Analyzing the impact of International Remittances upon Poverty Alleviation in Pakistan (using Propensity Score Matching)

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Abstract

Migration (both internal and international) has become an increasingly prevalent phenomenon in Pakistan which has caused remittances to become a main source of income for many migrant households. This paper aims to investigate whether international remittances have an impact on reducing household poverty in Pakistan? For this purpose, we use data from the nationally representative household survey named Pakistan Social and Living Standard Measurement survey (PSLM) for the year 2013-14. We use Propensity Score Matching (PSM) to reduce potential selection bias due to the existence of the observed differences in the socioeconomics characteristics between the remittance receiving and non-remittance receiving households. After propensity scores are calculated, households receiving remittances are matched with nonrecipient households that have close propensity scores (and which are therefore comparable to households receiving remittances based on the observed characteristics). Once we have done propensity score matching, we now take only the sample for which matching was successful. Using this sample, we can be sure that there is no potential selectivity bias. After this, we run various probit regression models to see the impact international remittances have upon poverty alleviation in Pakistan.

Introduction

Remittances have become the main source of income for many migrant households. People who have migrated to a foreign country for work or even moved inside the country from a rural setting to an urban are the driver of reducing poverty back homes. Now they can send their children to schools and research suggests that these households have better access to nutritional food. This trend has recently become so rampant due to the ease in international transaction mainly due to technology and a fair lock down on money laundering which otherwise could have gone undetected under the radar of national institutions. Taxes are paid to the national exchequer and the influx of remittances has positively contributed to the GDP growth. Remittances have increasingly become an external source of financing for developing countries. This phenomenon is not limited to developing countries, even people from developed countries are moving to other developed countries for careers that better match their passions and skills set. Many tech giants have outsourced their manufacturing sectors to these developing countries, resulting in remitting more dollars back home along with providing jobs in the country they operate.

Like other developing countries, remittances have become a rapidly growing phenomenon in Pakistan as well. Even the internal remittance base has gone up manifold in Pakistan which is a promising sign for both the government and the poor population. However, as internal remittance has totally different dynamics of its own, we shall be considering only international remittances in our paper. This is also because most of the households in our data set receive international remittances and only a handful of households receive internal remittances. Hence, the question that we evaluate is whether international remittances help reduce poverty?

Reviewing the extant literature, we found mixed results for the impact of international remittances and there is no extensive research on Pakistan. The primary purpose of the paper is to see if there exists a positive correlation between international remittances Pakistan receives and poverty alleviation as many of the papers on developing countries suggest. In lines with the findings of the paper we suggest the government and other policy making think-tanks to roll out migration friendly policies to reduce poverty among the poor segment the society.

For us to have a truly representative sample, we use a technique called propensity score matching that helps overcome possible selection bias in our sample. Using propensity score matching, the sample is generated after which we run our probit regression models in order to see whether international remittances affect poverty while controlling for other determinants of poverty.

Trend of International Remittances in Pakistan

The data from world bank (Figure 1 below) shows a sharp upswing of international remittances in Pakistan from the year 2000 onwards. The remittances are measured in millions of dollars, hence for the year 2018 it is almost touching 21,000 million USD. This upsurge is explained by Udo Kock and Yan Sun (2011) in the IMF working paper: *Remittances in Pakistan-Why have they gone up and why aren't they coming down* August 2011 in their concluding remarks "The results are encouraging, as they show that the skill level of immigrants, investment returns in the host country and in Pakistan, exchange rates (real and nominal), and Pakistan's economic conditions all play a strong role in explaining remittances."

