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Remittance and its Poverty Reducing Impacts in Nepal

2026

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1. Introduction

Like many other low-income and developing countries, remittance has become a crucial source of external finance for Nepal, helping to address various economic challenges and playing a vital role in the livelihoods of millions of families. Nepal has witnessed a steady increase in remittance inflows over the years, with workers, mainly abroad in countries like India, Qatar, Saudi Arabia, and the UAE, sending money back home. According to the World Bank, in 2023, Nepal received approximately USD 9.6 billion in remittances, which is equivalent to slightly over 25 percent of its GDP, making it one of the highest remittance-to-GDP ratios in the world (World Bank, 2024). This influx of resources has had significant implications for the country's economy, boosting consumption, investment, and the economy in general (Mishra et al., 2022; Lamichhane, 2024).

Remittances are widely associated with poverty reduction, especially in countries like Nepal where a large segment of the population live below the poverty line (Salike et al, 2022). The financial transfer by migrant workers contributes to household income to meet basic needs such as food, health care, education, and housing, improving the overall standard of living. These investments in modern human capital formation contributes to bring families out of the poverty spiral that had prevailed for generations (Mishra et al, 2022). Studies have shown that remittance inflows have also enabled families to invest in income-generating activities, such as agro-enterprises and small businesses (Shakya & Gonpu, 2021). This, in turn, fosters greater economic mobility for the next generation. In Nepal, it is estimated that remittances directly contribute to the alleviation of poverty for millions of families, helping to reduce income inequality and providing a buffer against external shocks like natural disasters and economic downturns (Pant, 2006; Mishra et al, 2022).

Nepal has been one of the interesting case countries with dominant emigration and remittance earning. Though the macroeconomic performance of Nepal has not been exceptional during this high emigration and remittance earning. Nepal has made notable progress in reducing poverty as an outcome that may be partly attributed to the growth in remittances from foreign employment. Several studies have examined this relationship. Lokshin et al. (2010), using earlier rounds of the Nepal Living Standards Survey, found that international migration and remittances were associated with higher household consumption and reduced poverty rates. They also note that while international migration plays a more significant role, domestic migration also has a meaningful impact. Similarly, Acharya and Leon-Gonzalez (2012) found that remittances contribute to poverty reduction, with a stronger impact in regions with higher levels of migration. Wagle and Devkota (2018) also observed significant poverty-reducing and economic well-being-enhancing effects of remittances, particularly when they originate from countries other than India. Similarly, Bansak and Chezum (2009), as well as Vogel and Korinek (2012), both use NLSS data to find a positive relationship between remittances and children's educational expenditures, although this effect is disproportionately greater for boys than for girls.

Studies that rely on cross-sectional data and standard regression techniques may suffer from selection bias as migration is not randomly assigned. This methodological limitation has been widely noted in migration literature (Lokshin et al., 2010; Slaike et al., 2022). Households that send migrants are systematically different from those that do not either because they may have higher education, better networks, or greater initial resources. Therefore, using traditional econometric techniques like OLS to estimate the impact of remittances can yield biased or overstated results. To address this issue, scholars have increasingly turned to Propensity Score Matching (PSM) methods (Rosenbaum & Rubin, 1983), which create a counterfactual scenario by matching remittance-receiving households with observationally similar non-receiving households based on a range of socioeconomic variables. This allows for more credible estimation of the causal impact of remittances on poverty and welfare.

Propensity Score Matching (PSM) has been widely applied in international studies, but its use in assessing Nepal's migration and remittances impacts remain limited. Thapa and Acharya (2017) employed PSM to show that remittance-receiving households tend to spend more on consumption, health, and education compared to non-receiving households. Similarly, Bohra-Mishra (2013) used PSM to demonstrate a positive relationship between labor migration and agricultural investment.

From a policy perspective, literature suggests that while remittances hold significant potential for poverty alleviation, their impact is neither automatic nor evenly distributed. Gender, education, geography, and caste, all mediate the extent to which remittance income can transform household welfare. This is especially relevant for Nepal, where historical exclusion of Dalits (socio-economically disadvantaged groups including those traditionally considered untouchables), rural populations, and women from formal economic processes creates structural inequalities in migration outcomes. In the light of this reality, there is a pressing need for more methodologically robust, disaggregated analysis using updated data.

This study seeks to fill this critical gap by estimating the causal effect of remittances on poverty reduction in Nepal using Propensity Score Matching (PSM) using data from the most recent nationally representative data from the Nepal Living Standards Survey (NLSS 2022/23). The analysis estimates the Average Treatment Effect (ATE), Average Treatment Effect on the Treated (ATT), and the Average Treatment Effect on the Untreated (ATU) to evaluate both realized and potential impacts of remittance income on poverty.

By comparing findings from NLSS 2022/23 with earlier rounds (particularly NLSS 2010/11), the study explores whether the poverty-reducing effects of remittances have become more inclusive over time or whether inequality in migration outcomes still persists. The goal is to generate evidence-based insights that can inform more equitable migration and policies ensuring that remittances not only alleviate poverty but do so in a way that supports structural transformation and social inclusion.

2. Methods

The methodology particularly focuses to examine the relationship between migration and poverty reduction considering the non-randomness and selection bias through propensity score matching technique.

2.1 Non-randomness and Selection Bias

The direct impact of remittances on poverty reduction may be more complex than it appears, especially when considering the challenges of accurately measuring this impact. One limitation of existing studies is that many of them use linear models to estimate the effect of remittances on household income and poverty, which may produce biased results. Such models could be plagued by selection bias, which occurs when the sample of households receiving remittances is not randomly selected but instead influenced by certain characteristics that also affect poverty. Selection bias can lead to inaccurate conclusions because the model fails to account for the differences between households that receive remittance and those that do not, potentially overestimating or underestimating the impact of remittances on reducing poverty.

2.2 Propensity Scores Approach

To address the non-random assignment of remittances and foreign employment, and to mitigate the potential selection bias in observational data, the method of propensity score matching (PSM) serves as an appropriate instrument. This technique matches households receiving remittances with similar households that do not receive remittances, based on observable characteristics, thus controlling for confounding variables that could influence both the likelihood of migration and poverty levels. By estimating the probability of receiving remittances (the propensity score) and matching treated (remittance-receiving) households with non-treated ones that have similar propensity scores, researchers can better isolate the causal impact of remittances on household welfare. This approach was first introduced by Rosenbaum and Rubin (1983), who demonstrated how propensity score matching can help reduce selection bias by making the treatment and control groups more comparable in terms of observable characteristics, allowing for a more accurate estimation of treatment effects (Rosenbaum & Rubin, 1983).

While this study employs propensity score matching (PSM) to mitigate selection bias from observable confounders, we acknowledge that unobserved heterogeneity such as household risk tolerance, entrepreneurial motivation, or informal social networks may still influence both migration decisions and poverty outcomes, potentially biasing our estimates (Rosenbaum, 2002). Instrumental variables (IVs) could theoretically address such endogeneity, but their valid application in this context faces insurmountable empirical challenges. First, conventional IVs (e.g., distance to migration agencies or historical migrant networks) likely violate the exclusion restriction by directly affecting poverty through channels beyond remittances, such as local labor market conditions or information access (McKenzie, 2012). Second, as Imbens & Wooldridge (2009) noted that, weak instruments common in migration studies can introduce greater bias than OLS. In Nepal's context, no theoretically defensible IV exists in the NLSS data that satisfies both relevance and exogeneity conditions. Consequently, while PSM remains imperfect, it represents the most feasible approach for causal inference given data constraints, consistent with recent remittance-poverty studies in similar settings.

This study examines two counterfactual scenarios: (a) the poverty status of households currently receiving remittances if they had not received them, and (b) the poverty status of households not receiving remittances if they had received them. Additionally, the study assesses the total impact of remittances on poverty, estimating Average Treatment Effect (ATE). The Average Treatment Effect on the Treated (ATT) and Average Treatment Effect on the Untreated (ATU) have been estimated for these counterfactual scenarios, respectively.

3. Data

3.1 Data

This study based on the Nepal Living Standards Survey (NLSS), a nationally representative dataset that provides detailed information on household income, expenditure, migration, and poverty. The NLSS is one of the most comprehensive sources for understanding the socio-economic dynamics of the country, produced by the Government of Nepal. It enables an assessment of how remittances influence household welfare and poverty across different time periods.

