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Impact of Humanitarian Assistance on Post-Conflict Livelihoods in the Northern District of Adamawa State, Northeast-Nigeria

*Jinga Clement JAHKNWA [a], Elizabeth ANDREW-ESSIEN [b], Musa SHALANGWA [ab]**

[a] *School of Environmental Sciences, Adamawa State Polytechnic, Yola -640001, Nigeria*
[b] *Faculty of Environmental Sciences, University of Calabar-540211, Calabar, Nigeria;*
[ab] *School of Social and Management Sciences, Adamawa State Polytechnic, Yola -640001, Nigeria ;*
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A B S T R A C T

This research assessed the impact of humanitarian assistance on post-conflict livelihood recovery of households in Adamawa state. It involved the determination of the impact of humanitarian aids on households. The unit of assessment used in this study is thus the household, with each of the sampled households head becoming the respondent. Quasi experimental approach was used to assess the impact of humanitarian assistance based on household access to an intervention or not. The propensity score matching method was used in data analysis. Results show that the treatment effects estimation provide compelling evidence supporting the stated hypothesis. Specifically, the unmatched sample analysis reveals a notable disparity in the Livelihood Recovery Index (LRI) between the treated and control groups, with treated individuals exhibiting a mean LRI of 2.0132 compared to 1.4826 for controls ($t = 32.14$, $p < .001$). The Average Treatment Effect on the Treated (ATT) analysis suggests a substantial treatment effect, with a mean LRI of 1.9818 for treated individuals compared to 1.6995 for controls ($t = 10.15$, $p < .001$). The Average Treatment Effect (ATE) coefficient indicates a substantial difference in LRI between individuals who received Humanitarian Intervention (HINT) and those who did not (No-HINT), with a coefficient of 0.2969 ($z = 8.96$, $p < .001$). Similarly, the Average Treatment Effect on the Treated (ATET) coefficient underscores the positive impact of HINT, with treated individuals experiencing a mean increase in LRI of 0.3170 compared to controls ($z = 11.54$, $p < .001$). The findings suggest that humanitarian aids have a positive impact on rebuilding livelihoods in post-disaster settings.

Keywords: Impact, Intervention, Livelihood, Humanitarian, Household, Post-Conflict, Disaster

Introduction

Disasters such as armed conflicts erode livelihoods of households and further exposes them to livelihood risks (Ferianto and Lampe (2022). The impacts of armed conflict are obviously negative. Gates et.al., (2012) was able to classify them into direct and indirect negative impacts. Direct impacts comprise deaths, maiming, torture, psychological traumas, destruction of assets, violation of human, political and social rights, indiscriminate attacks, lack of access to basic services such as health and education, and discrimination by humanitarian agencies. While the indirect impacts include: displacement, sexual gender-based violence, violation of housing, land and property rights, violation of rights of vulnerable groups especially children, older persons with disabilities and other risk populations, exclusion from humanitarian support and recovery activities.

Livelihoods have been described as what people do to meet their needs, cope with shortages and recover from shocks (Maxwell et.al., 2017). They are the capacities, assets and activities necessary for living (Stites and Bushby, 2017). Knowledge of the level of livelihood erosion will help in policy design on how best to intervene. It informs humanitarian partners on how best to tackle poverty in post disaster settings.

The recovery of such livelihoods in the post-conflict period(s) has always been a herculean task to rural households, the government and international non-governmental organizations aid providers. Armed conflicts such as insurgencies always rob a population of its socioeconomic management skills, assets, identity and choices that are the basic ingredients of a sustainable livelihood. Post-conflict periods viewed as the end of conflict and a transition to peace is thus characterized by poverty, hunger, lack of shelter, human rights abuse. unemployment and general lack of livelihood alternatives that triggers natural resource-based conflict (Andrew-Essien, 2014; ILO, 2010). This period is therefore more or less a poverty trap due to lack of local capacities that would ensure resilience. This is given the fact that most economies that have at one time or the other experienced armed conflicts had issues of loss of valuable human resource, displacement of a significant population that translates into a humanitarian disaster and a total halt on the societal functions. Hence, governments and international aid donor agencies are needed to facilitate livelihood recovery by means of providing relief materials and skills that would employment, trade and thus increase household income. Hence, Salazar-Xirinachs in “Local Economic Recovery in Post Conflict Guidelines” of the ILO (2010) argued that the role of international humanitarian actors should be to encourage local recovery efforts for the attainment of sustainable socioeconomic transformation during post-conflict periods.

Nigeria has been experiencing one form of violent conflicts or the other for the past two decades. Given the fact that all forms of socio-economic growth and developments all over the world normally thrive during periods of peace, drivers of socioeconomic growth are the livelihoods that have attained a certain degree of equilibrium with available and accessible environmental resources in a sustainable fashion. The question however, is how to achieve post-conflict livelihood recovery amidst weak human capacity, lack of government will and economic recession that is affecting Nigeria as a country given the prevailing impact of insurgency on livelihoods. As earlier stated, one sure way of spurring livelihood recovering is via humanitarian aids by both non-governmental and governmental organizations. However, most humanitarian activities have not been subjected to scholarly evaluation. Accordingly, this research assessed the impact of humanitarian interventions in terms of its potential to impede or promote livelihood.

