The Micro Level Impact of Foreign Remittances on Incomes in Bangladesh
A Measurement Approach Using the Propensity Score

Paper 73

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The present paper titled **The Micro Level Impact of Foreign Remittances on Incomes in Bangladesh: A Measurement Approach Using the Propensity Score** has been prepared under the CPD-UNDP collaboration programme on *Pro-Poor Macroeconomic Policies* which is aimed at developing pro-poor macroeconomic policies in the context of Bangladesh through research and dissemination. The research papers under the current programme attempt to examine the impact of various macroeconomic policies on poverty alleviation and to establish benchmarks for poverty reduction strategies. The outputs of the programme have been made available to all stakeholder groups including the government and policymakers, entrepreneurs and business leaders, and trade and development partners.

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List of Acronyms

ATET	Average Treatment Effect on the Treated
BBS	Bangladesh Bureau of Statistics
CIA	Conditional Independence
DFID	Department for International Development
DiD	Difference-in-Difference
HIES	Household Income and Expenditure Survey
IOM	International Organization for Migration
IV	Instrumental Variable
KM	Kernel Matching
LLM	Local Linear Matching
NN	Nearest Neighbour
PSM	Propensity Score Matching
RMG	Readymade Garments
RMMRU	Refugee and Migratory Movements Research Unit

1. INTRODUCTION

The importance of foreign remittances in the economy of Bangladesh is widely recognised and requires little reiteration. Along with the readymade garment (RMG) sector and non-farm activities in the agricultural sector, remittances have been identified as one of the three key factors that have been responsible for reducing the overall incidence of poverty in Bangladesh (Osmani 2004). The volume of remittances from Bangladeshi migrant workers exceeded USD 4 billion in early 2007 (the *Daily Star*, 27 February 2007), a figure which dwarfs the amount of yearly foreign direct assistance received by the country.

It is therefore striking that very limited empirical work has been done in relation to the actual impact of remittances on incomes. Azad (2004) and Siddiqui (1999) explored, in a mainly qualitative fashion, the potential of remittances as a source for micro-finance initiatives. Their line of reasoning suggests, without implying causality, that remittances can feasibly be considered as falling within the purview of pro-poor initiatives. de Bruyn and Kuddus (2005) examined the dynamics of remittance utilisation without drawing firm conclusions on its effectiveness as a poverty alleviating tool.

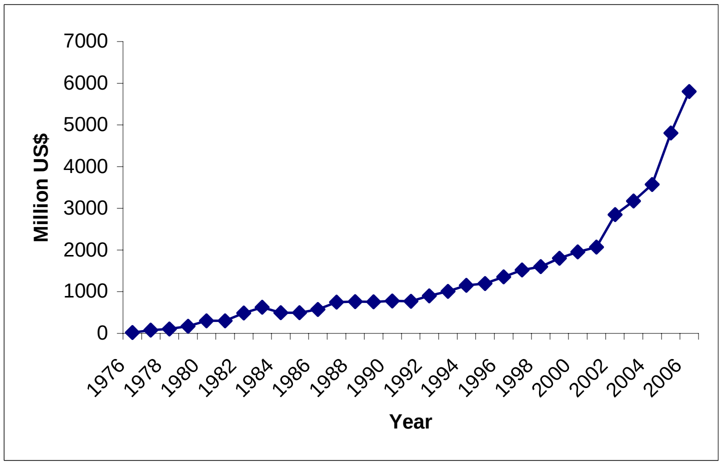
Indeed, any comment on the abovementioned aspect of remittances will at best be speculative unless supported by firm empirical evidence. We therefore propose to carry out a statistical study on the effect of remittances on percapita incomes, which have a direct implication on the welfare of households, in order to remove such speculation and channel the discourse away from the qualitative realm onto a more secure, quantitative footing. Such an effort is necessary in order to derive more accurate conclusions which will greatly assist in the formulation of guidelines for future policy.

This paper is set out as follows: section 2 is a general discussion of remittances vis-à-vis Bangladesh, section 3 lays down the analytical framework of the study, section 4 the objectives, methodology and scope. Section 5 provides the empirical evidence while section 6 concludes with a general discussion and provides a few policy recommendations.

2. REMITTANCES AND BANGLADESH

The outward migration of labour and the remittances that are generated as a result have been a feature of Bangladesh's post liberation history. The earliest official records on remittances indicate that the country received about US$24 million in overseas remittances in 1976. Since then foreign remittance receipts have grown at an exponential rate. Figure 1 charts this increase.

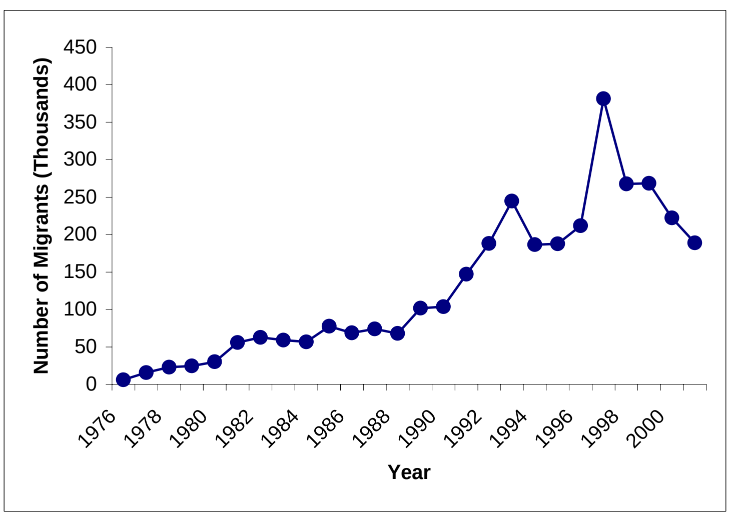
FIGURE 1: REMITTANCE INFLOW



Source*:* Sayed (2007), author's calculation.