Our analysis begins with the most recent round, NLSS 2022/23, which captures the contemporary state of remittance flows and their relationship with household welfare. Using the latest survey allows us to assess up-to-date trends and understand how recent shifts in migration and remittance patterns affect poverty reduction in Nepal. In total, 9,600 households were interviewed in this round, of which 9,420 households are used in this study after accounting for missing data. Among them, 1,758 households reported receiving remittances from abroad (excluding India). The official national poverty line for 2022/23 is estimated at NPR 72,908 per person per year, based on the combined food and non-food poverty lines.

For comparison, we extend the analysis to earlier rounds of the NLSS. In NLSS III (2010/11), 5,988 households were surveyed, of which 5,944 households are included in our study. Among them, 912 households reported receiving remittances from abroad (excluding India). The official national poverty line for 2010/11 was NPR 19,262 per person per year.

The slight difference between total households surveyed and those included in this study arises from missing data, particularly in the section on access to facilities. By combining insights from both the most recent and earlier NLSS rounds, our analysis not only benchmarks the current effects of remittances on poverty but also examines how these effects have evolved over time, thereby testing the robustness and consistency of findings.

When selecting control variables using NLSS data, the goal is to capture characteristics that influence both the likelihood of a household receiving remittances and their poverty status. This helps to reduce bias and isolate the effect of remittances. The table below shows the set of control variables that are used in our PSM analysis.

Table 1: Variable description

Variables	**Description**
Household Demographics	
Household Size:	Number of members in the household
Age of Household Head	Age of the person who is the head of the household.
Gender of Household Head	Whether the household head is male or female.
Marital Status of Household Head	Whether the household head is married or not.
Dependency Ratio	Ratio of dependents (children and elderly) to working-age members.
Education	
Education Level of Household Head	Highest level of education completed by the head of the household
Economic Characteristics	
Occupation of Household Head	Whether the household head has occupation or not
Land Ownership	Whether the household has land or not
Livestock Ownership	Whether the household has livestock or not
Geographic and Regional Variables	
Region/Province	Geographic location or region of the household, which can influence both access to opportunities and remittance flows.
Urban/Rural	Whether the household is in an urban or rural area.
Access to Infrastructure	Distance to roads, markets, and financial institutions.

Social and Cultural Factors (Caste/Ethnicity)	Caste/ Ethnicity

3.2 Comparison of Remittances between NLSS 2010/2011 and NLSS 2022/2023

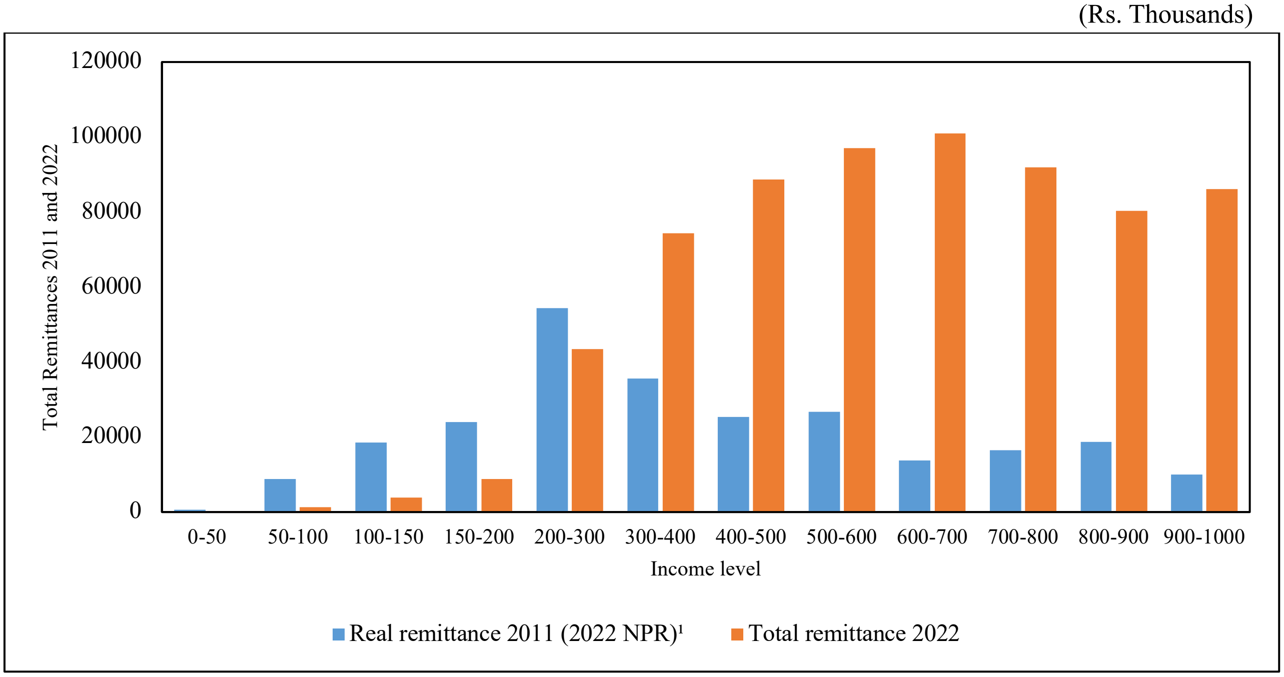
Before delving into estimating the causal effect of remittances on poverty reduction we present and overview of the remittance comparison between the latest two consecutive NLSS data to provide an overview of the trend in emigration and remittance earnings in Nepal. These findings provide the readers with the background information on the main analysis.

3.2.1 Remittance Growth

Although there is surge in percentage of poor households receiving remittances, the real remittances received by the poor households that belong to less than Nepali rupees (NPR) 300 thousand household income levels has declined as seen in figure 1 (1 NPR in 2011equals NPR 2.036 at 2022 (World Bank, 2024). For households with annual incomes below 300,000, real remittances have decreased compared to 2011 levels. This decline is severe in the lowest income brackets. For example, households earning less than 50,000 experienced a 91.4 percent decline in real remittance receipts, while those earning between 50,000 and 300,000 faced declines ranging between 20 percent and 91 percent.

Figure 1: Real Remittance growth 2011 vs. 2022

(Rs. Thousands)



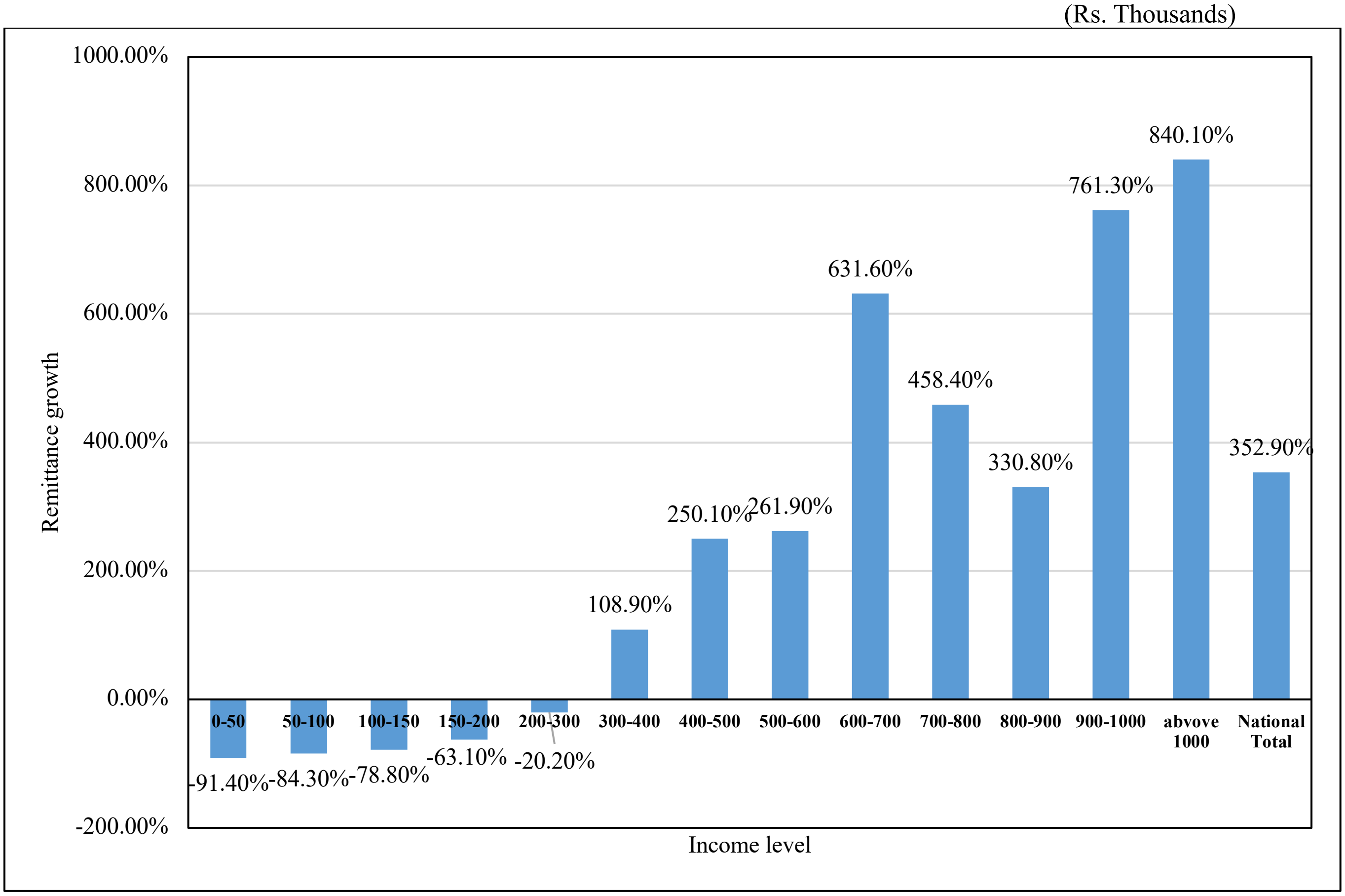
Note: [1] Inflation adjusted remittances for 2011