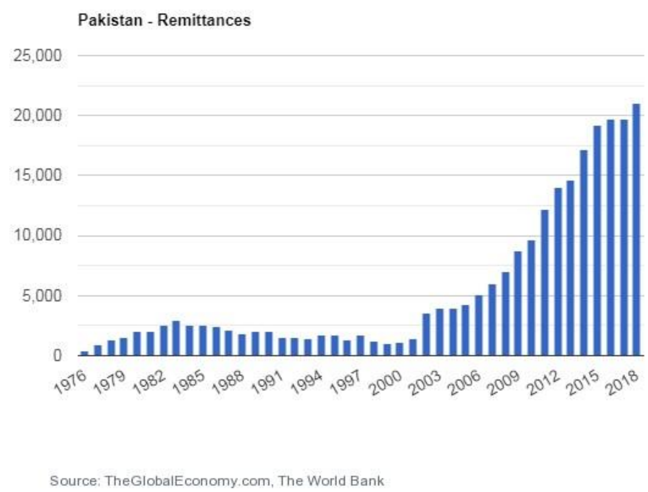

Figure 1 Trend for International Remittances in Pakistan

Figure 2 captures another interesting aspect of international remittances in terms of the countries from which remittances are received. Much of the remittance flow is from Gulf countries where majority of the workforce is low skilled labors while that sent back from the European countries and USA are highly skilled. There is a great potential for Pakistan to tap into those workers who are working in the Gulf countries mainly Saudi Arabia and UAE where workers are not highly skilled, despite this they remit a major chuck and contribute a lot to the national exchequer. In addition to this, Figure 3 shows the overall trend of international remittances to GDP ratio, early on from the late 1970s it has grown steadily except for few years even there is no such an irregular pattern for 2009 financial crisis until 2015-2016 where it has gone down.

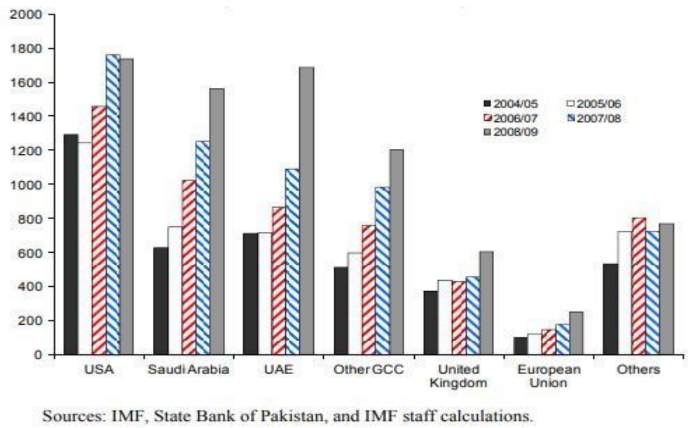

Figure 2 Country-Wise flow of International Remittances

Figure 3 Remittances to GDP

All these statistics suggest that international remittances are an important part of Pakistan's economy and a source of income for many households. Hence, studying this important source of income and seeing if it helps alleviate poverty can have meaningful policy implications.

<u>Literature Review</u>

Many studies have thoroughly investigated the empirical relationship between remittances and poverty alleviation. Some studies have remarked that there exists an ambiguous relation between the two variables resulting in no such a significant impact. These mixed results could be explained by the high international migration costs and could also be attributed to certain study limitations. Though some studies show a positive and some show negative relations, especially international remittances are found to have a positive correlation with poverty alleviation. Some authors argue that the zero impact of remittances could be due to the equivalent income these emigrants earned had the workers instead of emigrating to other places stayed back home. Kapur (2004) argues that most of the migrating families do not come from these poor households and hence this instead leads to improvement in the living standards in the well to do households.

López-Videla et al (2014) in their study of the impact of remittances on poverty alleviation in Bolivia, a developing country using a propensity score matching approach to account for sample heterogeneity and bias due to confoundedness' factors concluded that on average there is a positive effect of remittances on national level. At national level the remittance receiving households are 13% less probable to be in poverty. However, if the analysis is done on sub levels i.e. rural and urban levels, the effect is different. Remittances are responsible for reducing poverty in urban households, but rural households were found to have no impact. Even though the remittances are believed to be poor friendly but the case for the null impact of rural households is attributed to higher international migration costs.

Rashmi Banga and Pritish Kumar Sahu (2010) in their study on the impact of remittances on poverty in developing countries show that a 10% increase in remittances reduce the poverty headcount ratio by about 3.1% and poverty gap by about 3- 5%, depending on how poverty gap is measured in developing countries. The authors analyzed the impact of remittances taken as the share of GDP for the countries. Firstly, analyzing for the 77 developing countries which receive any form of international or internal remittances and secondly, breaking it down to 29 developing and 21 Asian countries. There findings consistently show that the positive relation for remittances and poverty alleviation holds true, but the results were seen more reliable for countries receiving remittances more than 5% of their GDP.