The fact that post-disaster livelihood recovery is often complex and difficult is what usually draws attention to the need for intervention by humanitarian stakeholders (Shah and Shahbaz 2014). Globally, several billions have been invested in the design and deployment of various types of intervention programmes. Success of this livelihood programming is however, still insignificant, because of some unverified latent interacting factors (Kumar, et.al.2-19). Furthermore, despite the enormous investment into intervention programs, yet only very little has been done in the assessment of the level of impact of intervention programmes.

So far, there are many humanitarian agencies with recovery aids in the study area. The interventions from various humanitarian stakeholders have been on-going since 2016. It is observed that despite the huge resources invested into humanitarian intervention in Adamawa state, there has never been any scholarly evaluation of the impact of humanitarian assistance on livelihood recovery. There is no known independent evaluation of the impact of such interventions at both the regional, local government or household scale. It is only the non-governmental organizations that are into humanitarian intervention that conduct what can best be regarded as in-house evaluation of their activities, which obviously is terrible bias in both qualitative and statistical terms. Consequently, this study assessed the level of success attained in achieving household's livelihood recovery attributable to humanitarian interventions.

Materials and Methods

The study area is located in Adamawa State situated on latitude 70N and 110N of the equator and longitudes 110E and 140E of the Greenwich meridian. Adamawa State lies between 70N and 110N and longitude 110Eand 140E sharing borders with Gombe State to the North, and Borno State to the North East, while it is bordered in West by Gombe, Taraba State to the south and the Republic of Cameroun to the east (Adebayo and Tukur, 1999). The State has a total area of 39,742.12km2 and has a projected population of over three million inhabitants (Adebayo and Tukur, 1999).

Figure 1: Map of Adamawa State

The target population for the study comprised people who have living in the study area since 2015. The unit of assessment is the household and the household head was chosen as the respondent for every household irrespective of gender or marital status. Two categories of households were identified: those that had access to humanitarian intervention (HINT) and those that did not have access (NO-HINT). The instruments of data collection for this study is a questionnaire. Other secondary sources of data came from extant literature on livelihood recovery. In this study, a semi-structured questionnaire was used, allowing both structured and unstructured responses suitable for statistical modeling. Questions were tailored for various respondent categories, aligning with the five capitals under investigation.

Methods of Data Analysis

The approach for modeling involved the use of the 5 capitals (Physical, Human, Financial, Social and Natural) as proxy for livelihood recovery. This involved the construction of a household Livelihood Recovery Index (LRI) based on identified proxy indicators for the 5 capitals of the Sustainable Livelihood Framework (SLF) in line with the context of this study. The LRI gives an idea of the level of recovery attained by households given a baseline data of situation before the insurgency vis-à-vis conditions at the time of this research. , an index for measuring a household's post-insurgency livelihood recovery based on the five capitals of the Sustainable Livelihood Framework (SLF) was developed by combining and weighing the five capital components as follows:

1. Defining the Variables: the variables for each of the five capitals were defined thus: Natural Capital Index (NCI); Human Capital Index (HCI); Social Capital Index (SCI); Physical Capital Index (PCI); Financial Capital Index (FCI). The formula for determining each capital index is given by equation 1:

CI =[(C1_after - C1_before) + …+ (Cn_after - Cn_before)] / (C1_before +… Cn_before) * 100 (1)

(where CI = capital index that could be Physical, Human, Social, Financial or Natural)

2. Assigning Weights: weights were assigned to each capital based on the perceived importance in post-insurgency livelihood recovery, and reflect the relative importance of each capital in the Adamawa context as follows:

(i) Natural Capital Index (NCI) @ 0.15: Natural capital includes natural resources like land, water, and biodiversity. In the Nigerian context, especially in rural areas affected by insurgency, access to arable land and water sources is crucial for agriculture and livelihoods. Land degradation due to conflict may have a significant impact (Smith, & Mavedzenge, 2017).

(ii) Human Capital Index (HCI) @ 0.25: Human capital reflects the skills, knowledge, and health of individuals. In the aftermath of insurgency, human capital is critical for rebuilding communities and livelihoods. Investments in education, healthcare, and vocational training are essential for recovery (Okojie, 2016).

(iii) Social Capital Index (SCI) @ 0.20: Social capital represents the networks, relationships, and community cohesion. In Nigeria, where communities play a vital role in supporting each other, social capital is significant for post-conflict recovery. Strong social networks can provide social support, access to resources, and security (IFPRI. 2016).

(iv) Physical Capital Index (PCI) @ 0.20: Physical capital encompasses infrastructure, housing, and assets. Rebuilding physical infrastructure like roads, schools, and healthcare facilities is crucial in post-insurgency areas. The impact of damage to these assets can be substantial (World Bank. 2018).

