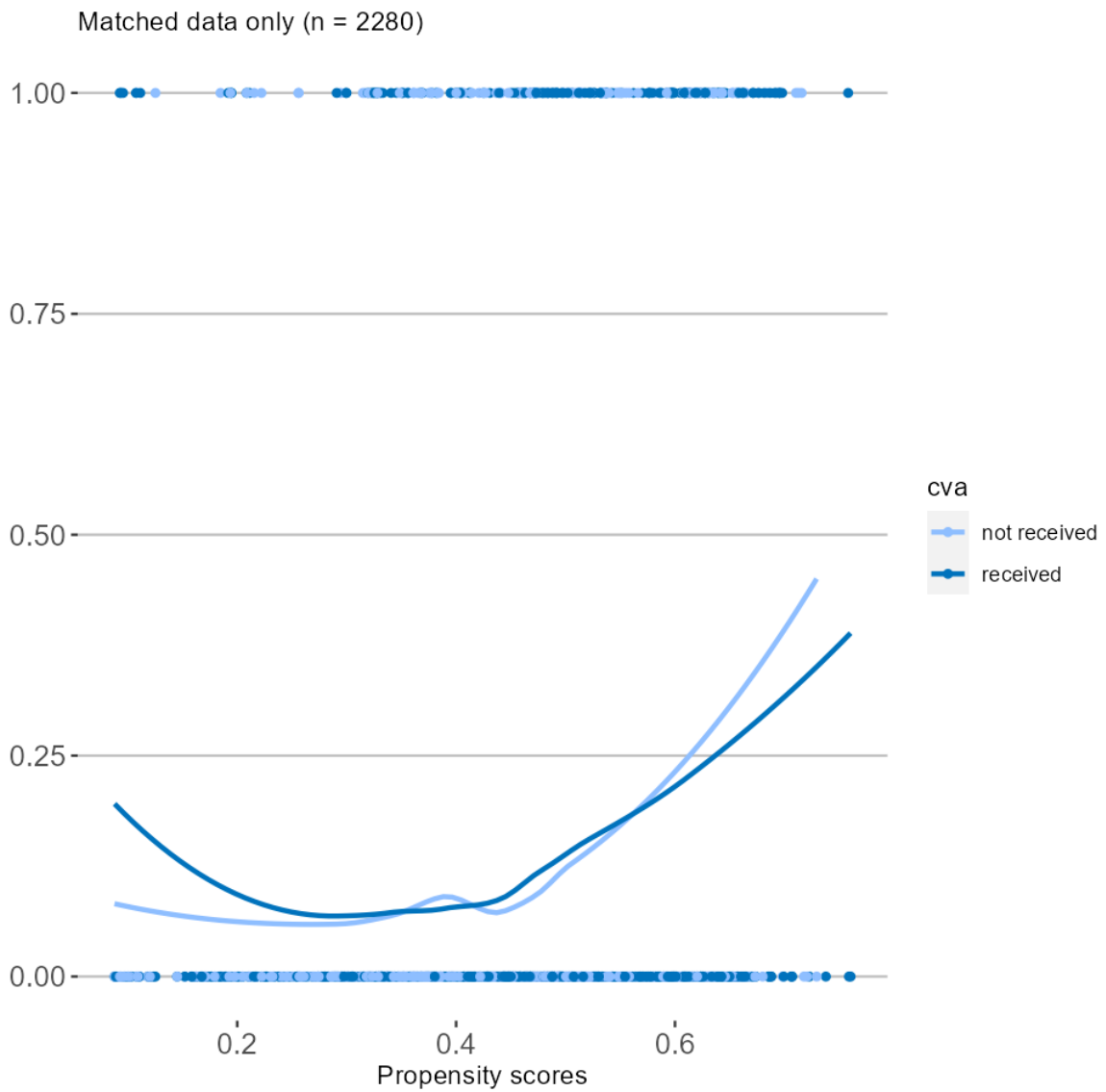
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Figure B11: Relationship between 'being female' and propensity scores across beneficiary groups



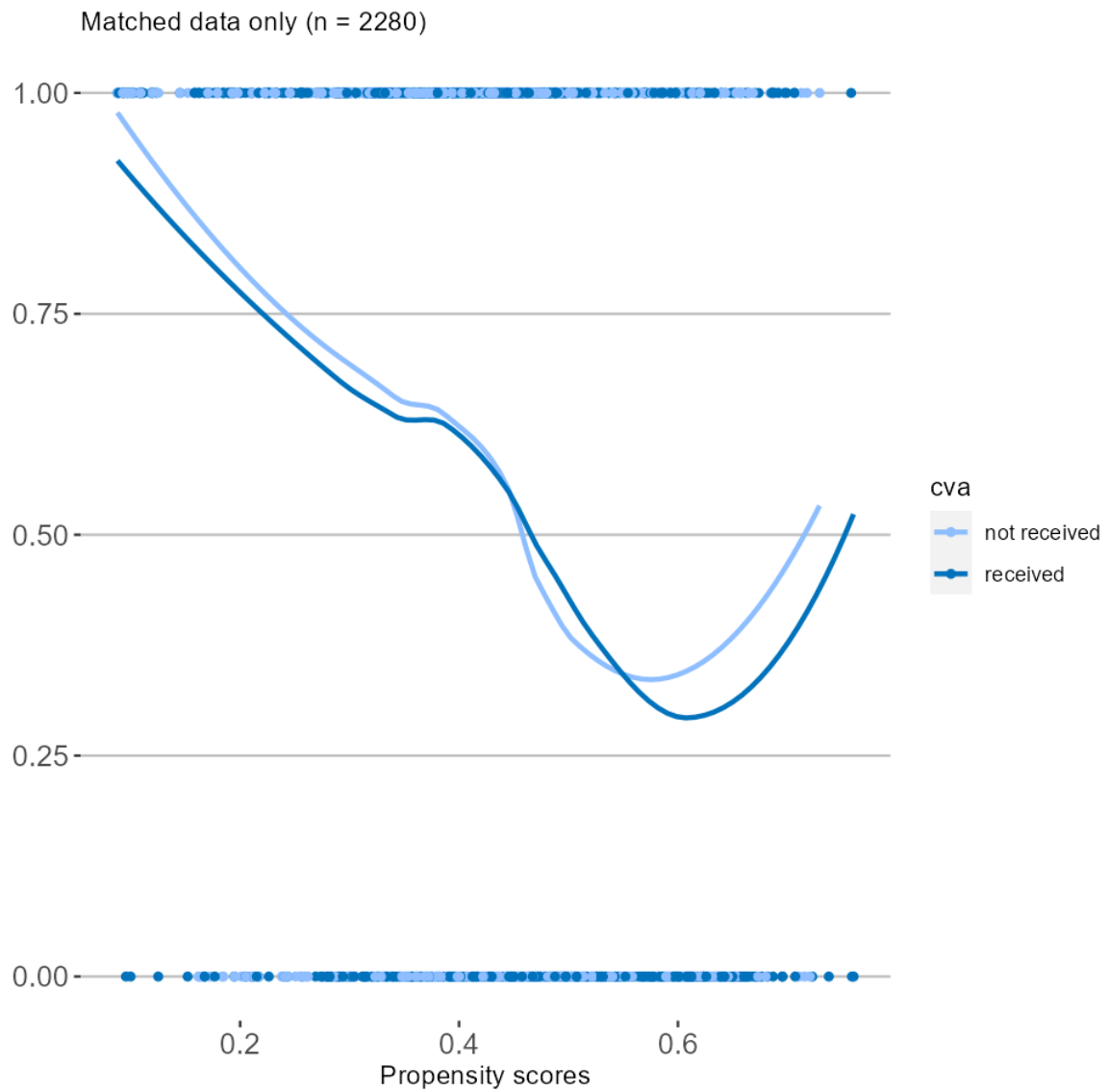