For any worker sending country, migration results in a mixture of benefits and costs.[1] The costs may include the loss of the labour supply in which substantial amounts of human capital are invested, possible distortions in the age structure of the population, rural depopulation and a "brain drain" to developed countries. On the benefits side, we may see a reduction in social tensions caused by unemployment and/or underemployment, skill acquisition of returning migrants and, most significantly, money transfers from migrants to their families back home. Figure 2 charts the annual outflow of migrants from Bangladesh.

FIGURE 2: OUTFLOW OF MIGRANTS FROM BANGLADESH



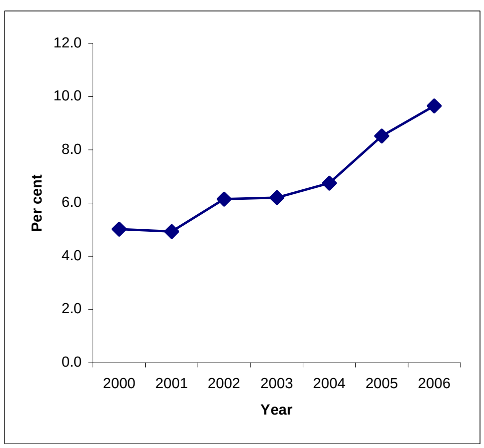
Source*:* DFID, author's calculation.

[1] Sayed (2007), unpublished BRAC University thesis.

The role of remittances in the economies of labour sending countries such as Bangladesh is assuming increasing importance. It is viewed as a very stable source of foreign exchange (Ratha 2005) and even as being counter-cyclical (Esquivel and Huerta–Pineda. 2006). The effect of remittances on the macro-economy of a country has been well documented in the literature. The incoming foreign exchange helps receiving countries to pay import liabilities, improve their balance of payments position, strengthen foreign exchange reserves and finance external debt.

At the micro level, which is the focus of this paper, remittances contribute towards increasing the income of receiving households with concomitant effects on the standard of living, while depending upon consumption patterns they have been known to increase the level of savings (Ratha 2005) which is a source of capital. Thus, in resource scarce countries like Bangladesh remittances have a great potential to generate positive economic and social impacts. This fact has been recognised by policymakers and has received attention from researchers. However, as has been mentioned, there are hardly any studies on the microeconomic impact of remittances on household or percapita incomes. Most research has tended to be on the potential *use* of remittances as a policy tool and, having acknowledged its importance, on possible avenues of further increasing the volume of official remittance receipts by channelising them through legal avenues and by promoting even greater export of labour. Figure 3, which charts remittances as percentage of GDP, highlights its growing importance in the economy of Bangladesh.

FIGURE 3: REMITTANCE AS PERCENTAGE OF GDP



Source*:* author's calculation.

3. ANALYTICAL APPROACH

The key research question we pose is whether or not there is an effect of overseas remittances on poverty in Bangladeshi households. In order to address the issue we aim to utilise an econometric technique commonly employed in the impact evaluation literature (see, for example, Esquivel and Huerta–Pineda. 2006). In particular, we intend to make use of a propensity score based *matching* approach (propensity score matching or *PSM*, Rosenbaum and Rubin. 1983, 1985). Under this approach we will match remittance-receiving households with other households that share similar characteristics but do not receive remittances. Once the matching is made we will be able to compute the effect of remittances on the probability of being in poverty. Our justification for adopting the *PSM* approach is based on a paucity of data, which prevents us from examining household situations before and after remittances have been received. In fact, any application of such a difference-in-differences approach requires longitudinal or panel data on remittance receiving households which do not exist to the best of our knowledge. A regression based approach to the issue is fraught with the problem of selection bias. Since international migration tends to be costly, it is possible that only the relatively well-off households are able to send workers abroad. If that is indeed the case, a simple ordinary least squares regression might overestimate the impact of remittances on the poor. An instrumental variables (IV) regression may be carried out as a remedy, but it is difficult to obtain appropriate instruments in natural settings.

To assess the effect of remittances on the well-being of a household, we must therefore compare the observed outcome (poverty situation) with the outcome that would have resulted had that household not received remittances. But in reality we observe only one outcome, which is known as the factual outcome. The counterfactual outcome, which we do not observe, on the other hand, is that which would have resulted had the remittance receiving household not received it. The major challenge of impact studies is to estimate this counterfactual in a reliable way. If we can make sure that receiving remittances is truly random, we can estimate its effect by comparing the outcome of recipients with that of the non-recipients. Such natural experiments are theoretically very attractive. But, in practice, we cannot (and should not wish to) restrict some households from sending family members abroad when they might benefit from it. Thus, natural experimentation, though theoretically the most reliable (Bryson, Dorsett and Purdon 2002), is not a feasible approach. In situations where random assignment of treatments is not possible, non-experimental methods are applied to evaluate the impact of programme participation (the programme being defined as receiving remittances). The most common non-experimental methods in the literature are the difference-in-differences (DiD) estimation, the IV technique and matching.