Similar analysis was drawn by Rehmat Ullah Awan et al (2017) working on the PSLM 2011-2012 data on Pakistan in their paper *Impact of Remittances on Expenditure and Poverty at Household Level*. Their empirical results indicate that on average, the likelihood of falling below poverty line for international remittances recipient household reduces 16.7% more than that of non-recipient households. Considering Per capita annual expenditures international remittances recipient households spend on average, Rs. 17779 more per year than that of non-recipient households. Moreover, in case of total annual expenditures, international remittances recipient households spend on average Rs. 78102.61 more per year than that of non-recipient households.

Another similar study done by Elliana V. Jimenz-Soto and Richard P. C. Brown (2012) of The School of Economics, University of Queensland in the case of Tonga, a poor pacific island country depending highly on the remittances of the migrants through propensity score matching and alternative counterfactual income estimation method posit that remittances reduce depth of poverty by 49% and the incidence of poverty by 31% because remittances provide the poor households with much needed social protection.

Matthieu Clement (2011) in his study working on the 2003 Tajikistan Living Standards Measurement Survey using a similar methodology concludes that though both internal and external remittances do not have any impact on investment expenditure, they are basically short-term coping strategies which the households depending solely on this income source use for basic level of consumption. More than 10% of the Tajik households receive international remittances and it is on average 39% of the income of the households. These remittances are mainly devoted to consumption expenditure. The findings confirm that the share devoted to consumption expenditures goes up by 1.7 percentage points of the external remittance recipient households. In his concluding remarks he is of the view that these household's increasing consumption shares result in bringing them out of poverty.

Working on the paper, *Migration, Labor Mobility and Household Poverty in Nigeria: A Gender Analysis* Mitsura Rufai et al (2019) observe that most of the working migrants who have a baggage of working experience sent back more remittances which relatively were more than female migrants. The study was done on Nigeria where half of the households are poor, and the labor mobility has significant impact on the extent of poverty reduction. The data used for the study was taken from the world bank 2009 Household Surveys for the African Migration Project in Nigeria and the analysis was done using logit regression model, propensity score matching and linear regression model. Gender-wise 54.76% males compared to 39.29% females sent remittances back home. The impact assessment show that overall labor mobility reduces poverty by 22.1%. Separately the reduction was lower among male migrants i.e. 20.1%. However, it was insignificant among female migrants, i.e.0.188%.

Data

For the purpose of this study, we use data from the nationally representative household survey named Pakistan Social and Living Standard Measurement survey (PSLM) for the year 2013-14. This survey contains data on 17,989 households consisting of a total of 119,018 individuals. PSLM comprises of questions about various social and demographic characteristics like income, wealth, education etc. The income and expenditures categories questions are asked for different time spans like fortnightly, monthly and annually. However, the information about the variable on receipt of remittances (international) is given for a year, for example, the receipt of remittances in last year. As this survey is meant to specifically collect information on migration and remittances, therefore, it does not provide a huge amount of information about migrants. From a total of 17,989 households, 93.4% households receive remittances, of which 61% lie in urban areas and the remaining 32.4% in rural areas. Out of the 6.58% remittance receiving households, 4.34% lie in urban areas and the remaining 2.2% in rural areas. From the 6.58% remittance receiving households, 6.1% lie below the poverty line and the remaining 0.48% lie above it. In case of non-remittance receiving (93.42%) households, 68.66% lie below the poverty line and the remaining 24.77% lie above the poverty line. These details are depicted in Table 1 below.

Table 1. Sample Distribution of Households by Region, Remittance-Receiving Status and Poverty Condition

	Rural (%)	Urban (%)	All Households (%)
Do not receive remittances	32.42	61	93.42
Receive remittances	2.23	4.34	6.58
	Poor (%)	Not Poor (%)	All Households (%)
Do not receive remittances	68.66	24.77	93.42
Receive remittances	6.1	0.48	6.58

For calculating poverty, we calculate per month per adult equivalent expenditure and then deflate it using the Pasche index (to account for regional food price variation). The poverty number generated using the PSLM 2013-14 is 29.06 which is very close to the one given in the Pakistan Economic Survey 2018.