(v) Financial Capital Index (FCI) @ 0.20: Financial capital relates to access to financial resources and assets. In a recovering economy, access to credit, savings, and capital for income-generating activities is essential. It can help households invest in rebuilding their livelihoods (UNDP, 2019).

3. Normalize Variables: each of the capital variables (NCI, HCI, SCI, PCI, FCI) were normalized by means of min-max scaling (scaling to a range of 0-1) to ensure they are on the same scale. Normalization helps prevent variables with larger values from dominating the index. The formula for min-max scaling is given by equation 2:

x_normalized=(x_max-x_min)/(x-x_min) (2)

(where x is the original value of the variable; x_min is the minimum value of the variable in the dataset; x_max is the maximum value of the variable in the dataset; x_normalized is the normalized value.)

4. Calculate the Index: the LRI for each household was then calculated using the following formula:

LRI = (NCI * Weight for NCI) + (HCI * Weight for HCI) + (SCI * Weight for SCI) + (PCI * Weight for PCI) + (FCI * Weight for FCI) Equation. 3

5. Interpretation: The LRI provides a single numerical value for each household, representing their post-insurgency livelihood recovery. A higher LRI indicates a better recovery, while a lower LRI suggests a poorer recovery.

The analysis was performed using the STATA 14.2 software. Descriptive statistics such as simple percentage, mean and standard deviations was used to examine post disaster recovery interventions. The propensity score matching was used to determine the impact of humanitarian aids on household's livelihood recovery.

Results

A propensity score matching analysis was employed to examine whether a statistically significant difference exists in the Livelihood Recovery Index (LRI) between households who received Humanitarian Intervention (HINT) and those who did not (No-HINT). This analysis aimed to determine whether the predictors, including AGEGRP (age group), GEN (gender), REST (return status), DPH (death per household), DL (damage level), PCHI (percentage change in household income), and EDUYRS (education years), have an effect on the recovery of livelihoods.

Descriptive statistics for the total sample are summarized in Table 1. The data includes 840 observations for each variable. Among these, approximately 59.76% of the total sample belonged to the treatment group, as indicated by the variable "GROUP," with a mean of 0.598 and a standard deviation of 0.491. The mean Livelihood Recovery Index (LRI) for the entire sample was 1.80, with a standard deviation of 0.35, indicating moderate recovery overall, ranging from 0.75 to 3.07. The average age group (AGEGRP) of household heads was 0.675, with a standard deviation of 0.469, suggesting a slightly older population within the sample. Regarding contextual factors, the mean percentage change in household income (PCHI) was approximately 14.97%, with a wide standard deviation of 15.17, indicating considerable variability in income changes across households, ranging from -29% to 93%. Additionally, the mean education years (EDUYRS) was 7.91, with a standard deviation of 5.35, reflecting variability in educational attainment among household members. Gender (GEN) distribution within the total sample was predominantly male-headed households, with a mean of 0.76 and a standard deviation of 0.42. The mean number of deaths per household (DPH) was 0.41, with a standard deviation of 0.49, indicating some variability in mortality rates among households. Lastly, the mean damage level (DL) experienced by households was 0.26, with a standard deviation of 0.44, suggesting varying degrees of damage incurred.

TABLE 1 Descriptive statistics for the total sample

Variable	Obs	Mean	Std. Dev.	Min	Max
GROUP	840	.597619	4906701	0	1
LRI	840	1.799714	.3504445	.75	3.07
AGEGRP	840	.675	.4686539	0	1
PCHI	840	14.96667	15.16603	-29	93
EDUYRS	840	7.910714	5.354012	0	16
GEN	840	.7642857	.4246973	0	1
DPH	840	.4071429	.4915946	0	1
DL	840	.2619048	.439933	0	1
REST	840	.2595238	.4386345	0	1

Descriptive statistics by group are summarized in Table 2. For households not receiving humanitarian intervention (NOHINT), comprising 338 observations, the mean Livelihood Recovery Index (LRI) was 1.48, with a standard deviation of 0.20, indicating a moderate level of recovery ranging from 0.75 to 1.98. The average age group (AGEGRP) of household heads in this group was 0.70, with a standard deviation of 0.46, suggesting a slightly older population within this subset. On average, these households experienced a percentage change in household income (PCHI) of 9.07%, with a wide standard deviation of 13.98, indicating variability in income changes ranging from -29% to 50%. Additionally, the mean education years (EDUYRS) for this group was approximately 7.80, with a standard deviation of 5.34, reflecting variability in educational attainment among household members. The majority of households in this group were male-headed (GEN), with a mean of 0.67 and a standard deviation of 0.47. Furthermore, the mean number of deaths per household (DPH) was 0.35, with a standard deviation of 0.48, indicating some variability in mortality rates among households, while the mean damage level (DL) experienced by these households was 0.61, with a standard deviation of 0.49, suggesting varying degrees of damage incurred. Regarding return status (REST), the mean value was 0.54, with a standard deviation of 0.50.