Considering the mentioned difficulties associated with random sampling, DiD and IV methods, a matching method has been applied in this study. This method assumes that selection can be explained in terms of observable characteristics. For every household in the treatment group, a matching household from the non-treatment group with similar characteristics is chosen. The mean effect of the paired individuals can then be treated as the average treatment effect on the treated (*ATET*) (Bryson, Dorsett and Purdon 2002). Following the notation of the evaluation literature, let us denote $D = 1$ if a household receives remittances and $D = 0$, otherwise. Then we can define the outcome for the recipients as $Y(1)$ and the outcome for non-recipients as $Y(0)$. In this study, the outcome variables will be per capita income, the squared income difference from a threshold poverty level and a poverty status code. In order to derive the threshold poverty level, we will use the definition of the Poverty Monitoring Survey (BBS 2004) which defines the poverty line as the monthly per capita expenditure on both food and non-food items combined at the poverty line calorie intake. These data allow us to measure poverty status against established thresholds.

The treatment variable of the study will be a binary variable, coded as 1 if the household receives remittances and zero otherwise. Since receiving remittances is similar to receiving treatment, we may estimate the average treatment effect of receiving remittances on the level of per capita income and other outcome variables. The parameter of interest is the *ATET*, which is calculated as:

$$ATET = E[Y(1) - Y(0) \mid D = 1] = E[Y(1) \mid D = 1] - E[Y(0) \mid D = 1]$$

The second term of the right hand side of the equation is known as the counterfactual mean for those being treated. It tells us about how a treated individual would have performed had he not received the treatment. In practice, this counterfactual effect is not observed and using the mean outcome for the untreated individuals, $E[Y(0) \mid D = 0]$, as an approximation would result in selection bias. To solve this problem, the propensity score matching technique is used to estimate the counterfactual. The propensity score is an index function defined as the probability of receiving treatment conditional on observed covariates X: $P(X) = \Pr(D = 1 \mid X)$. In matching based on propensity scores, outcomes of treated and control groups are compared based on a single index $P(X)$ instead of all variables in X. This takes care of the so-called problem of dimensionality. This technique, however, solves the selection bias only if two crucial assumptions are satisfied. The fundamental assumption is that of conditional independence (CIA), which requires that conditional on a set of observables X, the outcome must be independent of the true treatment status of the individuals. Since selection bias arises for some elements of X affecting the probability of getting treatment may also affect the outcome, if we can make sure that none of the variables in vector X is influenced by treatment, differences in outcomes based on $P(X)$ would be independent of the treatment status of the household, D. In that case, the following condition would be satisfied:

$$Y(0), Y(1) \perp D \big| X$$

Keeping this in mind, we will include observable characteristics in the model, which are not affected by treatment status of the households.

The second assumption is known as the common support or overlap condition, which requires that none of the households are either treated or not treated with certainty. Thus the overlap condition requires:

$$0 < P\ (D = 1) < 1$$

In this study the probability of being treated will be estimated by computing for each household the log-odds ratio derived from a logit regression and households not satisfying the overlap condition will be excluded.

It should also be mentioned here that, PSM estimators of *ATET* may vary for different neighbourhoods chosen for each treated individual and for different weights assigned to these neighbours. Hence, to check the robustness of the results, both un-weighted and weighted matching algorithms (radius and kernel) would be applied. The technical details pertaining to these algorithms, which have been implemented using the statistical software package STATA, have been relegated to Appendix 1.

4. OBJECTIVES, METHODOLOGY AND SCOPE OF RESEARCH

The objective of the study is to evaluate the impact of remittances on per capita incomes, examine the related poverty effect and to recommend relevant macroeconomic policies that are pro-poor in nature. There is a plethora of studies on remittance flows and usage within the purview of the migration literature. However, the number of studies which have quantitatively examined the specific effects of remittances on incomes and poverty is meagre. Esquivel and Huerta-Pineda (2006) use PSM to examine the impact of remittances on poverty in Mexico; otherwise, we are not aware of any other such studies. In particular, we are not aware of similar studies carried out for South Asia and certainly not Bangladesh. The reasons for this lacuna may well be a commonly held *a-priori* supposition that a remittance receiving household would improve its poverty status. This is, however, by no means obvious since the costs of migration may outweigh the benefits. We intend to confirm or deny the *a-priori* supposition. Thus, the contribution of this study, aside from being a first attempt, will be twofold: to assign a numerical value to the extent of poverty reduction induced by remittances if any, and, based upon the results, to propose policy measures to either encourage or mitigate the effects. As has already been mentioned, any policy discussion can only benefit if guided by numbers.