Apart from the variable Poor calculated above, we use numerous other variables in subsequent analysis. These variable definitions are given in Table 2 below. Along with that, Table 3 shows the summary statistics for all variables in the final representative sample (which is generated via propensity score matching and then dropping any missing values before regression analysis).

Table 2. Variable Definition

Variable Name	Variable Definition
Poor	=1 if a HH lies below the Poverty Line
Male_hh_head	=1 if the HH head is a male
HH_head_age	=Age of the HH head
No_of_dependents	=Number of people in the HH who do not work or are not willing to work
Illitrate	=1 if the HH head has never attended school
Lowly_educated	=1 if the HH head has between 1 to 5 years of education
Medium_educated	=1 if the HH head has between 6 to 10 years of education
Highly_educated	=1 if the HH head has more than 10 years of education
Rural	=1 if the region is rural
Urban	=1 if the region is urban
International_remittance_dummy	=1 if a HH receives international remittance
Small_hs	=1 if a HH has between 1 and 5 members
Large_hs	=1 if a HH has between 6 and 10 members
Medium_hs	=1 if a HH has greater than 10 members
No_land	=1 if the HH owns no land
Sub_land	=1 if the HH owns between 1 and 12.5 acres of land
Eco_land	=1 if the HH owns more than 12.5 and less than 25 acres
Large_land	=1 if the HH owns more than 25 acres of land
Livestock	=1 if the HH owns livestock
Financial_asset	=financial assets owned by the HH in millions of rupees

Note:
Other variables used are Sector of employment indicators which include agriculture & forestry, mining, manufacturing, electricity or gas, construction, wholesale and retail trade, transport, real estate, and social and personal services while employment status indicators include self-employed, paid employees and unpaid family workers. District variables (a total of 102 districts) include dummies for each district.

Table 3. Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Poor	10,043	0.229	0.420	0	1
Male_hh_head	10,043	0.933	0.251	0	1
HH_head_age	10,043	47.25	12.61	16	99
No_of_dependents	10,043	4.556	2.397	0	21
Lowly_educated	10,043	0.113	0.316	0	1
Medium_educated	10,043	0.303	0.460	0	1
Highly_educated	10,043	0.132	0.339	0	1
Rural	10,043	0.637	0.481	0	1
Urban	10,043	0.363	0.481	0	1
International_remittance_dummy	10,043	0.0672	0.250	0	1
Small_hs	10,043	0.369	0.482	0	1
Large_hs	10,043	0.0765	0.266	0	1
Medium_hs	10,043	0.555	0.497	0	1
KPK	10,043	0.233	0.423	0	1
Punjab	10,043	0.585	0.493	0	1
Sindh	10,043	0.147	0.354	0	1
Balochistan	10,043	0.0350	0.184	0	1
Illitrate	10,043	0.452	0.498	0	1
No_land	10,043	0.785	0.411	0	1
Sub_land	10,043	0.202	0.402	0	1
Eco_land	10,043	0.00886	0.0937	0	1
Large_land	10,043	0.00388	0.0622	0	1
Livestock	10,043	0.343	0.475	0	1
Financial_asset	10,043	126,543	726,741	0	5.100e+07

Note:
Other variables used are Sector of employment indicators include agriculture & forestry, mining, manufacturing, electricity or gas, construction, wholesale and retail trade, transport, real estate, and social and personal services while employment status indicators include self-employed, paid employees and unpaid family workers. District variables (a total of 102 districts) include dummies for each district.

Methodology

1) Propensity Score Matching

One possible way of trying to see the effect of remittances on poverty is to run a logit or probit model with remittance as the independent variable and poverty as the dependent variable, while we control for other possible factors that affect poverty. However, there is one big problem with this method. The sample of households that we select as those receiving remittances might not be a truly representative sample due to potential selectivity bias. The selectivity bias may occur because if we consider all households that receive remittances then that might include those households that are above the poverty line. If a household lying above the poverty line receives remittances, then it would not lead to decrease in overall poverty. Hence, including such households in our model can make our results flawed as the observed effect of remittances on poverty shall be diluted.

Therefore, in order to overcome this possible selection bias, we use a technique called Propensity Score Matching for generating a representative sample for our analysis. Propensity score matching produces a representative sample based on certain covariates that may impact if a household receives remittances or not. The first step of this process is generating the propensity scores which basically represent the probability of assignment to treatment group conditional on a subject's measured baseline covariates (or pretreatment characteristics). We consider various possible factors that may affect if a household receives remittances or not. The covariates used for propensity score matching included dummies for region, province, family size, number of dependents along with household head's gender, age and education.