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Figure B12: Relationship between ‘having disabilities’ and propensity scores across beneficiary groups



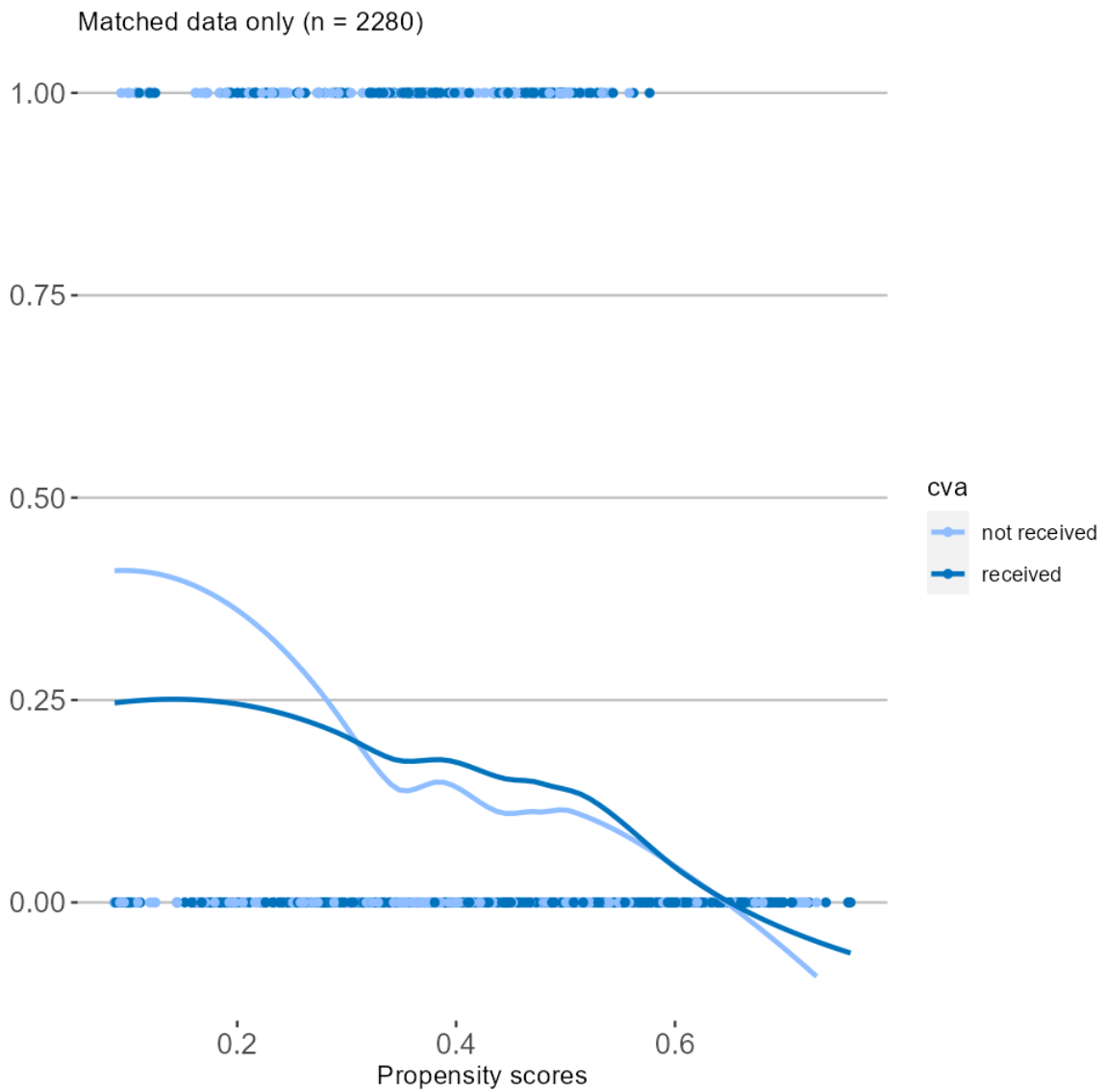
Source: endine 2023