The analytical framework of the study has already been outlined in detail. Ideally, we would have preferred to have conducted a sample household survey in order to obtain detailed primary data. However, as this was not possible, we made use of information contained in the Household Income and Expenditure Survey (HIES) 2005 of the Bangladesh Bureau of Statistics (BBS). This survey covers almost 10,000 households and has data on household characteristics, individuals, incomes and expenses. Using this information we calculate yearly per capita income in 2004 Taka as the monetary income of the household plus the monetary or transfers in kind received by the household divided by the total number of household members. Remittances are measured as the yearly transference in Taka received from overseas.

Our treatment group, i.e. the group receiving foreign remittances, consists of 905 separate households. This represents approximately 9% of all households covered under the survey. The figure is slightly higher than the 7% reported by Esquivel and Huerta-Pineda (2006) in their study on Mexican overseas remittances. Appendix 2 gives a district-wise breakdown of foreign remittance receiving households. According to the survey, all the districts of Bangladesh with the exception of Lalmonirhat contain households which receive overseas remittances. The district with by far the largest number of such households is Noakhali. Lakshmipur, Chittagong, Sylhet and Feni also have appreciable numbers of remittance receiving households. Table 1 shows some selected summary statistics for the treatment group. Our control group is a random sample of 1,000 households which do not receive remittances but otherwise share similar characteristics with the treatment group. Taken together, the entire dataset consists of 1,886 observations after some nineteen observations with missing or idiosyncratic data were dropped. We have called this dataset the "full" dataset. Table 2 shows the same summary statistics for the control group. It is noticeable that the means of all the variables in the control group are lower than their counterparts in the treatment group. Particularly striking are the levels of household and per capita incomes which are nearly 50 per cent lower in control group. In the matching exercises we will attempt to quantify the contribution of overseas remittances to this disparity.

In order to examine poverty related impacts more deeply, we constructed a second dataset, which we have called the "sub-dataset", by choosing only those households which have incomes below our defined poverty threshold of Tk.12,000 per capita per year. We arrived at this number by inflating the Tk.631 per month national, calorie-intake based, poverty measure reported in the Poverty Monitoring Survey 2004 by the

Bangladesh Bureau of Statistics. Using this measure we also coded poverty status. The sub-dataset has 1,034 observations.

The infeasibility of natural experimentation means that our estimator of the average treatment effect will obviously be non-experimental. However, such an estimator could be biased since the assignment of individuals to treatment and non-treatment groups will not be random. This means that matching between control and treated subjects becomes problematic if there is an *n*-dimensional vector of characteristics. A way around this problem is to use a propensity score matching technique. The score will summarise the pre-treatment characteristics of each individual into a single variable, the propensity score, which can then be used for matching. This will greatly minimise the bias associated with comparing similar treated and control groups. As has already been mentioned, for the purpose of this study, we will use the log-odds ratio of receiving treatment computed from a logit regression to estimate the propensity score for each individual.

For each dataset we formed two specifications for the logit regressions. One without any squared or interactive variables and the other with two squared variables (age squared and education squared) and one interactive variable (education x age). Using the results of the logit regressions we are then able to compute the propensity score (the log-odds ratio) for each household in our datasets. Using these scores we then carry out the matching using radius, kernel and local-linear regression (llr) algorithms for every outcome basis. This is done as a check for robustness.

TABLE 1: SELECTED SUMMARY STATISTICS OF TREATMENT GROUP (N = 902)

	Mean	Standard Error
Age of household head (years)	48.71	0.49
Number of rooms per household	3.09	0.05
House size (sft)	479.56	11.4
Education level	7.40	0.13
Yearly household income (Taka)	136,342	5920
Total family size (persons)	7.32	0.12
Per capita income (Taka)	20, 600	860.56

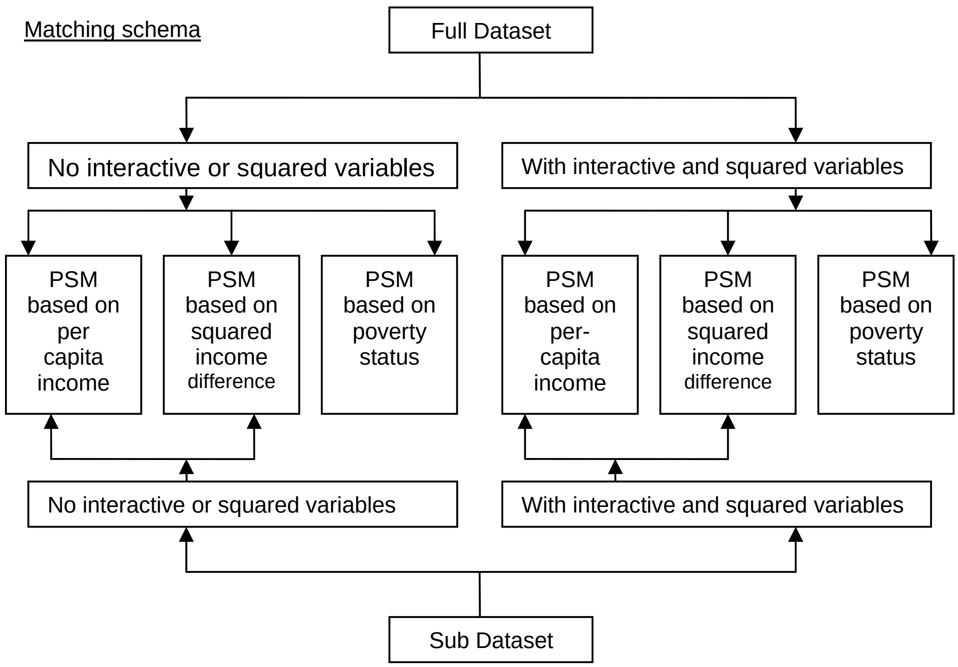
Source*:* BBS 2004 and author's calculation.