After propensity scores are calculated, the matching consists of constructing counterfactuals. Remittance receiving household's poverty levels are compared with statistically equivalent non remittance receiving household's poverty levels except for remittances. Hence, if there exists a difference in the poverty levels, then it can be attributed to exist due to remittances. There are no specific guidelines in literature with regards to which method should be used for matching. Various matching estimators compare exact matches asymptotically and hence, provide almost similar results. The general tendency in literature is to use kernel, mahalanobis or radius matching for data sets having large control groups. As our data set has a large control group (almost 93% households do not receive remittances), we go ahead with Mahalanobis matching. The results show that out of a total of 17,989 households, propensity scores for 6,727 households (almost 37%) were off support, i.e., the propensity scores for the treatment and non-treatment groups could not match for these households. Hence, our final representative sample shall consist of the 11,262 households for which the matching was successful. These results are shown in Table 4 below.

Table 4. Propensity Score Matching Results

psmatch2: Treatment assignment	psmatch2: Common Support		
	Off-Support	On-Support	Total
Untreated	6,684	10,122	16,806
Treated	43	1,140	1,183
Total	6,727	11,262	17,989

After matching has been done, the new demographic composition of remittance receiving households based on region (rural/urban) and being poor changes. The new composition is shown in the Table 5 below.

Table 5. Sample Distribution after Propensity Score Matching of Households (by Region, Remittance-Receiving Status and Poverty Condition)

	Rural (%)	Urban (%)	All Households (%)
Do not receive remittances	32.23	57.65	89.88
Receive remittances	3.43	6.7	10.12
	Poor (%)	Not Poor (%)	All Households (%)
Do not receive remittances	69.34	20.54	89.88
Receive remittances	9.39	0.73	10.12

In order to verify that the matching produces reliable results, we perform the balancing test. For the results to be reliable, it requires that the null hypothesis stating that the means of each covariate remains the same between the treatment and control groups is satisfied. Hence, for us to not reject the null hypothesis, the t-stat for the covariates used should be insignificant. Our results show exactly that as all the p-values are way greater than both 0.01, 0.05 or 0.1. Hence, all the variables are not significant, and we shall not reject the null hypothesis. Therefore, we can conclude that our matching was successful and can go ahead with our regression models using the new sample. The results for the balancing test are shown in table 5 below. The new sample generated after propensity score matching has now a different distribution of remittance receiving and non-remittance receiving households according to region and poverty. The new distribution of households is shown in the Table 6 below.

Table 6. Balancing Test Results

	Mean		t-test
Variable	Treated Control	%bias	t p>t
Male_hh_head	.59912 .59912	0	-0.00 1.000
HH_head_age	49.533 48.935	4	0.99 0.323
No_of_dependents	5.6412 5.5262	4	0.91 0.361
Lowly_educated	.11228 .11228	0	-0.00 1.000
Medium_educated	.27807 .27807	0	-0.00 1.000
Highly_educated	.12456 .12456	0	0.00 1.000
Small_hs	.40526 .40526	0	-0.00 1.000
Large_hs	.14825 .14825	0	0.00 1.000
Rural	.6614 .6614	0	0.00 1.000
KPK	.46228 .46228	0	-0.00 1.000
Punjab	.49386 .49386	0	0.00 1.000
Sindh	.02456 .02456	0	-0.00 1.000

2) Regression Models (Formulation and Results)

(i) Determinants of Poverty Probit Regression Model

The first model that we use is a basic probit regression model that tries to access whether various determinants of poverty that we shall be controlling in the next model behave as expected. Hence, the model uses a binary variable for poverty as the dependent variable and different determinants of poverty (excluding remittances) as the independent variables. The exact model is as follows:

$$\textbf{Poor} = \beta_0 + \beta_1\text{*Rural} + \beta_2\text{*HH\_head\_age} + \beta_3\text{*No\_of\_dependents} + \beta_4\text{* Lowly\_educated} + \beta_5\text{* Highly\_educated} + \beta_6\text{* Small\_hs} + \beta_7\text{*Rural} + \beta_8\text{* Large\_hs} + \beta_9\text{* Sub\_land} + \beta_{10}\text{* Eco\_land} + \beta_{11}\text{* Large\_land} + \beta_{12}\text{* Livestock} + \beta_{13}\text{* Financial\_asset} + \beta_i\text{* (District dummies)} + \beta_j\text{* (Provinces dummies)} + \beta_k\text{* (Sector \& Employment status dummies)} + \mu$$