Conversely, for households receiving humanitarian intervention (HINT), comprising 502 observations, the mean LRI was 2.01, with a standard deviation of 0.25, indicating a higher level of recovery ranging from 1.33 to 3.07. The average AGEGRP for this group was 0.66, with a standard deviation of 0.48. On average, these households experienced a PCHI of 18.93%, with a standard deviation of 14.64, reflecting substantial variability in income changes ranging from -23% to 93%. Similarly, the mean EDUYRS was approximately 7.99, with a standard deviation of 5.37, indicating variability in educational attainment among household members. The majority of households in this group were also male-headed (GEN), with a mean of 0.83 and a standard deviation of 0.38. Regarding DPH, the mean value was 0.45, with a standard deviation of 0.50, indicating some variability in mortality rates. Interestingly, the mean DL for this group was notably lower at 0.03, with a standard deviation of 0.16, suggesting minimal damage incurred. Additionally, the mean REST was 0.07, with a standard deviation of 0.25, indicating a higher likelihood of return to pre-crisis locations.

TABLE 2 Descriptive statistics by Group

Variable	Obs	Mean	Std. Dev.	Min	Max
GROUP = NOHINT					
LRI	338	1.482574	.2021389	.75	1.98
AGEGRP	338	.704142	.4571042	0	1
PCHI	338	9.073964	13.98443	-29	50
EDUYRS	338	7.798817	5.337933	0	16
GEN	338	.6715976	.4703283	0	1
DPH	338	.3491124	.4773963	0	1
DL	338	.6094675	.488593	0	1
REST	338	.5414201	.4990202	0	1
GROUP = HINT					
LRI	502	2.013247	.2542423	1.33	3.07
AGEGRP	502	.6553785	.4757188	0	1
PCHI	502	18.93426	14.64366	-23	93
EDUYRS	502	7.986056	5.368813	0	16
GEN	502	.8266932	.3788898	0	1
DPH	502	.4462151	.4975946	0	1
DL	502	.0278884	.1648175	0	1
REST	502	.0697211	.2549305	0	1

In Table 3a, a regression analysis was conducted to assess the effect of the treatment variable (HINT) on the Livelihood Recovery Index (LRI). The results indicate that the coefficient for the treatment variable (HINT) is 0.53673, with a standard error of 0.01651. The t-statistic value is 32.14, indicating a highly significant relationship between treatment and LRI ($p < .001$). The 95% confidence interval for the treatment coefficient ranges from 0.498 to 1.458, suggesting that the treatment variable has a substantial positive effect on the Livelihood Recovery Index. The regression model explains 55.21% of the variance in LRI, as indicated by the R-squared value.

Table 3b extends the analysis by including control variables (AGE, EDUYRS, PCHI, GEN, REST, DPH, DL) in the regression model alongside the treatment variable (HINT). The results show that the coefficient for the treatment variable (HINT) remains significant at 0.2774 ($p < .001$) after controlling for other variables. Additionally, the coefficients for the control variables suggest their varying degrees of influence on the LRI. For example, age group (AGEGRP), gender (GEN), and percentage change in household income (PCHI) have significant positive effects on LRI, while variables such as return status (REST), deaths per household (DPH), and damage level (DL) have significant negative effects. The model as a whole explains approximately 72.31% of the variance in LRI, with an adjusted R-squared value of 72.05%.

Overall, these findings suggest that while the treatment variable (HINT) has a significant positive effect on the Livelihood Recovery Index, other control variables also play crucial roles in explaining variations in LRI among households.

Table 3A

Regression analysis

reg LRI GROUP

Source	SS	Df	MS			
				Number of Obs	=	840
Model	56.8846634	1	56.8846634	F (1, 838)	=	1032.83
Residual	46.154068	838	.055076453	Prob > F	=	.0000
Total	103.038731	839	.122848955	R-squared	=	.5521
				Adj Rsquared	=	.5515

				Root MSE	=	.23468
LRI	Coef.	Std. Err.	t	P > ⎮t⎮	95% conf. Interval	
HINT	.53673	.0165125	32.14	0.000	.4982624	.5630837
_cons	1.482574	.01277651	116.14	0.000	1.457519	1.507629

Source: Author's Data Analysis, 2019

Table 3B

Regression with a dummy variable for treatment controlling for x

reg LRI GROUP AGE EDUYRS PCHI GEN DEATHS DL

Source	SS	Df	MS			
				Number of obs F (8, 831)	=	840
Model	74.5099276	4	9.3137		=	271.29
Residual	28.5288038	835	.0343	Prob > F	=	0.000
Total	103.038731	839	.1228	R-squared	=	0.7231
				Adj Rsquared	=	0.7205
				Root MSE	=	.18529