TABLE 2: SELECTED SUMMARY STATISTICS OF CONTROL GROUP (N = 984)

	Mean	Standard Error
Age of household head (years)	45.06	0.43
Number of rooms per household	2.37	0.04
House size (sft)	389.57	9.8
Education level	5.12	0.11
Yearly household income (Taka)	52,789	2980
Total family size (persons)	4.99	0.08
Per capita income (Taka)	11,515	623.40

Source*:* BBS 2004 and author's calculation.

Our matching exercise can be represented by the schema which follows. It is to be noted that since the sub-data sets are constructed exclusively with households below the poverty threshold level, we do not carry out a PSM with an outcome of poverty status for this group.



Note: For every PSM, three algorithms, radius, kernel and local-linear regression, will be implemented.
Source: Author's elaboration.

5. EMPIRICAL EVIDENCE

The first step in the empirical exercise is the estimation of the propensity score. For our purposes this is the propensity of being treated i.e. of receiving remittances. The following table is a description of the (linear) variables used for the logit regressions.

TABLE 3: VARIABLES

Variable	Description	Coding
educ	Education level of household head	0,1,2,…,9 for classes 1 to 9 respectively. 10 = secondary, 11 = higher secondary, 12 = graduate, 13 = post-graduate, 14 = medical degree, 15 = engineering degree, 16 = others
owner	Ownership status of household	1 = owner, 2 = tenant, 3 = occupier, 4 = rent free, 5 = government housing, 6 = others
hhsqft	Household size	Area in square feet
mobile	Presence of mobile phone	1 = yes, 2 = no
teleph	Presence of telephone	1 = yes, 2 = no
electr	Electricity connection	1 = yes, 2 = no
toiltype	Toilet type	1 = sanitary, 2 = built up with water supply, 3 = built up without water supply, 4 = undeveloped permanent, 5 = undeveloped temporary, 6 = open field
hhtype	Household type	1 = brick and mortar, 2 = tin and timber, 3 = mudbrick, 4 = bamboo and straw, 5 = others
martstat	Marital status of household head	1 = married, 2 = unmarried, 3 = widow/widower, 4 = divorced, 5 = separated
agehhh	Age of household head	Age in years
genderhhh	Gender of household head	1 = Male, 2 = Female

Source: Author's methodology.

The following tables show the results of the logit regressions for each of the model specifications and datasets. Barring the variable `hhsqft` which is statistically insignificant in every regression, most of the other variables are significant; since the coefficient value of this variable is so small, its impact on calculations is negligible. So we decided not to omit it. The column `dy/dx` indicates the marginal effects. The coefficients are then used to compute the propensity scores for each household.

Spec.1. Full Dataset, with No Interactive or Squared Variables

Logistic regression		Number of obs	=	1886
		LR chi2(11)	=	490.79
		Prob > chi2	=	0.0000
Log likelihood = -1060.0094		Pseudo R2	=	0.1880

treatment	Coef.	Std. Err.	z	P>|z|	dy/dx
educ	.1286758	.0160957	7.99	0.000	.0321422
owner	-.2472988	.0877394	-2.82	0.005	-.0617733
hhsqft	.0000512	.0001815	0.28	0.778	.0000128
mobile	-.3295282	.160762	-2.05	0.040	-.0823135
teleph	.2784154	.2665433	1.04	0.296	.0695460
electr	-.1506116	.1211245	-1.24	0.214	-.0376216
toiltype	-.1047477	.0366691	-2.86	0.004	-.0261651
hhtype	-.0499003	.0584019	-0.85	0.393	-.0124647
martstat	-.6961297	.1200953	-5.80	0.000	-.1738877
agehhh	.0248863	.003942	6.31	0.000	.0062164
genderhhh	2.682879	.2057628	13.04	0.000	.6701620
_cons	-3.422563	.6844522	-5.00	0.000	

Source: Author's estimation.

Spec.2. Full Dataset, with Interactive and Squared Variables

Logistic regression		Number of obs	=	1886
		LR chi2(15)	=	533.06
		Prob > chi2	=	0.0000
Log likelihood = -1038.8764		Pseudo R2	=	0.2042

treatment	Coef.	Std. Err.	z	P>|z|	dy/dx
educ	-.0999083	.0711873	-1.40	0.160	-.0249681
edusqd	.0191068	.0039958	4.78	0.000	.0047750
eduage	-.0000149	.0010217	-0.01	0.988	-3.73e-06
owner	-.2959	.0909024	-3.26	0.001	-.0739484
hhsqft	-.0000158	.000185	-0.09	0.932	-3.95e-06
mobile	-.2356179	.1651383	-1.43	0.154	-.0588833
teleph	.4439327	.275912	1.61	0.108	.1109433
electr	-.160072	.1227944	-1.30	0.192	-.0400036
toiltype	-.1027656	.0370802	-2.77	0.006	-.0256822
hhtype	-.0657524	.0591953	-1.11	0.267	-.0164322
martstat	-.4907317	.132077	-3.72	0.000	-.1226388
martgend	-.0521403	.0127041	-4.10	0.000	-.0130304
agehhh	.0596093	.0300288	1.99	0.047	.0148970
agesqd	.0002304	.0002347	0.98	0.326	.0000576
genderhhh	4.85542	.5774817	8.41	0.000	1.2134180
_cons	-5.500737	1.1908	-4.62	0.000	

Source: Author's estimation.