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Figure B13: Relationship between ‘being married’ and propensity scores across beneficiary groups



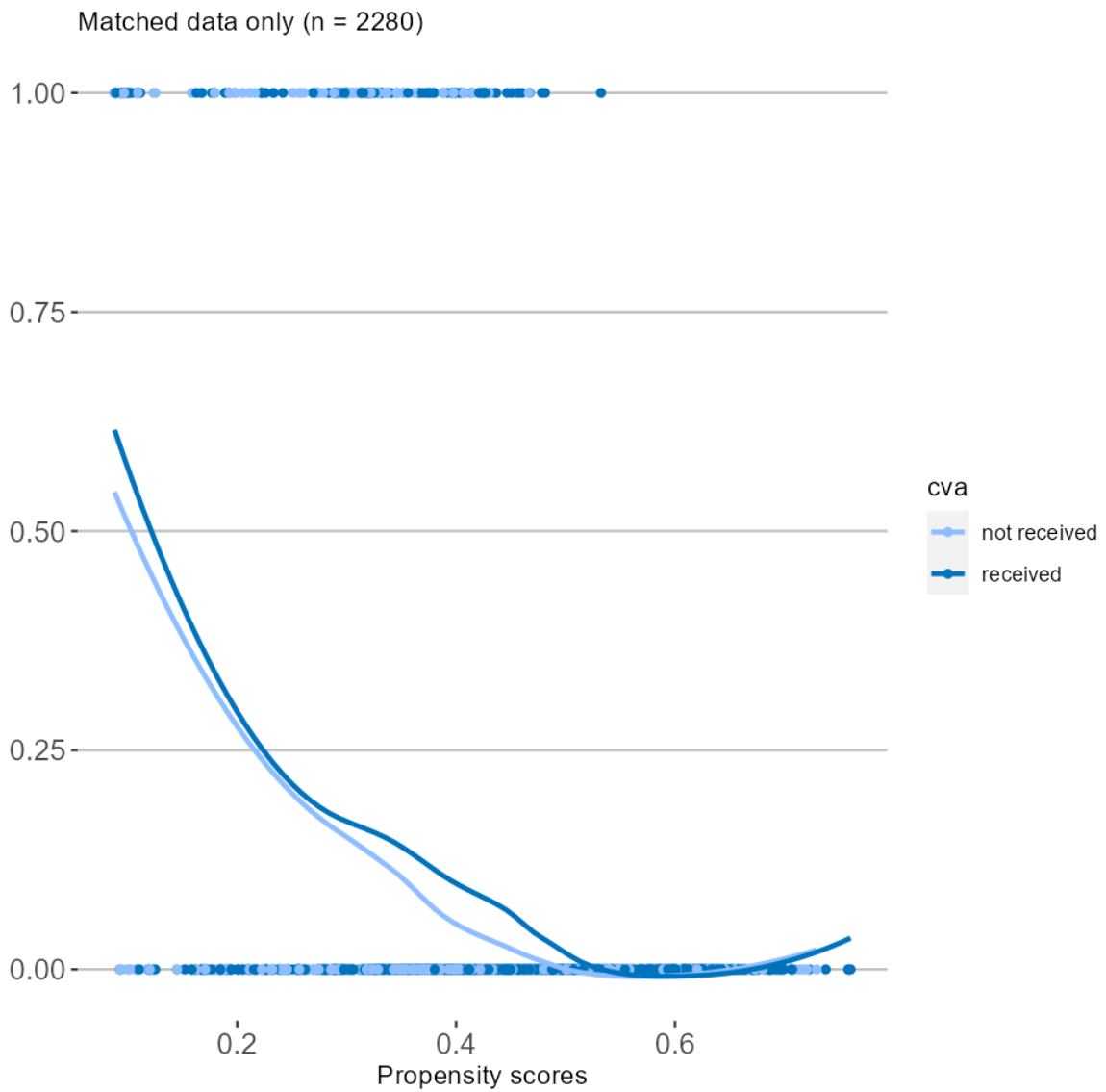
Source: endine 2023
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Figure