LRI	Coef.	Std. Err.	t	P > ⎮t⎮	95% conf. Interval	
HINT	.2774	.0184	15.05	0.000	.2412	.3135
AGEGRP	.0225	.0138	1.63	0.103	-.0045	.0495
GEN	.0818	.0159	5.13	0.000	.0505	.1131
REST	-.1947	.0209	-9.30	0.000	-.2358	-.1536
DPH	-.2196	.0156	-14.07	0.000	-.2503	-.1889
DL	-.2501	.0211	-1187	0.000	-.2915	-.2088
EDUYRS	.0004	.0012	.30	0.761	-.0019	-.0027
PCHI	.0026	.0005	5.58	0.000	.0017	.0035
_cons	1.7199	.0283	60.79	0.000	1.6644	1.7755

Table 4 is the algorithm to estimate the propensity score, a crucial part in propensity score matching analysis, to balance covariates between the treatment and control groups. The sample comprises 840 observations, with 338 (40.24%) belonging to the NOHINT group and 502 (59.76%) to the HINT group. A probit regression model was employed to estimate the propensity score, with predictors including AGEGRP, GEN, REST, DPH, DL, EDUYRS, and PCHI. The model yielded a pseudo R-squared value of 0.4452, indicating a moderate level of explanatory power. Notably, the balancing property is satisfied, indicating that the estimated propensity scores effectively balance covariates between the treatment and control groups.

In the region of common support, which ranges from 0.011 to 0.994, estimated propensity scores are distributed across various percentiles, from 1% to 99%. For instance, the median propensity score is approximately 0.717, while the 10th and 90th percentiles are 0.023 and 0.959, respectively. The distribution of propensity scores suggests that there is sufficient overlap between the treatment and control groups, facilitating meaningful comparisons.

Furthermore, Table 4 provides information on the distribution of individuals across blocks based on their propensity scores, ensuring comparability between treated and control units. The inferior bounds of propensity score blocks are delineated, along with the number of individuals in each block for both the treatment and control groups. This information aids in assessing the effectiveness of propensity score matching in achieving balance between groups.

TABLE 4 Algorithm to estimate the propensity score

GROUP	Freq.	Percent	Cumulative
NOHINT	338	40.24	40.24
HINT	502	59.76	100
Total	840	100	

Estimation of propensity score

Probit regression	Number of obs = 840					
Log likelihood = -314.08468	LR chi2(1) = 504.09					
	Pro > chi2 = 0.000					
	Pseudo R2 = 0.4452					
HINT	Coef.	Std. Err.	Z	P > |x|	[95% Conf. Interval]	
AGEGRP	-0.1763	0.1226	-1.44	0.150	-0.4166	0.0639
GEN	0.0115	0.1413	0.08	0.935	-0.2654	0.2885
REST	-1.5764	0.1774	-8.89	0.000	-1.9242	-1.2287
DPH	-1.0025	0.1472	-6.81	0.000	-1.2911	-0.7139
DL	-1.9758	0.1638	-12.06	0.000	-2.2969	-1.6547
EDUYRS	-0.0083	0.0106	-0.78	0.433	-0.0292	0.0125
PCHI	0.0124	0.0043	2.85	0.004	0.0039	0.0208
_cons	1.594	0.2115	7.53	0.000	1.1791	2.0082
ATE	.3213	.0327	9.81	0.000	.2571	.3854

Note: the common support option has been selected The region of common support is [.01105543, .99425396]

Description of the estimated propensity score in the region of common support

Estimated Propensity Scores

	Percentiles		Smallest		
1%	.0125715	.0166348	.0110554		
5%	.0232007	.3946143	.0112118		
10%			.011682	Obs	824
25%	.7172143		.0118151	Sum of Wgt.	824
50%	.933406	.9593684		Mean	.6146485
	.9680199		Largest	Std. Dev.	.3398043
75%	.9837042		.9901988		
90%			. .9903869	Variance	.1154669
95%			.9904749	Skewness	-.7581189
99%			.994254	Kurtosis	2.126403

The final block number is 9

The balancing property is satisfied

Table showing the inferior bound, the number of t and the number of controls for each block

Inferior of block of pscore	NOHINT	HINT	TOTAL
.0110554	131	7	138
.05	22	5	27
.1	5	1	6
.2	34	3	37

.4	20	9	20
.5	16	21	37
.6	83	186	269
.8	6	32	38
.9	5	238	243
Total	322	502	824

Evaluation of match graphically is presented in FIG. 1, while the evaluation of the match using the statistics called pstest is presented in Table 5.

The graph in FIG 1, generated with the psgraph syntax in Stata 14.2 visualizes the evaluation of match quality based on the support distribution between the treatment and control groups. It displays a visualization of the support distribution, illustrating the overlap between treated and untreated individuals in terms of propensity score support. From the graph based on the evaluation of common support by ps2match, it is found that among the untreated group, 338 individuals were on support, while none were off support. Conversely, in the treated group, 65 individuals were off support, and 437 were on support, out of a total of 502 treated individuals. This distribution indicates that a substantial portion of the treated group has good support matches. Overall, out of the total sample of 840 individuals, 65 were off support, and 775 were on support. A well-balanced distribution of support between the treatment and control groups suggests successful matching, indicating that treated and untreated individuals share similar propensity score distributions. This is crucial for ensuring the validity of the causal inference drawn from the propensity score matching analysis. Therefore, the graph serves as a visual confirmation of the adequacy of the match between the treated and control groups, bolstering the reliability of the study's findings. This graphical representation enhances the interpretability of the propensity score matching analysis results by providing a clear visual indication of the quality of match achieved between the treatment and control groups. It offers valuable insight into the comparability of individuals across groups, thereby strengthening the validity of the study's conclusions.