Spec.3. Sub-dataset, with No Interactive or Squared Variables

```
Logistic regression                               Number of obs   =      1,044
                                                  LR chi2(11)     =     158.68
                                                  Prob > chi2     =     0.0000
Log likelihood = -596.34854                       Pseudo R2       =     0.1174
------------------------------------------------------------------------------
   treatment |      Coef.   Std. Err.      z    P>|z|      dy/dx
-------------+----------------------------------------------------------------
        educ |   .0744005   .0214861     3.46   0.001     .0165116
       owner |  -.1920594   .1297305    -1.48   0.139    -.0426235
      hhsqft |  -.0000235   .0002654    -0.09   0.929    -5.22e-06
      mobile |  -.1358251   .2899945    -0.47   0.640    -.0301435
      teleph |   .6046387   .5831333     1.04   0.300     .1341866
      electr |  -.1449541   .1584262    -0.91   0.360    -.0321695
    toiltype |  -.1250025   .0452533    -2.76   0.006    -.0277416
      hhtype |  -.0868917   .0747349    -1.16   0.245    -.0192837
    martstat |  -.6242137   .1682763    -3.71   0.000    -.1385309
      agehhh |   .0253018   .0052759     4.80   0.000     .0056152
   genderhhh |   2.319406   .2937299     7.90   0.000     .5147427
       _cons |  -3.948442   1.306261    -3.02   0.003
------------------------------------------------------------------------------
Source: Author's estimation.
```

Spec.4. Sub-dataset, with Interactive and Squared Variables

```
Logistic regression                               Number of obs   =      1,044
                                                  LR chi2(15)     =     204.54
                                                  Prob > chi2     =     0.0000
Log likelihood =   -573.415                       Pseudo R2       =     0.1514
------------------------------------------------------------------------------
   treatment |      Coef.   Std. Err.      z    P>|z|        dy/dx
-------------+----------------------------------------------------------------
        educ |  -.4125052   .0963803    -4.28   0.000      -.0918597
      edusqd |   .0297993   .0057421     5.19   0.000       .0066359
      eduage |   .0033493   .0014685     2.28   0.023       .0007458
       owner |  -.2267681   .1321517    -1.72   0.086      -.0504984
      hhsqft |  -.0001342   .0002796    -0.48   0.631      -.0000299
      mobile |  -.0878198   .3009394    -0.29   0.770      -.0195564
      teleph |   .7308712   .5987022     1.22   0.222       .1627558
      electr |  -.0878102   .1639894    -0.54   0.592      -.0195542
    toiltype |  -.1019562   .0466329    -2.19   0.029      -.0227044
      hhtype |  -.1380186   .0773459    -1.78   0.074      -.030735
    martstat |   1.199351    .570184     2.10   0.035       .2670803
    martgend |  -1.138869   .3450971    -3.30   0.001      -.2536118
      agehhh |   .0371367   .0341437     1.09   0.277       .0082699
      agesqd |  -.0002532   .0003141    -0.81   0.420      -.0000564
   genderhhh |   4.135733   .6355606     6.51   0.000       .9209754
       _cons |  -6.227288   1.789261    -3.48   0.001
------------------------------------------------------------------------------
Source: Author's estimation.
```

Tables 4 through 6 report the results of the PSM matches under the various outcome variables and model specifications discussed above. STATA does not automatically report the standard errors and associated *t* values for local linear regression (llr) matching (these may be obtained using a bootstrap or Monte-Carlo method), so they have not been reported against that particular algorithm. In Table 4, for every specification and for every matching algorithm, the *ATET* is positive, which means that remittances account for a positive and statistically significant difference in per capita income (measured in Taka) between the matched treated (remittance receiving) and control groups.

The entries of Table 5 show the results when the outcome variable for the basis of matching is squared income difference from the threshold poverty level per capita income of Tk.12,000 per year. The results are essentially a difference in differences. Consider the entry of 365,090,363 (Taka) for the *ATET* generated by kernel matching under specification 1 (full dataset, no interactive or squared variables). This figure represents the disparity between 744,213,943 (Taka),[2] which is the amount by which squared per capita income differs from the poverty threshold level for the treated group and 379,123,580 (Taka), which is the amount by which squared per capita income differs from the poverty threshold level for the control group. Once again the positive and statistically significant differences are attributable to remittances. Specifications 3 and 4 are for households which are *below* the threshold poverty level; hence, we would expect the *ATET* outcomes to be negative, it still means that, for matched pairs, the treatment group per capita incomes are closer to the threshold than the untreated groups.