For them, the reals remittances have fallen compared to 2011 figures. This is clearer from real growth rate of remittance as shown in figure 1. In Figure 2 below, we can observe that for income group of less than 300 thousand with real growth of remittances being negative, ranging from -20 percent to -91 percent, for the poorest income bracket of less than 50,000 the remittances declined by 91 percent. Households in higher income brackets (above 300,000) witnessed substantial growth in remittances. For these groups, remittance inflows in 2022 are significantly higher than their inflation-adjusted 2011 counterparts, showing that the benefits of remittance growth are disproportionately concentrated among middle- and higher-income households.

Conversely, wealth consolidation can be observed for higher income groups above three thousand as remittances increased from 108 to 840 percent (Figure 2). This is mainly due to two reasons Firstly for the poorest households, migration became unaffordable (costs 3 times annual income for 50-100 thousand households) (Kharel et al, 2023). Secondly barriers to overseas employment for the poorest, and possible substitution of low-income migrants by relatively wealthier migrants may partly explain this outcome. (Amnesty International, 2017)

Figure 2: Remittance growth rate for various income levels

(Rs. Thousands)

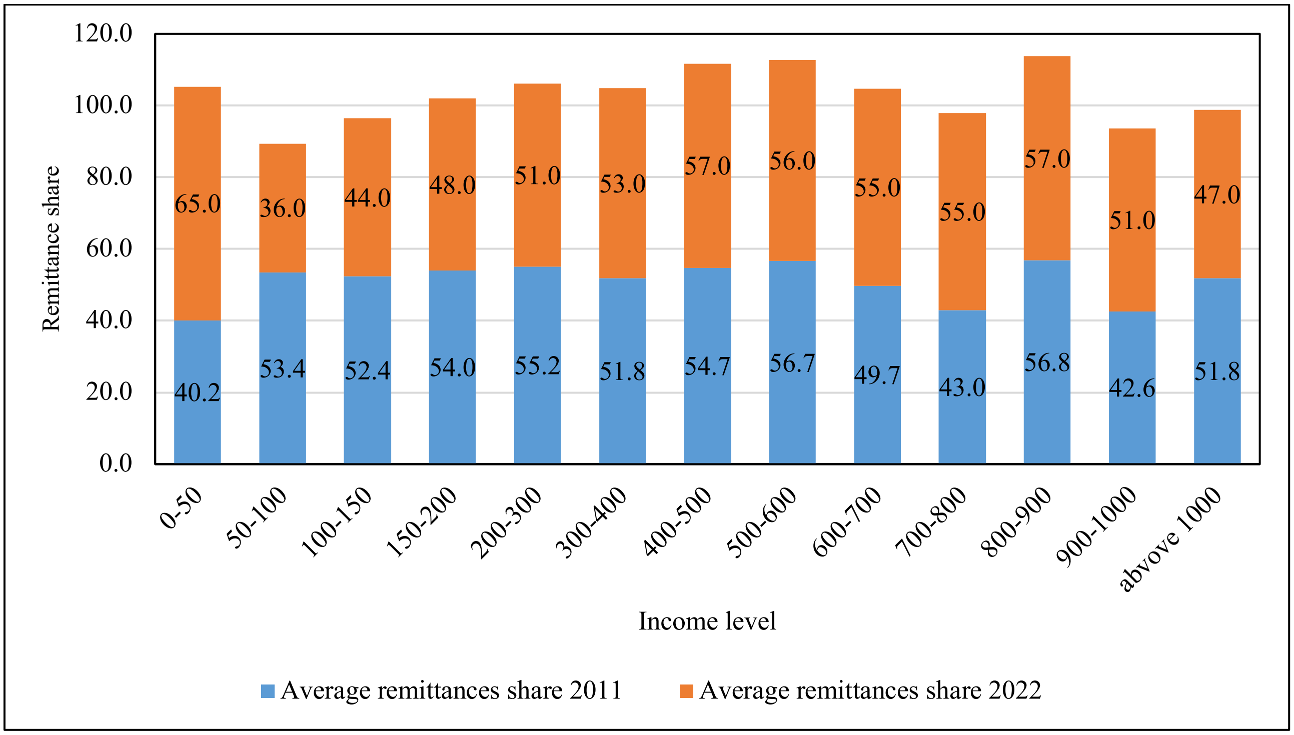


3.2.2 Remittance Shares in Household Income

In figure 3 below a clear divergence is observed in the share of remittances across household income groups between 2011 and 2022. For the lower- and middle-income brackets (below 300,000), the share of remittances in household income has declined markedly. The sharpest decline is seen among households earning between 50,000 and 100,000 annually, where remittance dependence dropped from 53.4 percent in 2011 to just 36 percent in 2022.

Figure 3: Remittance income share

(Rs. Thousands)



In contrast, upper-middle income households, particularly those in the 600–700 thousand, 700–800 thousand, and 900–1,000 thousand brackets, saw increases in remittance shares of 5.3 percent, 12 percent, and 8.4 percent, respectively. The wealthiest households (above 1,000,000) also maintained relatively high remittance shares, though with a moderate decline compared to 2011.

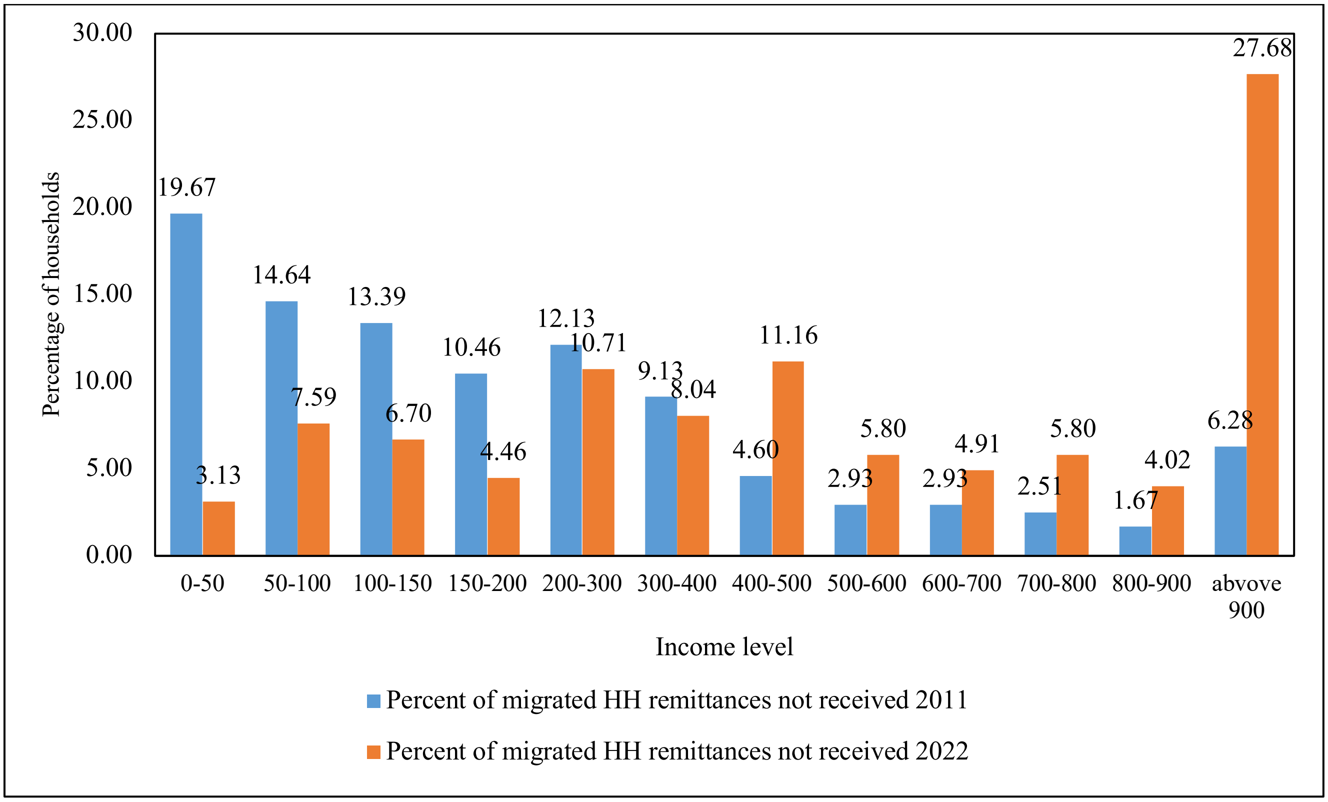
This shift suggests that poorer households are increasingly constrained from labor migration, likely due to rising migration costs, limited access to credit, and structural barriers. Unable to afford overseas employment, they rely more on non-remittance income sources. Meanwhile, relatively better-off households, who can afford the upfront migration costs, have become more successful in leveraging foreign employment, resulting in a growing reliance on remittances in higher income brackets.