The average marginal effects produced via probit regression show that various determinants of poverty, while controlling for provincial, district, sector & employment status controls, behave in the same way as we expect them to. There is an increase in poverty when the region is rural or when the number of dependents (i.e. the people who do not work or are not willing to work) increase. The education of the household head decreases poverty with having a highly educated household head causing the most decrease (10.8%) in poverty. An increase in the household size causes poverty to decline less with largest households having the least reduction (0.8%) in poverty. Landholding is expected to cause lessen poverty and the results also suggest a similar trend with large landholding causing the greatest decline (8.21%) in poverty. The negative coefficients of livestock and financial assets suggest that owning these two is expected to reduce poverty. Having a male household head causes poverty to increase by 1.7%. Even though this value is not significant however the direction of the effect of having a male household head on poverty is in line with the existent literature. Except for a couple of variables, all the coefficients in the table are significant at the 99% confidence interval. Complete results for this model are shown in Table 7 below. The number of observations is less than our initial value of 11,262 because observations having missing values for sector and employment status controls were dropped from our regression.

Table 7. Determinants of Poverty Probit Regression Model Results (Average Marginal Effects)

VARIABLES	Probit regression (Average marginal effects) Poor
Rural	0.0389***
	(0.00703)
Male_hh_head	0.0169
	(0.0108)
HH_head_age	-0.00144***
	(0.000260)
No_of_dependents	0.0239***
	(0.00222)
Lowly_educated	-0.0440***
	(0.00651)
Medium_educated	-0.0890***
	(0.00668)
Highly_educated	-0.108***
	(0.00619)
Small_hs	-0.0998***
	(0.00792)
Large_hs	-0.00869
	(0.0126)
Sub_land	-0.0532***
	(0.00915)
Eco_land	-0.0818***
	(0.00821)
Large_land	-0.0821***
	(0.0103)
Livestock	-0.00255
	(0.0110)
Financial_asset	-4.85e-07***
	(2.81e-08)
Province controls	Yes
District controls	Yes
Sectors and employment status indicators	Yes
Observations	10,043

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

Note:
Sector of employment indicators include agriculture & forestry, mining, manufacturing, electricity or gas, construction, wholesale and retail trade, transport, real estate, and social and personal services while employment status indicators include self-employed, paid employees and unpaid family workers. District and province fixed effects are introduced by specifying district and province dummy variables, one each for each district and province.

(ii) International Remittances Probit Regression Model

As all the determinants of poverty in the previous model show the same trend as in existing literature, we can safely say that our data set is correct. Therefore, we can now proceed on to our main model where we add international remittances dummy as an independent variable in our model and see how it impacts poverty levels, while controlling for other determinants of poverty. This probit regression model can be written as follows:

Poor = β_0 + β_1*International_remittance_dummy + β_2*Rural + β_3*HH_head_age + β_4*No_of_dependents + β_5* Lowly_educated + β_6* Highly_educated + β_7* Small_hs + β_8*Rural + β_9* Large_hs + β10* Sub_land + β_{11}* Eco_land + β_{12}* Large_land + β_{13}* Livestock + β_{14}* Financial_asset + β_i* (District dummies)+ β_j* (Provinces dummies) + β_k* (Sector & Employment status dummies) + μ

The average marginal effects produced via probit regression show that households that receive remittances are 6.9% less likely to lie below the poverty line than households that do not receive remittances. This result is significant at 99% confidence interval. The sign of coefficients for all the other determinants of poverty remain the same as our earlier model, only the magnitude of coefficients changes. The complete regression results are shown in table 5 below. The number of observations is less than our initial value of 11,262 because observations having missing values for sector and employment status controls were dropped from our regression.