TABLE 4: OUTCOME: PER CAPITA INCOME

Specification →	1	2	3	4
(kernel)				
ATET	6278	5294	2093	2008
S.E.	1500	1398	404	381
t	4.19	3.79	5.18	5.27
(radius)				
ATET	7017	6401	2068	2016
S.E.	1753	1651	424	395
t	4.00	3.88	4.88	5.11
(llr)				
ATET	7063	6543	1982	2044
S.E.	-	-	-	-
t	-	-	-	-

Source: Author's estimation.

TABLE 5: OUTCOME: SQUARED INCOME DIFFERENCE FROM THRESHOLD POVERTY LEVEL

Specification →	1	2	3	4
(kernel)				
ATET	365,090,363	301,256,548	- 43,159,138	- 36,272,622
S.E.	230962459	219927893	24011597	22324657
t	1.58	1.37	- 1.80	- 1.62
(radius)				
ATET	384,994,180	344,853,932	- 42,704,276	- 35,586,305
S.E.	258685108	246205701	25424568	23304309
t	1.49	1.40	- 1.68	- 1.53
(llr)				
ATET	368,583,433	338,869,341	- 35,414,767	- 35,201,154
S.E.	-	-	-	-
t	-	-	-	-

Source: Author's estimation.

[2] Unreported STATA output, available from author upon request.

TABLE 6: OUTCOME: POVERTY STATUS

Specification →	1	2
(kernel)		
ATET	- 0.160	- 0.151
S.E.	0.033	0.031
t	- 4.84	- 4.89
(radius)		
ATET	- 0.170	- 0.190
S.E.	0.040	0.037
t	- 4.29	- 5.05
(llr)		
ATET	- 0.172	- 0.207
S.E.	-	-
t	-	-

Source: Author's estimation.

The entries in Table 6 show the results when the outcome variable used for matching is a dummy coded as 1 for per capita incomes less than Tk.12,000 per year, zero otherwise. The *ATET* outcomes have the expected signs, are statistically significant and can be interpreted as the (marginal) probabilities of being in a situation of poverty. In other words, the receipt of overseas remittances contributes to an approximately 18 per cent decline in poverty situation on the average across households.

6. NATURE OF OUTPUT, POLICY RELEVANCE AND DISCUSSION

The results of the empirical exercise tend to support the conclusion that remittances have a positive impact on per capita incomes and, crucially, as shown by the results reported in Table 6, contribute to approximately 18 per cent towards a decline in poverty status. The magnitude of the poverty decline is roughly twice the level reported for Mexico by Esquivel and Huerta-Pineda (2006). This does not appear surprising since Bangladesh is a much poorer country than Mexico and the marginal impact of remittance receipts is likely to be that much higher.

By establishing a quantified microeconomic result on the effect of foreign remittances in Bangladesh, we strengthen the case for remittances as a poverty alleviating policy tool. We have already mentioned the fact that remittances have received increasing attention in recent years for their possible use in just such a manner. In essence, the beneficial consequences of foreign remittances may lead us towards the path of adopting a “foreign employment” policy so as to “bring in” more of the same. In this regard, some policy considerations under different objective headings are offered below.

Economic Development Objectives:

- Reduction in unemployment
- Generation of greater foreign exchange income

- Increased savings rates
- Increased social returns on investment in education

Social Development Objectives:

- Improvement in the wages and conditions of employment of nationals working abroad
- Reduction in the cost of emigration by curbing recruitment abuses
- Provision of safety nets for migrants and their families
- Stopping irregular migration and making migration processes more orderly

Strategic Objectives:

- Expansion and diversification of the countries of employment
- Improving the skill component of the emigrant workforce
- Using migration as a vehicle for the acquisition of new skills and know-how
- Minimising the dislocation of domestic industries due to loss of skilled labour
- Reduction of wage distortions caused by an extension of the labour market

In conclusion, it should be mentioned that a corresponding aspect of the current study was not addressed empirically due to lack of data. The absence of data on the *use* of remittances by wealth-class not only makes it difficult to establish a more exact magnitude of relief experienced by the poor, but it also prevents us from examining the effects of foreign remittances on inequality. The nature of utilisation of remittance receipts has an important bearing on this aspect. The identification, assessment and measurement of the impact of remittances on income inequality are crucial for a more complete understanding of the whole economic phenomenon. However, we leave it as an agenda for future research.

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APPENDIX 1 : THE MODEL

Provided that the CIA and overlap conditions are satisfied, the PSM estimator of ATET, following Caliendo and Kopeinig (2005), is calculated as follows:

$$\Gamma_{PSM}^{ATET} = E_{P(X)|D=1}\left\{E\left[Y(1)\middle|D=1, P(X)\right] - E\left[Y(0)\,D=0, P(X)\middle|\right]\right\}$$

Since the PSM estimators of average treatment effect on the treated may vary for different neighbourhoods chosen for each treated individual and for different weights assigned to these neighbours, to check the robustness of the results, different matching algorithms should be applied. The most straight forward matching algorithm is the nearest neighbour (*NN*) matching in which each treated individual is matched with the control individual that has the closest propensity score. This method can be applied with or without replacement. When replacement is allowed, each treated individual is matched with the control individual more than once. Following Becker and Ichino (2002), let *T* and *C* denote the set of treated and control units respectively and let Y_i^T and Y_j^C be the outcomes of the treated and control individuals, respectively. Then individual *i* is matched to the non-treated individual *j* such that

$$C(i) = \min_{(j)} \left\| P_i - P_j \right\|$$

Where *C*(*i*) is the set of control individuals matched to the treated individual *i* with a propensity score *P*(*i*). In the *NN* matching each treated individual finds a match. However, if the closest neighbour is far away, this gives poor matches. To overcome this problem, radius matching can be used. In radius matching *C*(*i*) is defined such that

$$C(i) = \left\{P_j \left\| \left\| P_i - P_j \right\| < r\right.\right\}$$

which means that in this method all the control individuals which have propensity scores P_j within radius *r* from P_i are matched to the treated individual *i*.