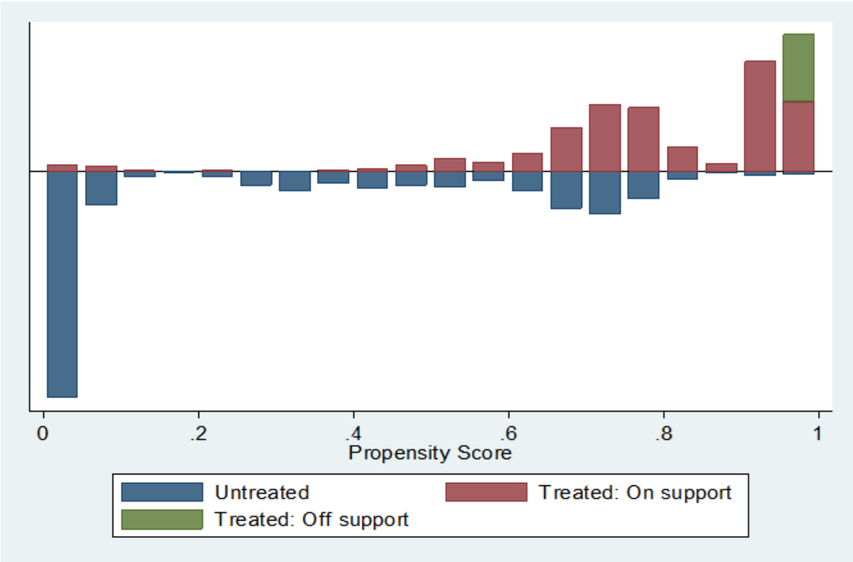

FIG 1 Graphical evaluation of match

Table 5 presents the evaluation of match using statistical tests conducted with the pstest syntax in Stata 14.2. The table compares the means of key variables between the treated and control groups and assesses the balance achieved after propensity score matching. For the variable AGEGRP (age group), the mean in the treated group is 0.6865, while in the control group, it is 0.4897. The t-test value is 6.03, indicating a significant difference between the groups ($p < .001$). This suggests that there might be some residual bias in age group between the treated and control groups after matching. Similarly, for GEN (gender), REST (return status), DPH (deaths per household), and DL (damage level), the means between the treated and control groups are comparable, with non-significant t-test values, suggesting successful balance in these variables.

However, for the variables EDUYRS (education years) and PCHI (percentage change in household income), there are noticeable differences in means between the treated and control groups. The mean difference in education years is small but statistically significant, with a t-test value of 0.27 ($p = 0.787$), suggesting some residual bias even after matching. In contrast, the mean difference in percentage change in household income is more pronounced, with a significant t-test value of 2.11 ($p = 0.035$), indicating potential residual bias in this variable between the treated and control groups.

Additionally, the Ps R2, representing the proportion of variance explained by the propensity score model, is 0.033, suggesting a moderate level of explanatory power. The likelihood ratio chi-square statistic (LR chi2) is 39.67, with a corresponding p-value of 0.000, indicating a significant difference in covariate distributions between the treated and control groups. Furthermore, the table provides measures of mean bias and median bias, which quantify the average and median differences in covariate values between the treated and control groups, respectively. In this case, the mean bias is reported as 9.5, indicating a moderate level of residual bias even after propensity score matching. Similarly, the median bias is reported as 1.9, suggesting some degree of imbalance in covariate distributions between the groups. The metrics B and R are also provided, which evaluate the balance achieved after matching. The value of B is 43.4*, indicating that there is a substantial imbalance between the treated and control groups, as it exceeds the threshold of 25%. Additionally, the value of R is 1.10, suggesting that the balance achieved is within an acceptable range (0.5 to 2). Thus, while the propensity score matching has reduced some of the bias between the treated and control groups, there are still residual imbalances in covariate distributions, as indicated by the significant LR chi2 statistic and the moderate levels of mean and median bias.

Overall, while some variables exhibit significant differences between the treated and control groups after matching, suggesting residual bias, others demonstrate successful balance, highlighting the effectiveness of propensity score matching in minimizing covariate imbalance and facilitating valid comparisons between groups.