After doing the analysis for the overall population, we then do the same regression analysis for rural and urban areas. Remittance receiving households are more likely to lie below the poverty line in rural areas than in urban areas. The average marginal effect of receiving international remittances in rural areas is that poverty decreases by 13.1 percent. These results for rural areas are significant at 99% confidence interval. Apart from this, other determinants of poverty are also significant and have the same sign for coefficients as discussed earlier.

Meanwhile in urban areas, poverty decreases by 1.89 percent for households that receive international remittances. These results for urban areas are significant at 99% confidence interval. In addition to this, other determinants of poverty are also significant and have the same sign for coefficients as discussed earlier.

These results are significant in showing that international remittances play a vital role in alleviating poverty in both rural and urban areas. However, this effect is much greater n rural areas. Hence, policies that help flow of international remittances to rural areas can have a significant impact in reducing overall poverty.

Table 8 on the next page shows complete regression results for all three probit regression models.

Table 8.International Remittances Probit Regression Model Results (Average Marginal Effects Reported)

VARIABLES	Overall Population	Rural	Urban
International_remittance_dummy	-0.0691***	-0.131***	-0.0189***
	(0.00717)	(0.0134)	(0.00522)
Rural	0.0395***	-	-
	(0.00702)	-	-
Male_hh_head	0.00648	0.0285	-0.00336
	(0.0118)	(0.0215)	(0.00887)
HH_head_age	-0.00137***	-0.00198***	-0.000627***
	(0.000259)	(0.000473)	(0.000204)
No_of_dependents	0.0250***	0.0436***	0.00807***
	(0.00224)	(0.00391)	(0.00191)
Lowly_educated	-0.0433***	-0.0840***	-0.00846*
	(0.00651)	(0.0123)	(0.00508)
Medium_educated	-0.0889***	-0.140***	-0.0357***
	(0.00668)	(0.0112)	(0.00680)
Highly_educated	-0.107***	-0.162***	-0.0504***
	(0.00620)	(0.00972)	(0.00787)
Small_hs	-0.0976***	-0.143***	-0.0452***
	(0.00791)	(0.0136)	(0.00837)
Large_hs	-0.00334	0.00156	-0.00929
	(0.0132)	(0.0251)	(0.00694)
Sub_land	-0.0520***	-0.0962***	-0.00999
	(0.00916)	(0.0171)	(0.0137)
Eco_land	-0.0815***	-0.151***	-
	(0.00801)	(0.0174)	-
Large_land	-0.0820***	-0.154***	-
	(0.00995)	(0.0216)	-
Livestock	-0.00361	-0.00632	-0.00842
	(0.0110)	(0.0186)	(0.0117)
Financial_asset	-4.60e-07***	-7.47e-07***	-1.48e-07***
	(2.83e-08)	(6.11e-08)	(1.82e-08)
Province controls	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Sectors and employment status indicators	Yes	Yes	Yes
Observations	10,043	6374	3,402

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

Note:
Sector of employment indicators include agriculture & forestry, mining, manufacturing, electricity or gas, construction, wholesale and retail trade, transport, real estate, and social and personal services while employment status indicators include self-employed, paid employees and unpaid family workers. District and province fixed effects are introduced by specifying district and province dummy variables, one each for each district and province.

Conclusion and Policy Implications

The purpose of this study is to analyze the impact of international remittances upon poverty in Pakistan using data from Pakistan Social and Living Standard Measurement survey (PSLM) 2013-14. For reducing sample selectivity bias, we use a technique called Propensity Score Matching for generating our sample. Regression models run on this sample show that international remittances cause poverty to go down by 6.9% in overall population. At regional level, this change is 13.4% in rural areas and 1.89% in urban areas. These results show that international remittances help reduce poverty as they can help improve the living standard of households.

These results have significant policy implications as it shows that government should form policies that facilitate the flow of international remittances, especially for rural areas. One vital step that can be taken is to have vocational education programs and labor training programs in rural areas. Both these programs can help have skilled labor that can then go overseas for work and send remittances back home. The training programs shall help people get jobs overseas as their skillset improves. Another step that can be taken is to set up help centers which can tell people about relevant jobs based on their skill set and help them with the visa process.

Our paper backs existing research about the effect of international remittances upon poverty in developing countries. In addition to that, it also lays ground for further research on this topic or may be seeing the effect of internal remittances upon poverty in Pakistan.

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