3.2.3 Migrant Households not Receiving Remittance

Figure 4 shows the percentage of migrated households that are not receiving remittances by household income category. This shows decline in non-remitting households among the poor (≤ 200,000). In 2011, a large share of the poorest migrant households (0–50 thousand: 19.67 percent, 50–100 thousand: 14.6 percent) did not receive remittances. By 2022, these numbers declined to (0–50 thousand: 3.13 percent, 50–100 thousand: 7.59 percent).

Figure 4: Comparison of migrated households not receiving remittances by household income category 2011 vs. 2022

(Rs. Thousands)



Source: NLSS 2011 & 2022

In Contrast, this shows rising non-remitting households among middle- and high-income groups (> 200,000). Example, above 900 thousand income group jumped from 6.3 percent in 2011 to 27.68 percent in 2022. This indicates that more affluent households stop sending remittance to their home country. Instead, migrants may retain earnings abroad (for investments on permanent settlement in their destination country. This suggests growing financial fragility among higher-income migrant households as remittances no longer remain a guaranteed inflow.

4. Findings

4.1.1 Descriptive Analysis

Descriptive Statistics

Table 2 below shows the comparison of descriptive statistics between NLSS 2011 and 2022. The NLSS 2011 and NLSS 2022 have estimated the national average poverty lines as well as regional poverty lines based on the minimum food and non-food expenses. Households were classified as either poor or non-poor based on this criterion. The comparison shows a surge in average remittance recipiency among poor households, from 8.6 percent in 2011 to 10.3 percent in 2022 indicating improved migration access. However, this inclusion remains fragile: after adjusting for Nepal's increase in CPI of 113 percent between these two reference periods, average remittance amounts for poor households in 2022 was NPR 26925.06 which is a mere 28 percent of the average receipt by the non-poor of NPR 93818.64.

Demographic shifts point to reduced average household size of all households (4.77 to 3.97 members), yet poor households size remains larger than non-poor by a member (poor 4.85 and non-poor 3.78). Dependency ratios highlight vulnerability, with poor households supporting more dependents (2.27 vs. 1.29) alongside a rise in elderly members (0.282 to 0.370). Years of education favored the non-poor, rising from 5.19 to 5.88 years on average, while the poor advanced from 2.69 to 3.65. Although the gap between poor and non-poor households narrowed slightly (2.5 to 2.2 years), poor households remain locked in relative educational deprivation.

Despite national progress in infrastructure (road access up 49 percent), spatial inequality deepened: poor households live 42 percent farther from markets and 64 percent farther from banks, limiting their ability to leverage remittances or access services. Asset vulnerability deepened as livestock ownership declined (−7 percent among poor) and agricultural land ownership showed 4 percent decline for poor households. Overall, this highlights a paradox: migration has expanded access for the poor, but declining real remittances, persistent education gaps, and unequal access to markets and financial services threaten sustainable poverty reduction.

Table 2: Descriptive statistics: means and standard deviations

Covariates	All Households (2011)	Poor Households (2011)	Non-Poor Households (2011)	**All Households (2022)**	**Poor Households (2022)**	**Non-Poor Households (2022)**
HH size	4.77(2.32)	6.037(2.39)	4.49(2.21)	3.97(1.95)	4.85(1.98)	3.78(1.89)
Age 15-64	2.81(1.53)	2.95(1.58)	2.78(1.52)	2.50(1.42)	2.58(1.48)	2.48(1.40)
Education	4.73(4.32)	2.69(2.89)	5.19(4.45)	5.48(4.34)	3.65(3.48)	5.88(4.40)
Child at school	1.75(1.40)	2.14(1.50)	1.67(1.36)	1.14(1.16)	1.44(1.33)	1.08(1.11)
Remittance received HH	.153(.360)	.086(.28)	.168(.37)	.186(.389)	.103(.304)	.204(.403)
Remittance received Amt	28886.65(135130.5)	9482.87(50142.47)	33253.7(147314.2)	81831.76(305539.4)	26925.06(129673.6)	93818.64(330554.4)
Agri land	.71(.45)	.76(.421)	.69(.45)	.702(.45)	.72(.44)	.69(.45)
Livestock	.68(.46)	.842(.34)	.65(.47)	.660(.47)	.77(.41)	.63(.48)
Population under 15	1.67(1.51)	2.79(1.60)	1.42(1.36)	1.15(1.19)	1.90(1.35)	.99(1.09)
Population over 64	.28(.55)	.282(.562)	.28(.55)	.314(.598)	.37(.64)	.30(.588)
Age HH head	46.02(14.14)	44.82(13.74)	46.26(14.21)	45.36(14.96)	44.41(15.75)	45.57(14.77)
Dependent population	1.96(1.58)	3.08(1.68)	1.70(1.45)	1.47(1.29)	2.27(1.37)	1.29(1.20)
Distance pave road	12.57(28.36)	21.02(38.39)	10.67(25.19)	6.44(16.23)	10.90(22.65)	5.47(14.27)
Distance market	8.07(16.80)	12.72(23.30)	7.02(14.75)	6.35(9.42)	8.39(11.16)	5.90(8.93)
Distance Bank	11.36(16.53)	18.30(19.48)	9.80(15.36)	5.62(7.52)	8.30(9.34)	5.04(6.92)
Observations	5944	1092	4852	9420	1688	7732

Note: Standard deviations in parentheses ( )

Balance Test

Before Matching covariates had large Standardized Mean Difference (SMD) values (e.g., sex1: -50.88 percent in 2011, agriland1: 6.36 in 2022), indicating significant imbalance. Variance ratios deviated substantially from unity for key covariates (e.g., distance paved road: 0.45 in 2011, -23.13 in 2022). Most p-values were highly significant (p<0.001p < 0.001p<0.001), confirming statistical differences in means (See Appendix Table 1 & 2).

After Matching the SMD values improved significantly for most covariates (e.g., age 15_64: -29.26 percent to -16.13 in 2022). Variance ratios became closer to 1, and most p-values became non-significant, indicating improved balance. However, residual imbalance remained for some variables (e.g., age of household head and distance to market). This shows that matching significantly improved balance for most covariates in both datasets. Residual imbalance remained for a few key variables (See Appendix Table 1 & 2).

4.1.2 Propensity Score Estimation

Propensity Score Results (2011)

The table 3 below shows logit model estimates of the probability of receiving remittances based on various covariates. The results show that several demographic and geographic factors significantly influence the likelihood of households receiving remittances. Households with a larger number of dependents are more likely to receive remittances, suggesting that migration and remittance flows may be motivated by household's livelihood pressures.

Similarly, education is positively associated with the probability of receiving remittances, though the negative coefficient on the squared term indicates diminishing returns at higher levels of education. Female-headed households are substantially less likely to receive remittances, reflecting possible gender-based constraints in migration and earning opportunities abroad. Occupation of the household head (e.g., being in the skilled categories) also plays an important role in reducing the likelihood of remittance inflows. Households located in Koshi, Madesh, and Gandaki provinces are more likely to receive remittances, whereas those in Sudhurpaschim and Karnali are significantly less likely. These disparities highlight uneven migration patterns and regional differences in access to remittance networks.