B14: Relationship between 'having completed primary' and propensity scores across beneficiary groups



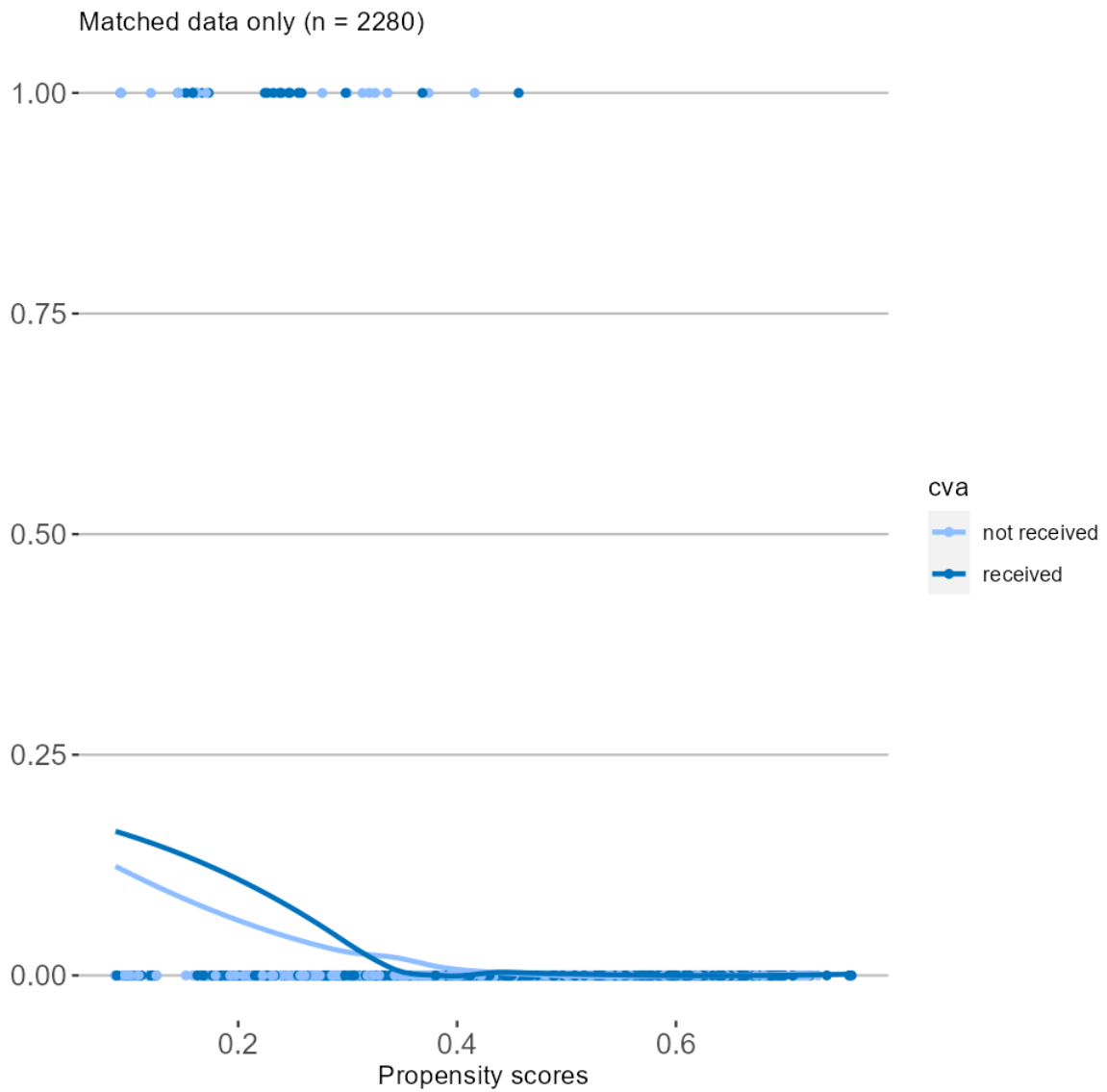
Source: endine 2023
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Figure B15: Relationship