The PSM estimator of average treatment effect on the treated is a weighted measure of the mean difference of outcomes (of the treated and non-treated control individuals) over the common support. The weight is defined as $w_{ij} = 1/N_i^c$ if $j \in C\,(i)$ and $w_{ij} = 0$ otherwise, where N^c_i is the total number of matched control individuals. Following Becker and Ichino (2002) and by denoting N^T as the number of individuals in the treated group, the formula for both nearest neighbour and radius matching estimators can be written as:

$$\begin{aligned}\Gamma^M &= \frac{1}{N^T}\sum_{i\in T}\left[Y_i^T - \sum_{j\in C(i)} w_{ij}Y_j^C\right] \\ &= \frac{1}{N^T}\left[\sum_{i\in T}Y_i^T - \sum_{i\in T}\sum_{j\in C(i)} w_{ij}Y_j^C\right]\end{aligned}$$

$$= \frac{1}{N^T}\sum_{i\in T} Y_i^T - \frac{1}{N^T}\sum_{j\in C} w_j Y_j^C$$

Both *NN* and radius matching, though intuitively appealing, are in fact inefficient. In NN matching only one observation and in radius matching only a few observations are used from the comparison group to construct the counterfactual outcome. On the other hand, Kernel matching (*KM*) and local linear matching (*LLM*) use weighted average of all individuals in the control group to construct the counterfactual outcome. Thus, these non-parametric approaches have advantages because they use more information (Caliendo and Kopeinig 2005). The Kernel matching is in fact a weighted regression of the counterfactual outcome on an intercept with weights given to non-treated units *j* in proportion to the closeness between the treated unit *i* and the non-treated unit *j*. The *LLM* approach, on the other hand, includes a linear term in addition to the intercept. In applying *KM* one needs to choose the Kernel function and a bandwidth parameter. The default Kernel function is the Gaussian one and the default bandwidth is 0.06. Following Becker and Ichino (2002), we can estimate the Kernel matching estimator as follows:

$$\Gamma^K = \frac{1}{N^T}\sum_{i\in T}\left\{ Y_i^T - \frac{\sum_{j\in C} Y_j^C G\left(\frac{P_j - P_i}{h_n}\right)}{\sum_{k\in C} G\left(\frac{P_k - P_i}{h_n}\right)} \right\}$$

Where $G(.)$ is the Kernel function and h_n is the bandwidth parameter.

The local linear regression matching can be defined as constructing the counterfactuals by solving for the following minimisation problem for each treated individual (Ham, Li and Reagan 2005):

$$\min_{\pi,\theta_1,\ldots,\theta_{N_T}} \sum_{j=1}^{N_0}\left\{ P(X_j) - \pi - \sum_{l=1}^{N_T}\theta_l (P(X_j) - P(X_i))^l \right\}^2 k\left(\frac{P(X_j) - P(X_i)}{h\big(P(X_i)\big)}\right)$$

Where, N_T and N_0 are the numbers of treated and non-treated individuals, respectively. $k(.)$ is the Kernel function and $h(.)$ is the bandwidth parameter.

(*Adapted from Shahriar 2007*)

Appendix 2: District-wise Breakdown of Overseas Remittance Receiving Households.

District remittances	# of HH receiving	District remittances	# of HH receiving
Bandarban	1	Barisal	8
Dinajpur	1	Jessore	8
Jaipurhat	1	Kishoreganj	8
Netrokona	1	Kushtia	8
Panchagarh	1	Maulvi Bazar	8
Gaibandha	2	Satkhira	8
Gazipur	2	Shariatpur	8
Naogaon	2	Gopalganj	9
Natore	2	Habiganj	9
Thakurgaon	2	Madaripur	9
Chuadanga	3	Narsingdi	10
Khagrachhari	3	Cox's Bazar	11
Pabna	3	Nawabganj	11
Bagerhat	4	Rajbari	11
Meherpur	4	Manikganj	12
Rangpur	4	Sunamganj	12
Jamalpur	5	Mymensingh	16
Jhalokati	5	Faridpur	19
Jhenaidaha	5	Munshiganj	27
Khulna	5	Narayanganj	28
Magura	5	Chandpur	29
Patuakhali	5	Brahmanbaria	32
Rajshahi	5	Tangail	38
Sherpur	5	Dhaka	40
Sirajganj	5	Comilla	50
Narail	6	Feni	51
Bhola	7	Sylhet	55
Pirojpur	7	Chittagong	57
Rangamati	7	Lakshmipur	74
Barguna	8	Noakhali	123

Source: BBS 2004 and Author's estimation.