TABLE 5 Evaluation of match using statistical test (pstest)

Variable	Mean		t-test				V(T)/ V(C)
	Treated	Control	%bias	t	p>|t|		
AGEGRP	.6865	.4897	42.2	6.03	0.000		.
GEN	.81693	.78032	8.6	1.35	0.178		.
REST	.08009	.08009	0.0	-0.00	1.000		.
DPH	.51259	.52174	-1.9	-0.27	0.787		.
DL	.03204	.03204	0.0	0.00	1.000		.
EDUYRS	8.2243	8.1259	1.8	0.27	0.787		0.96
PCHI	16.037	14.302	12.1	2.11	0.035		1.04
* if variance ratio outside [0.83; 1.21]							
Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.033	39.67	0.000	9.5	1.9	43.4*	1.10	0
* if B>25%, R outside [0.5; 2]							

Table 6 presents the results of treatment effects estimation using propensity score matching. The first section provides treatment effects on the Livelihood Recovery Index (LRI) for both the unmatched sample and the sample subjected to Average Treatment Effect on the Treated (ATT) analysis. In the unmatched sample, the mean LRI for treated individuals is 2.0132, while for controls, it is 1.4826. The difference in means (treatment effect) is 0.5307, with a standard error of 0.0165 and a t-statistic of 32.14, indicating a significant difference between treated and control groups. In the ATT analysis, which focuses only on the treated sample, the mean LRI for treated individuals is 1.9818, while for controls, it is 1.6995. The difference in means is 0.2822, with a standard error of 0.0278 and a t-statistic of 10.15, also indicating a significant treatment effect.

The second section presents treatment effects estimation using propensity score matching. The Average Treatment Effect (ATE) represents the overall treatment effect for the entire sample. The coefficient for HINT (Humanitarian Intervention) compared to No-HINT is 0.2969, with a standard error of 0.0331 and a z-statistic of 8.96, indicating a statistically significant treatment effect ($p < .001$). Similarly, the Average Treatment Effect on the Treated (ATET) represents the treatment effect for the treated individuals. The coefficient for HINT compared to No-HINT is 0.3170, with a standard error of 0.0274 and a z-statistic of 11.54, also indicating a statistically significant treatment effect ($p < .001$).

These results suggest that receiving Humanitarian Intervention (HINT) has a significant positive effect on the Livelihood Recovery Index (LRI) compared to not receiving the intervention. Overall, propensity score matching demonstrates a substantial treatment effect, highlighting the effectiveness of the intervention in enhancing livelihood recovery.

TABLE 6 Treatment-effects estimation

Treatment Effects						
Variable	Sample	Treated	Controls	Differences	S.E.	T-Stat
LRI	Unmatched	2.0132	1.4826	.5307	.0165	32.14
	ATT	1.9818	1.6995	.2822	.0278	10.15

Treatment-effects estimation						
Estimator: PS matching	Number of obs = 840					
Outcome model = Matching	Matches = 1					
Treatment model = logit	min = 1					
	max = 4					
LRI	Coef.	Std. Err.	Z	P > │x│	[95% Conf. Interval]	
ATE						
HINT						
(HINT vs NoHINT)	.2969	.0331	8.96	0.000	.2319	.3618
ATET						
HINT						
(HINT vs NoHINT)	.3170	.0274	11.54	.000	.2632	.3709

Table 7 presents the results of post-regression analysis using weights. The model includes predictors such as age group (AGEGRP), education years (EDUYRS), gender (GEN), percentage change in household income (PCHI), deaths per household (DPH), damage level (DL), and a dummy variable for Humanitarian Intervention (HINT), with Livelihood Recovery Index (LRI) as the outcome variable.

The regression model demonstrates a significant overall fit (F(8, 865) = 153.39, p < .001), with an R-squared value of 0.5865, indicating that approximately 58.65% of the variance in LRI can be explained by the predictors included in the model. After controlling for the other variables, several predictors emerge as statistically significant.

Specifically, the coefficients for gender (GEN), return status (REST), deaths per household (DPH), damage level (DL), percentage change in household income (PCHI), and the dummy variable for Humanitarian Intervention (HINT) are all statistically significant (p < .001). Notably, the coefficient for HINT is particularly substantial, with a coefficient of 0.2716 (t = 25.18), indicating a significant positive effect of Humanitarian Intervention on the Livelihood Recovery Index.

However, age group (AGEGRP) and education years (EDUYRS) do not exhibit statistically significant effects on LRI in this model. This suggests that, in this particular context, factors such as gender, return status, deaths per household, damage level, percentage change in household income, and the provision of Humanitarian Intervention play more significant roles in influencing livelihood recovery outcomes.