Infrastructure accesses matter further with greater distances from paved roads and banks, reducing the likelihood of receiving remittances, reflecting how remittance inflows are shaped not only by household characteristics but also by accessibility to financial and transport services.

Table 3: Propensity score logit model results, 2011

Coefficients	Estimate (Std. Error)	z value	Pr(>|z|)
(Intercept)	-1.95e+00 (4.5e-01)	-4.29	0.000 ***
Age hh head	8.46e-03 (1.8e-02)	0.46	0.641
urb_rur1	-6.26e-02 (1.0e-01)	-0.57	0.566
age_15_64	3.56e-02 (2.7e-02)	1.30	0.193
Dependent pop	7.24e-02 (2.5e-02)	2.79	0.005 **
Agri land	3.37e-02 (1.1e-01)	0.30	0.763
Livestock	1.68e-01 (1.1e-01)	1.42	0.153
Education	1.41e-01 (4.2e-02)	3.36	0.00***
Head nsco1	-5.37e-01 (1.0e-01)	-5.32	0.000***
Marital status1	1.45e-01 (2.6e-01)	0.55	0.582
I(educ^2)	-1.06e-02 (3.3e-03)	-3.16	0.001 **
Madesh caste	-2.64e-01 (1.6e-01)	-1.64	0.099
Hill janajati	2.03e-01 (9.4e-02)	2.16	0.030 *
Terai janajati1	-1.42e-02 (1.7e-01)	-0.08	0.933
Hill dalit	1.45e-01 (1.5e-01)	0.96	0.334
Terai dalit	-4.99e-01 (2.4e-01)	-2.01	0.044 *
Sex	-1.28e+00 (9.3e-02)	-13.7	0.000 ***
Koshi	3.79e-01 (1.1e-01)	3.19	0.001 **
Madesh	4.06e-01 (1.6e-01)	2.49	0.012 *
Sudhurpaschim	-1.64e+00 (2.5e-01)	-6.49	0.000 ***
Gandaki	4.13e-01 (1.3e-01)	3.12	0.001 **
Lumbini	2.68e-02 (1.2e-01)	0.21	0.832
Karnali	-7.43e-01 (2.5e-01)	-2.89	0.003 **
Distance paved road	-5.65e-03 (2.3e-03)	-2.42	0.015 *
Distance bank	-8.44e-03 (3.9e-03)	-2.13	0.032 *
Distance market	1.22e-03 (2.26e-03)	0.54	0.589

*Note: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.*
Null deviance: 5095.4 on 5943 degrees of freedom, Residual deviance: 4566.0 on 5917 degrees of freedom, AIC: 4620

These findings suggest that remittance flows are not evenly distributed across households in Nepal. Instead, they are shaped by household composition (dependents, education, and gender of head), occupational background, and locational factors (province, infrastructure access). This indicates potential inequities in how remittances contribute to household welfare, with households in remote regions, female-headed households, and those with limited infrastructure access being disadvantaged.

Propensity Score Distribution (2011)

The table 4 below summarizes the distribution of propensity scores across different household groups, including poor, non-poor, treated (remittance receivers), and control (non-receivers) households. The average propensity score for treated households (0.229) is higher than that for control households (0.139), which indicates that the model successfully differentiates between remittance-receiving and non-receiving households.

Table 4: Propensity score distribution, 2011

Group	**Min**	**Mean**	**Max**	**(S.D)**
Non-Poor	.001	.157	.615	.111
Poor	0.005	.135	0.54	.103
Treated (N=912)	.013	.229	.613	.117
Control (N=5032)	.001	.139	.615	.103

Note: S.D is the standard deviation of propensity scores.

The distribution shows that non-poor households have slightly higher mean propensity scores (0.157) than poor households (0.135), implying that non-poor households are relatively more likely to receive remittances. Furthermore, the overlap in the range of propensity scores between treated and control groups indicates that the common support condition is satisfied. This overlap ensures that valid counterfactual comparisons can be made between treated and control households using propensity score matching techniques.

Propensity Score Model Results (2022)

The table 5 below presents the logit model results used to estimate the propensity scores. Older household heads are more likely to receive remittances, although the negative squared age term suggests the relationship is nonlinear (the effect diminishes at higher ages). Similarly, education of the household head increases the likelihood of receiving remittances, but the squared education term indicates a diminishing marginal effect. Female-headed households are significantly less likely to receive remittances.

Table 5: Propensity score model results, 2022.

Coefficients	Estimate (Std. Error)	z value	Pr(>|z|)
(Intercept)	-2.81(0.33)	-8.41	0.000 ***
Age HH head	0.03(0.01)	2.45	0.014 *
Urban/ Rural	0.11 (0.06)	1.83	0.067
Age_15_64	-0.04 (0.02)	-1.95	0.055
Dependent pop	0.06 (0.02)	2.88	0.03**
Agri land	0.16 (0.07)	2.55	0.024*
Livestock	0.31 (0.07)	4.27	0.000***
Education	0.17 (0.02)	5.90	0.000**
Head nsco	-0.63(0.06)	-9.43	0.000**
Marital status	0.81 (0.21)	3.77	0.000**
I(age_hhhead^2)	-0.00(0.00)	-2.53	0.011*
I(educ^2)	-0.011(0.002)	-5.17	0.000**
Madesh caste	-0.44(0.11)	-3.79	0.000**
Hill janajati	0.07(0.07)	1.03	0.302
Terai janajati	-0.41(0.121)	-3.42	0.000**
Hill dalit	-0.020(0.09)	-0.20	0.837
Terai dalit	-0.51(0.177)	-2.85	0.003**
Sex	-1.06(0.06)	-15.82	0.000***
Koshi	.23(0.09)	2.43	0.014*
Madesh	0.77(0.12)	6.44	0.000***
Sudhurpaschim	-1.45(0.15)	-9.66	0.000***
Gandaki	0.25(0.09)	2.73	0.006**
Lumbini	0.007(0.09)	0.07	0.938
Karnali	-0.80(0.134)	5.96	0.00***
Distance paved road	-0.006(0.002)	-2.240	0.025*
Distance bank	0.008(0.005)	-1.57	0.114
Distance market	0.001(0.003)	0.31	0.755

*Note: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*
Null deviance:9.67.5 on 9419 degrees of freedom, Residual deviance: 8034.1 on 9393 degrees of freedom, AIC: 8.8

A higher number of dependents significantly raises the probability of receiving remittances, while a larger working-age population (15–64) reduces it. This suggests that migration is often a household strategy to support dependents. Households with agricultural land and livestock are more likely to receive remittances, implying that migration is not limited to landless poor but is also common in agrarian households.

Hill Dalit households show a higher likelihood of receiving remittances, while Terai Dalit, Terai Janajati, and Madesh caste households are significantly less likely, highlighting ethnic and regional disparities in migration opportunities. Compared to Bagmati, households in Madesh, Sudurpaschim, Lumbini, Gandaki, Karnali, and Koshi have significantly higher probabilities of receiving remittances, reflecting the regional concentration of labor migration. Greater distance from paved roads reduces the likelihood of receiving remittances, consistent with migration being more feasible in better-connected areas. Distance to banks and markets, however, is not significant.

Propensity Score Distribution (2022)

Table 6 below summarizes the distribution of propensity scores for different household groups in 2022, namely poor, non-poor, treated (remittance receivers), and control (non-receivers) households. The mean propensity score is higher for remittance-receiving households (0.278) compared to non-receivers (0.165), which indicates that the logit model effectively distinguishes between the two groups.

Table 6: Propensity score distribution, 2022

Group	Min PS score	Mean PS score	Max PS score	(S.D) PS score
Non-Poor	.003	.191	.714	.13
Poor	.007	.164	.610	.11
Treated (Remittances receivers) (N=1758)	.010	.278	.714	.14
Control (non-receivers) (N=7762))	.003	.165	.703	.11

Note: S.D is the standard deviation of propensity scores.

The overlap in the range of propensity scores between treated and control households suggests that the common support condition is satisfied, ensuring the validity of treatment effect estimation using matching methods.

Comparison of Propensity Score Distributions: 2011 vs. 2022

The comparison of propensity score distributions between 2011 and 2022 highlights some important changes in the characteristics of remittance-receiving households. In 2011, treated households (remittance receivers) already exhibited higher mean propensity scores compared to non-receivers, reflecting their greater likelihood of participating in international migration and remittance inflows. By 2022, the difference between treated and control households has widened further, with treated households showing a mean propensity score of 0.278 compared to 0.165 for controls. This indicates that remittance-receiving households in 2022 are increasingly selected on observable characteristics such as household size, education, land ownership, and dependency ratios. In other words, the probability of receiving remittances has become more concentrated among specific household types over time.