between ‘having completed secondary’ and propensity scores across beneficiary groups



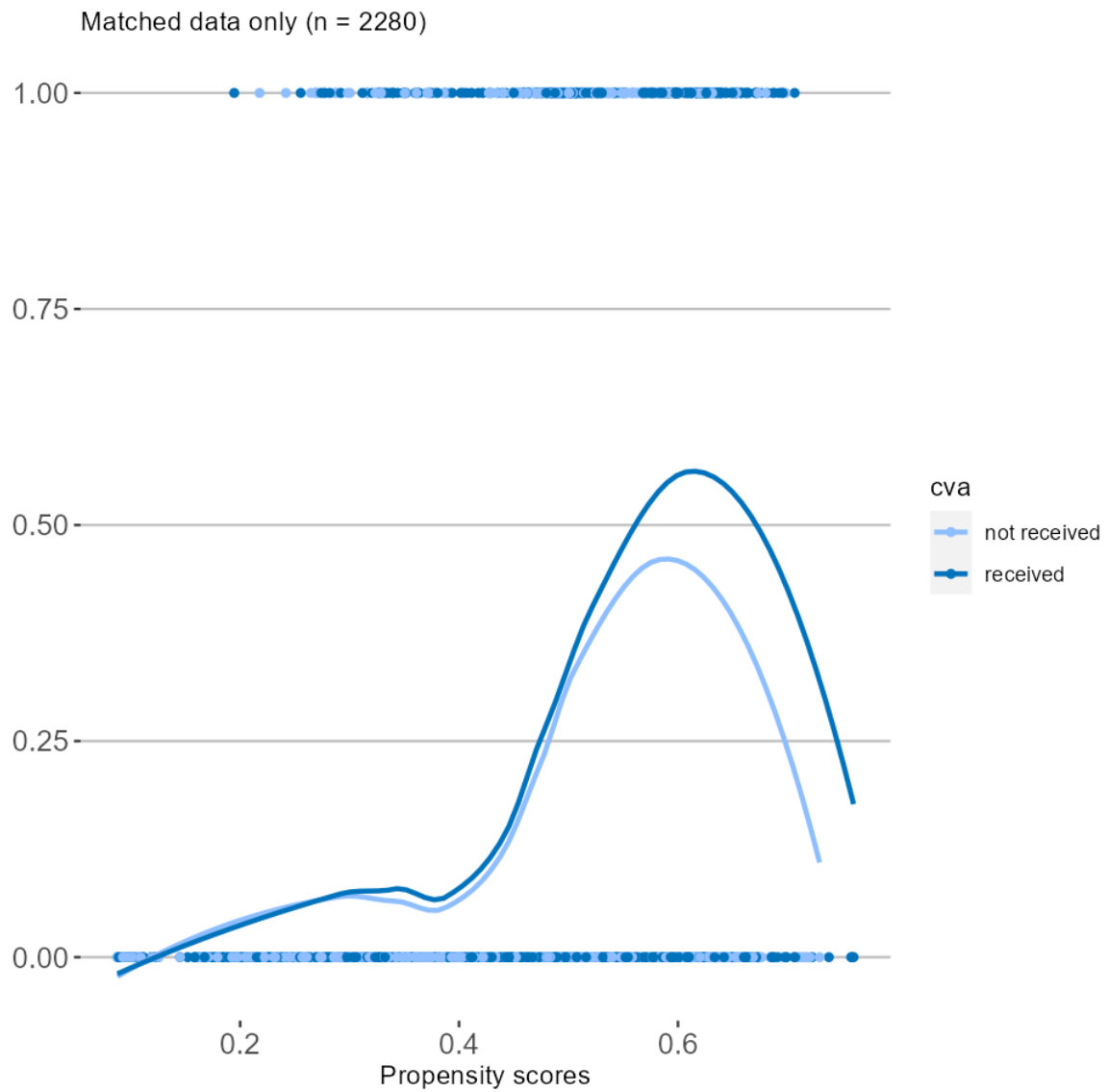
Source: endine 2023
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Figure B16: Relationship between 'having