TABLE 7 Post regression by weights

.reg SLRI AGE EDUYRS GEN PCHI DEATHS DL HINT [fweight= _weight]							
Source	SS	df	MS		Number of Obs	=	840
Model	29.7951	8	3.7244		F(8,865)	=	153.39
Residual	21.0026	865	.0243		Prob>F	=	0.0000
Total	50.7977	873	.0582		R-squared	=	0.5865
					Adj. R-squared	=	0.5827
					Root MSE	=	0.15582
LRI	Coef.	Std. Err.	t	P >│z│	95% conf. Interval		
AGEGRP	.0081177	.0111874	0.73	0.468	-.0138399		.0300754
GEN	.101038	.0139658	7.23	0.000	.0736271		.1284489
REST	-.2416279	.0212422	-11.37	0.0000	-.2833202		-.1999355
DPH	-.1958919	.0112851	-17.36	0.0000	-.2180412		-.1737426
DL	-.1521452	.0311012	-4.89	0.0000	-.2131879		-.0911026
EDUYRS	.0006138	.0009958	0.62	0.538	-.0013407		.0025684

PCHI	.0019928	.0004543	4.39	0.000	.0011011	.0028845
HINT	.2716127	.0107869	25.18	0.0000	.2504411	.2927843
_cons	1.709713	.0162783	105.03	0.0000	1.677763	1.741662

Discussion of Findings

The findings of the treatment effects estimation analysis reveal compelling evidence regarding the effectiveness of Humanitarian Intervention (HINT) in promoting livelihood recovery. Across various analyses, including unmatched sample comparison and propensity score matching, treated households consistently exhibit higher Livelihood Recovery Index (LRI) scores compared to their untreated counterparts. This disparity suggests that HINT plays a pivotal role in fostering positive outcomes in post-disaster recovery efforts.

One notable finding is the substantial treatment effect observed in the Average Treatment Effect on the Treated (ATT) analysis, where treated households demonstrate a significantly higher mean LRI compared to controls. Specifically, treated households exhibit a mean LRI of 1.9818, whereas controls have a mean LRI of 1.6995 ($t = 10.15$, $p < .001$), underscoring the direct impact of HINT on improving livelihood recovery outcomes among the treated population.

Moreover, the propensity score matching analysis further corroborates these findings by demonstrating significant treatment effects, both in terms of Average Treatment Effect (ATE) and Average Treatment Effect on the Treated (ATET). These analyses reveal a clear advantage for individuals who received HINT, with treated individuals experiencing an increase in mean LRI of 0.3170 compared to controls ($z = 11.54$, $p < .001$).

The significant treatment effects observed in these analyses underscore the importance of considering various factors, including age group, gender, return status, deaths per household, damage level, percentage change in household income, and education years. For instance, the regression coefficients for HINT compared to No-HINT indicate a coefficient of 0.2969 ($z = 8.96$, $p < .001$) for Average Treatment Effect (ATE), emphasizing the positive impact of HINT on livelihood recovery.

Overall, the findings suggest that targeted interventions such as HINT can play a crucial role in facilitating livelihood recovery in disaster-affected communities. By addressing key predictors and providing targeted support, interventions like HINT have the potential to catalyse positive changes and enhance overall resilience in vulnerable populations. These insights are valuable for policymakers, practitioners, and organizations involved in disaster response and recovery efforts, highlighting the importance of implementing evidence-based interventions to promote sustainable recovery and well-being in affected communities.

4. Conclusion

The results of our treatment effects estimation provide compelling evidence supporting the stated hypothesis that insurgency-related humanitarian interventions have a significant impact on households' livelihoods in northern Adamawa. The analysis of the unmatched sample reveals a notable disparity in the Livelihood Recovery Index (LRI) between the treated and control groups, with treated individuals exhibiting a mean LRI of 2.0132 compared to 1.4826 for controls ($t = 32.14$, $p < .001$). This substantial difference underscores the effectiveness of the humanitarian interventions in enhancing livelihood recovery. Furthermore, focusing solely on the treated sample, the Average Treatment Effect on the Treated (ATT) analysis demonstrates a substantial treatment effect, with a mean LRI of 1.9818 for treated individuals compared to 1.6995 for controls ($t = 10.15$, $p < .001$). These findings highlight the direct benefits experienced by those who received the interventions. Propensity score matching analysis further bolsters these conclusions, revealing significant treatment effects. The Average Treatment Effect (ATE) coefficient indicates a substantial difference in LRI between individuals who received Humanitarian Intervention (HINT) and those who did not (No-HINT), with a coefficient of 0.2969 ($z = 8.96$, $p < .001$). Similarly, the Average Treatment Effect on the Treated (ATET) coefficient underscores the positive impact of HINT, with treated individuals experiencing a mean increase in LRI of 0.3170 compared to controls ($z = 11.54$, $p < .001$). Based on the regression analysis and propensity score matching results, we accept the hypothesis that insurgency-related humanitarian interventions have a significant impact on households' livelihoods in northern Adamawa. The analysis demonstrates that households receiving humanitarian interventions had significantly higher levels of livelihood recovery compared to those that did not receive such interventions. These findings suggest that humanitarian interventions play a crucial role in rebuilding livelihoods in post-disaster settings, offering a pathway to recovery and stability for affected communities. The positive outcomes observed in this study underscore the importance of continued support for humanitarian efforts in conflict-affected regions. These interventions not only address immediate needs but also contribute to long-term recovery and resilience, enabling households to rebuild their lives and communities more effectively.

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