At the same time, the overlap in the range of propensity scores between treated and control households in both periods suggests that the common support condition remains satisfied, ensuring valid estimation of treatment effects. However, the broader spread of scores in 2022, particularly at the upper end for treated households, signals a greater stratification of households by migration and remittance access. Overall, this shift reflects structural changes in Nepal's migration economy, where remittance inflows are increasingly linked to household socioeconomic characteristics, thereby shaping patterns of poverty reduction and welfare outcomes.

4.1.3 Treatment Effect Estimation (2011)

In this section, we present the results of the average treatment effects on the treated and untreated, estimated through different matching techniques such as nearest neighbor, caliper, radius, and kernel matching, using the NLSS 2011 dataset. Furthermore, the results of the balance tests conducted before and after matching for all variables are presented in Appendix Table 1.

Average Treatment Effect on the Treated (ATET) by Matching Method

The table 7 below shows the Average Treatment Effect on the Treated (ATET), which is consistently negative across all matching methods, with estimates ranging from -0.083 to -0.098. This indicates that, relative to similar households not receiving remittances, remittance- receiving households have the likelihood of being poor decreases by approximately 8 to 10 percent point.

Table 7: ATET estimates by matching method

Matching Method	ATET estimates (S.E)	Confidence interval
Nearest Neighbor Matching	-0.083(0.015)	-0.114 (-0.052)
Radius Matching	-0.095(0.012)	-0.120 (-0.070)
Caliper Matching	-0.098(0.022)	-0.141 (-0.054)
Kernel Matching	-0.087(0.009)	-0.106 (-0.685)

Note: Upper CI in Parentheses, bootstrapped standard error in parentheses ( )

Across all methods, the estimates are negative, confirming that remittances significantly lower the probability of being poor for households already receiving them. Among the methods, Kernel Matching yields the precise estimate, with the smallest standard error, strengthening the evidence of a poverty-reducing effect of remittances.

Average Treatment Effect (ATE) by Matching Method

Table 8 presents the ATE estimates obtained from various matching methods. The results range from -0.097 to -0.109, indicating that, on average, remittances reduce the probability of being poor for the overall household by 9 to 10 percentage points. The consistency of the estimates across all matching methods highlights the robustness of the findings. Remittances significantly lower poverty not only for recipient households (ATT) but also when considering the entire household population (ATE). The finding that the national poverty rate could decrease by nearly one-tenth, underscore the transformative role of remittances in poverty reduction.

Table 8: ATE estimates by matching method

Matching Method	ATE estimates (S.E)	Confidence interval
Nearest Neighbor Matching	-0.097(0.014)	-0.125(-0.06)
Radius Matching	-0.109(0.016)	-0.142 (-0.07)
Caliper Matching	-0.109(0.010)	0.124 (-0.09)
Kernel Matching	-0.097(0.015)	-0.127 (-0.06)

Note: Upper CI in Parentheses, bootstrapped standard error in parentheses ( )

Average Treated Effect on the Untreated (ATU)

The ATE represents the average causal effect across the entire population, which includes both treated and untreated units. Since ATE is a combination of ATET and ATU weighted by the proportions of treated and untreated units, the equation reflects this combination accurately. (Imbens, & Wooldridge, 2009). Since untreated units were not exposed to the treatment, we cannot directly observe their outcomes under treatment.

$$\textbf{ATU}= \frac{\boldsymbol{ATE-P(T=1)ATET}}{\boldsymbol{P(T=0)}} \text{.................................}\textbf{(i)}$$

Where,
P(T=1): Proportion of HH receiving remittances
P(T=0): Proportion of HH not receiving remittances
ATE: Average treatment effect
ATET: Average treatment effect on treated

Therefore, this study infers ATU by using the difference between ATE and the weighted ATET (Rosenbaum & Rubin, 1983). This approach ensures consistent estimation of counterfactual outcomes for untreated units, making it appropriate for causal inference studies. We estimate the ATU by using equation (ii).

Table 9: ATU estimates by matching method

Matching Method	ATU estimates (i)
Nearest Neighbor Matching	-0.081
Radius Matching	-0.092
Caliper Matching	-0.092
Kernel Matching	-0.081

Note: ATU i, calculated from equation (i)

Table 9 presents the ATU estimates from different matching methods. The results are consistently negative, ranging from -0.081 to -0.092, suggesting that if households currently not receiving remittances were to start receiving them, their probability of being poor would decline by approximately 8 to 10 percentage points. The similarity of results across methods reinforces the robustness of the findings. Unlike ATT, which captures the poverty reduction effect for households already receiving remittances, the ATU reflects the potential impact on non-recipient households. This highlights the potential of remittances to alleviate poverty even for households that are not currently benefiting from them.

Comparison of ATE, ATET, and ATU (2011)

The estimates from table 10 consistently show negative values for ATE, ATET, and ATU, confirming that remittances significantly reduce poverty in Nepal. Specifically:

- ATE indicates that if all households received remittances, the overall poverty rate would decline by 9-11 percentage points.
- ATET shows that households already receiving remittances experience a reduction in poverty of 8-10 percentage points compared to if they had not received them.
- ATU suggests that even households currently not receiving remittances could reduce their poverty incidence by 8-9 percentage points if they began receiving them.

This triangulation strengthens the evidence that remittances are a powerful poverty-alleviation mechanism, benefiting both current recipients and potential future recipients.

Table 10: Comparison of ATE, ATET, and ATU estimates (2011)

Matching Method	Nearest Neighbor Matching	Radius Matching	Caliper Matching	Kernel Matching
	Coeff (S.E)	Coeff (S.E)	Coeff (S.E)	Coeff (S.E)
ATE	-0.097(0.01)	-0.109(0.01)	-0.109(0.01)	-0.097(0.01)
ATET	-0.083(0.01)	-0.095(0.01)	-0.098(0.02)	-0.087(0.00)
ATU	-0.081	-0.092	-0.092	-0.081

Note: Upper CI in Parentheses and Bootstrapped standard error in parentheses ( )

The similarity of results across matching methods demonstrates robustness. Importantly, the gap between ATET and ATU is narrow, meaning that the poverty-reducing impact of remittances is not limited to households already receiving them, non-recipient households would benefit similarly if they had access to remittances.

4.1.4 Treatment Effect Estimation (2022)

In this section, we present the results of the average treatment effects on the treated and untreated, estimated through different matching techniques such as nearest neighbour, caliper, radius, and kernel matching, using the NLSS 2022 dataset. Furthermore, the results of the balance tests conducted before and after matching for all variables are presented in Appendix Table 2.

Average Treatment Effect on the Treated (ATET) by Matching Method

Table 11 presents the ATET results using different matching methods for 2022. The negative ATT estimates across all methods indicate that remittances contribute to reducing poverty among households that receive them. The estimated reduction in poverty ranges from 8 to 9.4 percentage points, depending on the matching method applied. All results are statistically significant, as the confidence intervals do not cross zero, suggesting that the poverty-reducing effect of remittances in 2022 is consistent across estimation approaches.

Table 11: ATET estimates by matching method

Matching Method	ATET estimates (S.E)	Confidence interval
Nearest Neighbour Matching	-0.083(0.006)	-0.090(-0.070)
Radius Matching	-0.08(0.013)	-0.106(-0.053)
Caliper Matching	-0.094(0.015)	-0.12(-0.064)
Kernel Matching	-0.086 (0.011)	-0.109(-0.063)

Note: Upper CI in Parentheses, bootstrapped standard error in parentheses ( )

Average Treatment Effect (ATE) by Matching Method

Table 12 provides the Average Treatment Effect estimates, which reflect the expected effect of remittances if all households in the population were to receive them. The negative ATE values consistently indicate that remittances reduce poverty across the entire household population. On average, if all households received remittances, poverty would fall by about 8 to 9 percentage points. This reinforces the broad poverty-reducing potential of remittances beyond only the households that currently receive them.

Table 12: ATE estimates by matching method

Matching Method	**ATE estimates (S.E)**	**Confidence interval**
Nearest Neighbour Matching	-0.089(0.019)	-0.111(-0.066)
Radius Matching	-0.080(0.007)	-0.095(-0.065)
Caliper Matching	-0.080(0.011)	-0.103(-0.057)
Kernel Matching	-0.089(0.013)	-0.116(-0.062)

Note: Upper CI in Parentheses, bootstrapped standard error in parentheses ( )

Average Treatment Effect on the Untreated (ATU)

Table 13 reports the Average Treatment Effect on the Untreated (ATU), which measures the expected effect of remittances if households that currently do not receive them were to start receiving them. The negative ATU values indicate that if currently non-receiving households were to start receiving remittances, their poverty incidence would decline by 7.6 to 9.0 percentage points, depending on the matching method. Although the estimated effect is smaller compared to current recipients (ATET), the findings highlight that remittances carry a significant poverty-reducing potential for the untreated group.