completed university' and propensity scores across beneficiary groups



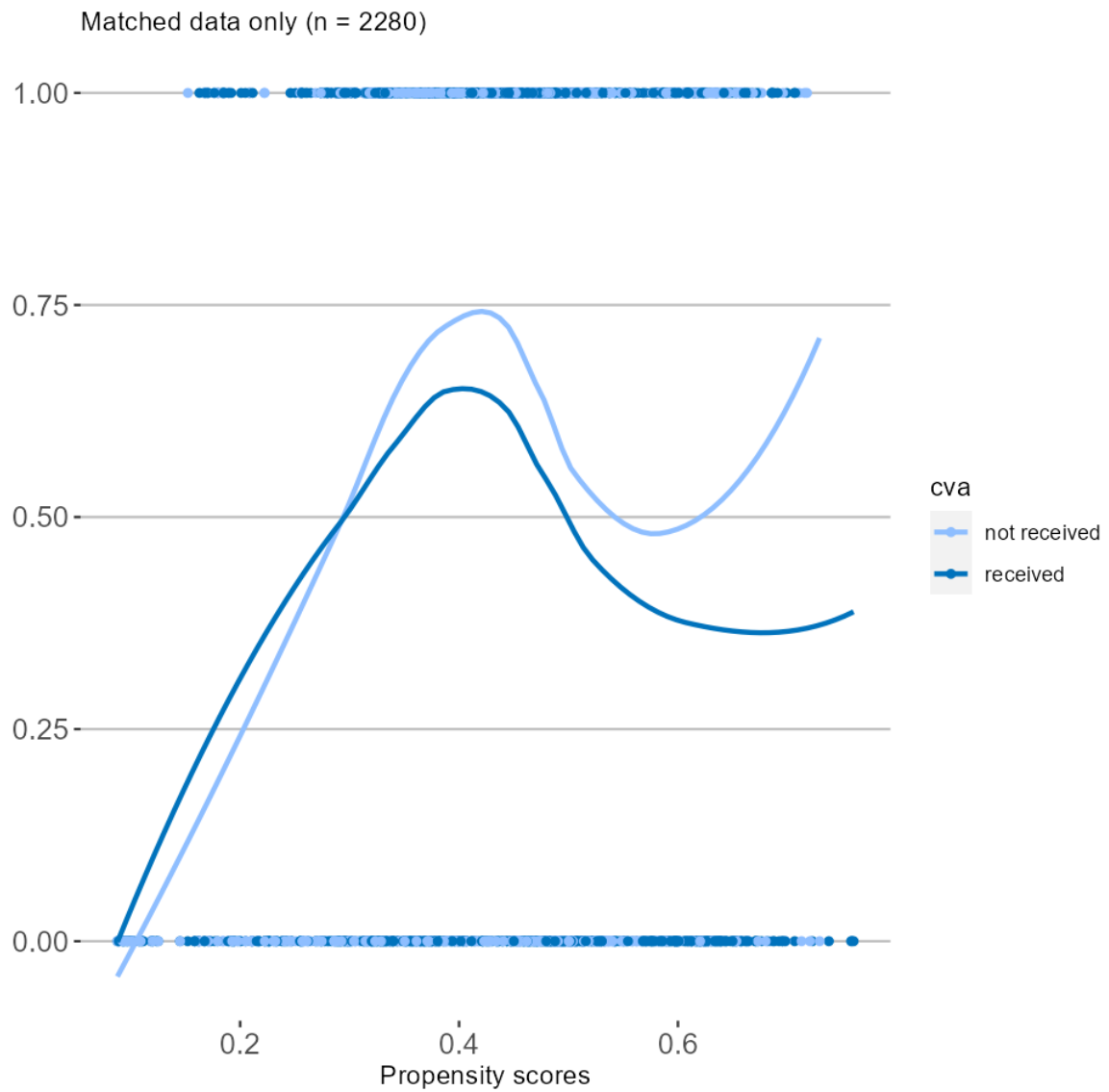
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Figure B17: Relationship between 'not having attained any degree' and