Table 13: ATU estimates by matching method

Matching Method	**ATU**
Nearest Neighbour Matching	-0.090
Radius Matching	-0.079
Caliper Matching	-0.076
Kernel Matching	-0.083

Note: ATU i, calculated from equation (i),

Comparison of ATE, ATET, and ATU (2022)

The 2022 results in table 14 below show that remittances significantly reduce poverty across all households, including both those currently receiving remittances and those who could potentially receive them. The effect is stronger for treated households (ATT) compared to the general population (ATE) and untreated households (ATU). ATE shows that, on average, remittances reduce poverty by around 8 to 9 percentage points across the entire population. ATET indicates a stronger effect (up to 9.4 percentage points) among households already receiving remittances, suggesting that remittances are especially beneficial for current recipients. ATU shows that if non-recipient households were to start receiving remittances, their poverty would decline by 7.6 to 9.0 percentage points, which is smaller than the effect for treated households but still meaningful.

Table 14: Comparison of ATE, ATET, and ATU estimates (2022)

Matching Method	**Nearest Neighbour Matching**	**Radius Matching**	**Caliper Matching**	**Kernel Matching**
	Coeff (S.E)	Coeff (S.E)	Coeff (S.E)	Coeff (S.E)
ATE	-0.089(0.019)	-0.080(0.007)	-0.080(0.011)	-0.089(0.013)
ATET	-0.083(0.006)	-0.08(0.013)	-0.094(0.015)	-0.086(0.011)
ATU	-0.090	-0.079	-0.076	-0.083

Note: Upper CI in Parentheses, Bootstrapped standard error in parentheses ( )

The findings indicate that remittances play a significant role in reducing poverty in Nepal, with stronger effects observed among households currently receiving remittances compared to those that do not. While remittances reduce poverty across the entire population, the larger impact for recipient households suggests that they are better positioned to leverage these financial flows, possibly due to greater amounts received or stronger migration networks. In contrast, the relatively smaller gains for non-recipient households highlight disparities in access and benefits, underlining the need for targeted policies to expand migration opportunities, reduce transfer costs, and promote the productive use of remittances, particularly among poorer and marginalized households.

4.1.5 Comparison of ATE, ATET and ATU: 2011 vs. 2022

The comparison of results from 2011 and 2022 in table 15 below highlights important shifts in the poverty-reducing role of remittances in Nepal. On ATE, 9-10 percentage points' reduction in poverty in 2011 and 8-9 percentage points' reduction in poverty in 2022 indicates the poverty-reducing effect of remittances on the entire households declined between these periods. This indicates that while remittances remain a key poverty reduction mechanism, their marginal impact on poverty reduction at the national level has weakened over time.

On ATET, in 2011, remittance-receiving households shows an 8.3–9.8 percentage point reduction in poverty, while in 2022 the effect declined slightly to 8–9.4 percentage points. Notably, in 2011 ATET was close to or slightly below ATE, implying that the benefits of remittances extended beyond recipient households. By 2022, however, ATET is greater than ATE, showing that remittance-receiving households gained disproportionately more relative to the population average. This reflects an increasing concentration of benefits among current recipients, likely due to higher remittance volumes or stronger migration networks within these households.

Table 15: Comparison of ATE, ATET, and ATU estimates (2011 vs. 2022)

Measure	**NLSS 2011**	**NLSS 2022**	**Difference (2022 - 2011)**	**Inference**
ATE	-0.09 to -0.10	-0.080 to -0.089	+0.010 to +0.011	The average poverty reduction effect of remittances for the entire population weakened.
ATET	-0.083 to -0.098	-0.08 to -0.094	+0.010 to +0.015	The poverty reducing effect for households that actually receive remittances diminished.
ATU	-0.081 to -0.092	-0.076 to -0.090	+0.005 to +0.011	The potential for remittances to lift non-receiving households out of poverty also declined.

According to ATU results, in 2011 if the non-receiving households had begun to receive remittances, their likelihood of being poor would have fallen by 8-9.2 percent. By 2022, this potential poverty reduction had declined to 7.6-9 percent. Although the difference appears numerically small, it is significant when adjusted for inflationary erosion of real remittance value. Nepal's Consumer Price Index rose from 109.2 in 2011 to 222.3 in 2022 (World Bank, 2024), meaning the purchasing power of remittances more than halved. Consequently, remittances in 2022 lifted fewer families out of poverty compared to a decade earlier, with diminishing effectiveness particularly among poorer non-recipient households. This declining effectiveness for the poorest segments of society aligns with findings from Latin America, where remittances were also found to have a diminished impact on poverty reduction over time (Acosta et al., 2008).

This concludes that the role of remittances in poverty reduction has declined over time in Nepal. Remittances continue to be important but are less transformative nationally than they were in 2011. The distribution of benefits has shifted, remittance-receiving households still gain substantially, but non-receiving households have less probability of reduction of poverty. This trend signals a need for inclusive migration opportunities for disadvantaged groups, reducing migration costs, and supporting productive use of remittances to make poverty reduction self-sustaining.

5. Discussion and Conclusion

The findings of this study provide evidence that remittances play a substantial role in reducing poverty in Nepal, though their impact is not uniform across income groups. Using Propensity Score Matching (PSM) on nationally representative NLSS data from 2010/11 and 2022/23, across both survey rounds, the Average Treatment Effect on the Treated (ATET) ranges from 8 to 10 percentage point reduction in poverty likelihood, and the Average Treatment Effect (ATE) indicates that remittances would reduce overall poverty by 8 to 9 percentage points if extended to all households. This affirms earlier findings by Lokshin et al. (2010) and Wagle and Devkota (2018) and strengthens the argument that remittances continue to serve as a vital social safety net and an important pathway for getting out of poverty.

However, a deeper disaggregated analysis shows a more complex and concerning picture. While the share of poor households receiving remittances increased over time, real remittance income has declined for the poorest households. Specifically, households earning below NPR 3 hundred thousand experienced a sharp drop in real remittance income between 2011 and 2022, with those in the lowest income bracket (below NPR 50,000) seeing a staggering 91 percent decline. This suggests that while more poor households now engage in migration, they are either receiving smaller amounts or are burdened by debt-financed migration that limits the ability to send money home (Amnesty International, 2017; IOM, 2023). In contrast, higher-income households have seen significant increases in remittance income.

The ATU estimates ranging from a 7.6 to 9 percentage point potential reduction in poverty indicate that remittances could still help many currently non-receiving households, especially among the poor. However, barriers such as high upfront migration costs (often triple a poor household's annual income) and spatial disparities in access to remittance infrastructure (e.g., banks, roads) appear to restrict these benefits (Kharel et al, 2023). Moreover, the data reveal an alarming increase in migrant households not receiving any remittances, particularly in the middle-income and the very high-income brackets, indicating a growing financial vulnerability and perhaps the erosion of the migration-remittance link over time. It might be indicative of a permanent loss of skilled labor force among high income households and consequently to the national economy. The pattern of declining remittance shares in total income for the lowest income households, combined with rising shares among wealthier groups, hints at a phenomenon of "remittance capture” where relatively better-off families leverage migration for long-term asset accumulation, while poorer families face increasing constraints (Adams & Quequecha, 2010).

The findings imply that while remittances remain a critical tool for poverty reduction, their long-term developmental impact depends on addressing structural constraints that limit access for the most vulnerable. Future migration and remittance-related policies must focus on reducing migration barriers for poor and marginalized households, enhancing the productive use of remittances, and ensuring equitable access to migration pathways and financial services. Only through such inclusive strategies can remittances contribute not just too short-term poverty relief but also to broader economic transformation and social equity in Nepal.

6. Policy Implications

The evidence from both 2011 and 2022 consistently shows that remittances significantly reduce poverty, with the strongest effect for households already receiving them (ATET) but also meaningful for those currently excluded (ATU). These findings highlight the critical role of remittances in enhancing household welfare, while also pointing to the need for policies that expand access, ensure sustainability, and maximize their developmental impact.

First, policies should expand safe and inclusive migration opportunities, particularly for marginalized and poorer households who stand to gain the most. This requires lowering recruitment costs, providing subsidized migration loans and insurance, and diversifying destinations and skill profiles through bilateral agreements and targeted training. Such measures would ease access to foreign employment and reduce the inequalities currently observed.