propensity scores across beneficiary groups



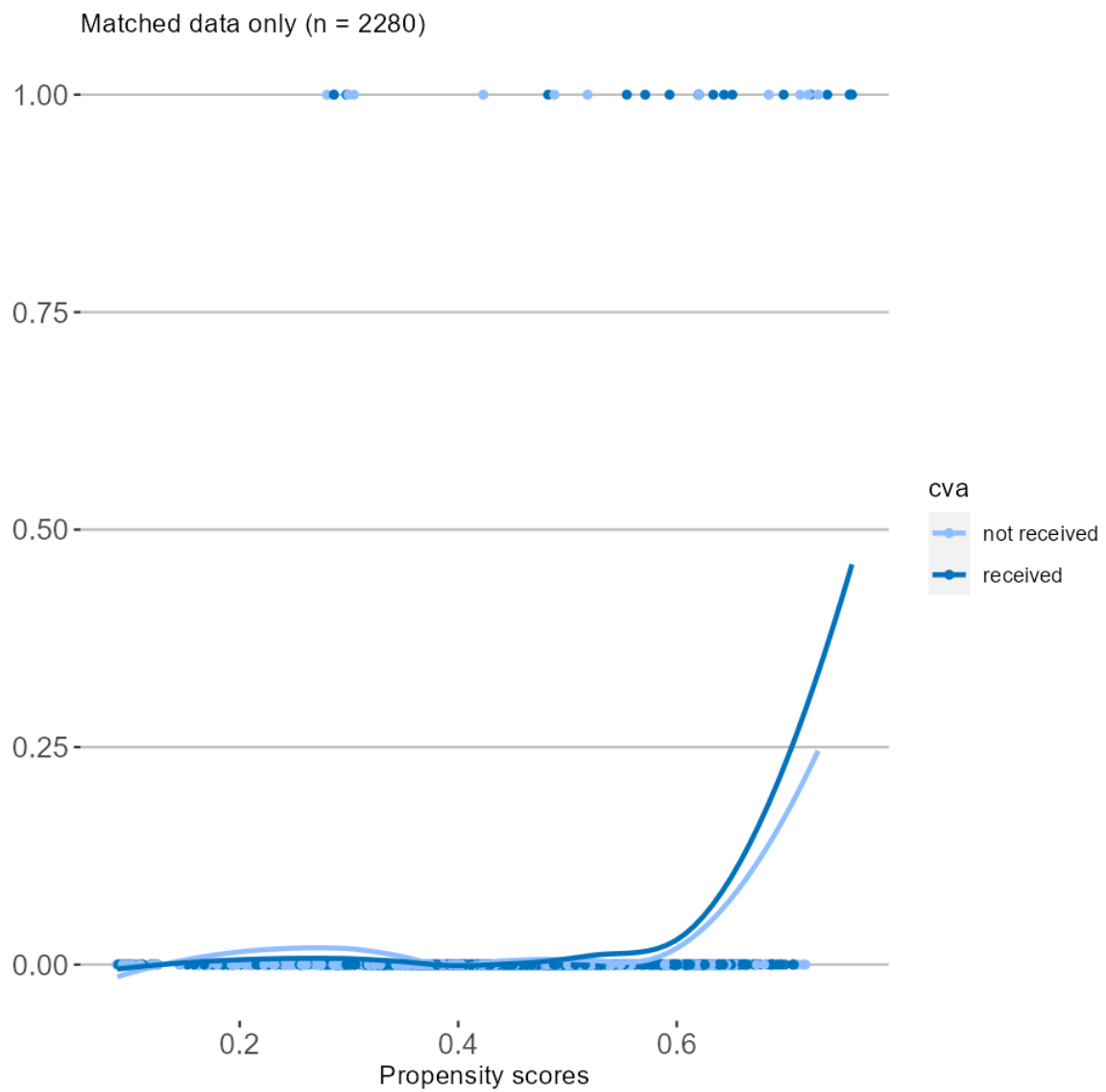
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Figure B18: Relationship between ‘not having started any education’ and propensity scores across beneficiary groups



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Figure B19: Relationship between ‘having completed any other education’ and propensity scores across beneficiary groups



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