Second, remittances must be leveraged for productive and sustainable investments rather than primarily consumption or debt repayment. Policymakers can design remittance-linked savings and credit products, create matching grant schemes for small enterprises, and establish remittance investment funds to channel household earnings into agriculture, local businesses, and community development. Complementary financial literacy and entrepreneurship programs for migrant families and returnees would further strengthen this transition.

Finally, harnessing the broader potential of the Nepali diaspora is essential. Reducing remittance transfer costs, introducing diaspora bonds, and providing attractive investment incentives can encourage formal remittance flows and capital inflows from wealthier migrants. Structured platforms for diaspora engagement can also unlock knowledge transfer, innovation, and technology partnerships, reinforcing the long-term developmental benefits of migration.

Together, these measures would not only reduce poverty more equitably across households but also ensure that migration and remittances serve as a foundation for inclusive and sustainable economic transformation in Nepal.

7. References

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8. Appendix

Table 1: balance diagnostics for all covariates before and after matching 2011 (all)

Covariates	Before Matching					After Matching				
	Mean T	**Mean C**	**SMD**	**Var r**	**P value**	**Mean T**	**Mean C**	**SMD**	**Var r**	**P value**
Age HH Head	47.27	45.77	10.19	1.11	0.004	48.31	46.20	15.28	0.94	0.000*
urb_rur1	0.33	0.35	-5.20	0.96	0.149	0.034	0.34	0.055	1.00	0.975
age 15_64	2.68	2.84	-9.77	1.22	0.006	2.88	2.82	3.82	0.90	0.036*
dep_pop	2.01	1.95	4.05	1.12	0.256	1.65	1.96	-19.78	0.97	0.000
agriland1	0.74	0.70	10.28	0.90	0.004	0.68	0.71	-5.72	1.05	0.001*
livestock1	0.73	0.67	13.65	0.88	0.0001	0.65	0.68	-6.34	1.04	0.002*
educ	4.02	4.86	-21.57	0.78	0.000	4.95	4.71	5.15	1.09	0.002*
head_nsco1	0.24	0.41	-40.40	0.75	0.000	0.40	0.38	2.98	1.01	0.056
mari_status1	0.97	0.96	5.31	0.74	0.15	0.96	0.96	-4.76	1.29	0.005*
age_hhhead^2	2453	2291.5	11.342	1.07	0.001	2525.3	2337.3	14.43	0.85	0.000*
educ^2	31.32	42.88	-24.12	0.71	0.000	45.009	40.96	6.66	1.20	0.000*
madeshcaste1	0.09	0.10	-5.87	0.86	0.10	0.10	0.10	-1.38	0.96	0.45
hilljanajati1	0.18	0.30	15.05	1.10	0.000	0.34	0.32	4.50	1.03	0.011*
teraijanajati1	0.06	0.06	0.81	1.03	0.820	0.05	0.06	-5.22	0.81	0.0048
hilldalit1	0.08	0.08	0.09	0.00	0.978	0.069	0.08	-5.31	0.84	0.005*
teraidalit1	0.02	0.04	-8.63	0.66	0.020	0.040	0.038	1.01	1.05	0.571
sex1	0.51	0.77	-50.88	1.41	0.000	0.72	0.73	-1.91	1.02	0.117
Koshi1	0.22	0.16	13.70	1.24	0.001	0.16	0.17	--3.51	0.94	0.050*
Madesh1	0.13	0.12	3.10	1.07	0.38	0.11	0.12	-2.43	0.94	0.18
Sudhurpaschim	0.02	0.10	-56.06	0.22	0.000	0.09	0.088	2.49	1.07	0.062
Gandaki	0.015	0.08	18.8	1.67	0.000	0.09	0.093	-0.37	0.98	0.82
Lumbini1	0.18	0.16	4.80	1.08	0.17	0.18	0.17	2.24	1.05	0.21
Karnali	0.023	0.06	-24.64	0.39	0.000	0.03	0.05	-9.18	0.69	0.000*
Distance paved road	9.50	13.12	-18.07	0.45	0.000	11.86	12.67	-2.92	0.95	0.09
Distance Bank	9.86	11.64	-14.06	0.53	0.0002	10.67	11.43	-4.85	0.84	0.009*
Distance Market	7.99	8.09	-0.531	1.31	0.880	9.99	8.07	5.73	4.62	0.000*

Before Matching Minimum p.value: < 2.22e-16 Variable Name(s): age_hhhead age_15_64 educ head_nsco1 I(age_hhhead^2) I(educ^2) sex1 sudurpachim1 dist_bank Number(s): 1 3 7 8 10 11 17 20 25 After Matching Minimum p.value: < 2.22e-16 Variable Name(s): age_hhhead age_15_64 dep_pop educ I(age_hhhead^2) I(educ^2) dist_pavedroad dist_market Number(s): 1 3 4 7 10 11 24 26

Table 2: balance diagnostics for all covariates before and after matching 2022 (all)

Covariates	Before Matching					After Matching				
	Mean T	**Mean C**	**SMD**	**Var r**	**P value**	**Mean T**	**Mean c**	**SMD**	**Var r**	**P value**
Age HH Head	44.86	45.48	-4.26	0.94	0.109	45.12	45.70	-3.92	1.00	0.026*
urb_rur1	0.59	0.57	3.81	0.98	0.149	0.59	0.59	0.71	0.99	0.833
age 15_64	2.31	2.54	-16.31	0.93	0.00	2.33	2.37	-2.69	1.02	0.00*
dep_pop	1.56	1.45	8.56	0.99	0.001	1.53	1.52	0.86	0.911	0.801
agriland1	0.72	0.69	6.36	0.94	0.01	0.718	0.720	-0.259	1.00	0.940
livestock1	0.70	0.64	13.02	0.90	0.00	0.701	0.704	-0.638	1.005	0.848
educ	5.31	5.52	-5.06	0.87	0.05	5.28	5.199	2.16	1.02	0.515
head_nsco1	0.25	0.44	-41.79	0.77	0.00	0.26	0.26	0.92	1.01	0.761
mari_status1	0.98	0.95	24.59	0.35	0.00	0.98	0.98	-2.30	1.21	0.483
age_hhhead^2	2225.8	2295.2	-4.99	0.88	0.062	2251.1	2301.4	-3.60	0.94	0.026*
educ^2	45.12	49.80	-9.15	0.78	0.00	45.04	43.76	2.49	1.00	0.460
madeshcaste1	0.12	0.116	2.26	1.05	0.39	0.124	0.130	-1.76	0.96	0.60
hilljanajati1	0.31	0.25	12.78	1.13	0.000	0.314	0.315	-0.12	0.99	0.97
teraijanajati1	0.06	0.092	-9.20	0.76	0.000	0.07	0.06	0.68	1.02	0.84
hilldalit1	0.11	0.11	-0.18	0.99	0.94	0.113	0.108	1.47	1.03	0.666
teraidalit1	0.03	0.03	-2.23	0.89	0.40	0.034	0.025	5.12	1.35	0.10
sex1	0.405	0.66	-53.60	1.08	0.000	0.416	0.414	0.23	1.00	0.921
Koshi1	0.162	0.13	8.18	1.18	0.00	0.165	0.162	0.942	1.017	0.781
Madesh1	0.19	0.13	15.87	1.36	0.000	0.193	0.190	0.730	1.01	0.82
Sudhurpaschim	0.038	0.14	-53.22	0.30	0.000	0.03	0.04	-3.01	0.87	0.32
Gandaki	0.17	0.11	16.76	1.44	0.000	0.17	0.17	0.77	1.01	0.817
Lumbini1	0.160	0.144	4.41	1.09	0.09	0.15	0.16	-1.59	0.97	0.64
Karnali	0.060	0.11	-23.46	0.55	0.000	0.006	0.05	1.21	1.046	0.708
Distance paved road	4.44	6.90	-23.13	0.38	0.00	4.53	4.32	1.94	1.24	0.018*
Distance Bank	5.11	5.74	-9.77	0.689	0.000	5.17	5.20	-0.57	1.17	0.86
Distance Market	6.55	6.30	2.70	0.93	0.309	6.56	6.65	-0.94	1.04	0.78

Before Matching Minimum p.value: < 2.22e-16 Variable Name(s): age_15_64 dep_pop educ head_nsco1 I(educ^2) sex1 sudurpachim1 dist_pavedroad dist_market Number(s): 3 4 7 8 11 17 20 24 26
After Matching Minimum p.value: < 2.22e-16 Variable Name(s): age_15_64 Number(s): 3

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