Ibero-Amerika Institut für Wirtschaftsforschung
Instituto Ibero-Americano de Investigaciones Económicas
Ibero-America Institute for Economic Research
(IAI)

Georg-August-Universität Göttingen
(founded in 1737)

Diskussionsbeiträge · Documentos de Trabajo · Discussion Papers

Nr. 244

Migration and Remittances in Haiti: Their Welfare Impact on Poor and Non-Poor Households

Adriana Cardozo, Felicitas Nowak-Lehmann, Calvin Zebaze Djiofack

October 2019

Platz der Göttinger Sieben 3 · 37073 Goettingen · Germany · Phone: +49-(0)551-398172 · Fax: +49-(0)551-398173
e-mail: uwia@gwdg.de · http://www.iai.wiwi.uni-goettingen.de

Migration and Remittances in Haiti: Their Welfare Impact on Poor and Non-Poor Households

Adriana Cardozo (University of Goettingen), Felicitas Nowak-Lehmann (University of Goettingen) and Calvin Zebaze Djiofack (World Bank)[f]

ABSTRACT

The purpose of this study is to identify a person's likelihood of emigrating to another country and to identify a household's likelihood of receiving remittances. We also compute average treatment effects as well as the marginal impact of receiving remittances on household welfare, across welfare quantiles. The novelty of our approach is to control for omitted variable bias by including the difference between individual and average propensity scores obtained in an auxiliary regression. The fact that an individual or household is above or below the average propensity score can thus be considered as a proxy of being different from the average for a variety of characteristics that might also be unobservable or unquantifiable. Based on Haitian household survey data from 2012, we find that non-poor individuals are more likely to emigrate but the welfare level of a household per se does not trigger the receipt of remittances. The receipt of remittances favors non-poor households in absolute terms but not in relative terms. While remittances can help overcome extreme poverty (for the poorest 10% but not for the poorest 1%), they do not help people escape moderate poverty.

Keywords: Migration; Remittances; Household Welfare; Average Treatment Effect; Omitted Variable Bias

JEL Codes: C 18; C 21; D19; F22; F24

[f] Corresponding author: Adriana Cardozo (University of Goettingen): acardoz@uni-goettingen.de; Platz der Goettinger Sieben 3, 37073 Goettingen/Germany; Ph. 0049551 3912269; Felicitas Nowak-Lehmann (University of Goettingen): fnowak@uni-goettingen.de; Ph: 0049 551 397487; Calvin Djiofack (World Bank): cdjiofack@worldbank.org

1. Introduction

Haiti is the poorest country in the Western Hemisphere with a per capita income of about 1,228 USD (in PPP). It has a population of about 10.9 million inhabitants, of which 1.1 million live and work in the United States, the Dominican Republic, Canada, France, and the Bahamas (UNICEF, Migration Profiles, 2018). Haiti's remittance inflows are the highest in Latin America and the Caribbean and the third highest in the world (after Nepal and Kyrgyzstan) according to World Bank data (2018). Remittances account for 29.4% of GDP and are considered a particularly stable source of foreign exchange. In the past decade, Haiti's remittances have substantially increased compared to other sources of foreign exchange and totaled 2,722 million USD in 2017. Since 2000, the level of remittances has been greater than official development aid (ODA) or foreign direct investment (FDI), apart from ODA in 2010-11 that was given to compensate for the damages of the earthquake in 2010.

Remittances contribute substantially to household income in Haiti. About a quarter of Haitian households receive remittances either from a relative or a friend abroad. Remittances are relatively more important, the poorer the household is: remittances received by households in the first quintile of per capita income amount on average to 38 percent of income compared to 17 percent for households in the richest quintile. However, the absolute amount of remittances is almost 30 times larger for the average household in the richest quintile of per capita income compared to the poorest. Given these figures, the impact of remittances on the income of the poor can be enormous. If remittances were to be excluded from household income, the share of the population with incomes below the moderate and extreme poverty lines would increase substantially.

The amount by which remittances increase welfare (in terms of per capita expenditures),[1] however, is difficult to calculate not only due to data shortcomings but also because calculations are based on household surveys in which remittances are typically underreported. On the one hand, simple

[1] We follow the literature on poverty analysis by measuring poverty as per capita expenditures that defines the poverty line (Development Initiatives, 2016). In Haiti, the poverty line for moderate poverty lies at about 680 USD per capita per annum and for extreme poverty, lies at around 346 USD per capita per annum. These lines were fixed in 2012 by the World Bank.

calculations of a scenario that is free of remittances would overestimate the poverty impact of migration when assuming for simplicity that had migrants remained in Haiti, they would be earning no income. On the other hand, it is hard to find adequate counterfactuals. Moreover, remittances may also have indirect effects on welfare as they play some role in changing the behavior of those left behind, for instance by changing their consumption and investment behavior. Most importantly, calculating the welfare effect of remittances can be burdensome as researchers are very often confronted with omitted variable bias and selection bias in migration and remittance decisions.

These decisions, to migrate or not, depend on migrant, household, and region-specific characteristics (some of them are clearly unobservable or unquantifiable). It should also be noted that selection bias is often related to omitted variable bias as unobserved variables can drive selection into treatment. In addition, the decision to send remittances and how much, are endogenous as are other determinants of household income.

Our paper contributes to the literature on migration and remittances by dealing with issues such as omitted variable bias, endogeneity, and selection bias. Moreover, it aims to produce reliable estimates for the impact of remittances on household welfare. To disentangle the complex decision-making process that households are confronted with, we unpack our research question into several steps and use a multi-step approach.

First, we analyze who emigrates and why, addressing the omitted variable problem by controlling for individual observable and unobservable differences. Second, we estimate which type of household tends to receive remittances by controlling for observable and unobservable differences at the household level. Third, we calculate the average treatment effect of remittances on different strata of the population controlling for differences between treatment and control groups. Finally, we calculate the (marginal) impact of an increase in the amount of remittances on per capita expenditures for the average household and over different household strata accounting for omitted variable and selection bias.

Overall, we find that being male and being in a relationship increases the propensity to migrate. A female household head and a more educated household head also increases the individual migration propensity, while coming from a poor household decreases the likelihood to emigrate.

In terms of remittances, households with a larger number of adults and a smaller number of children are more likely to have an emigrant and hence are more likely to receive remittances. Also, both poor and non-poor households are about equally likely to receive remittances.

We find that rich households have the highest average treatment effects from receiving remittances in absolute terms and hence, benefit the most in absolute terms. In these households, the marginal effect from one more dollar of remittances is also highest. However, in relative terms (computing per capita remittances as share of per capita expenditures), the poorest and poor households benefit the most.

In section 2, we address the methodological issues that burden the modeling of decision-making processes and that might threaten both the internal and external validity of our results. In section 3, we describe our way of answering the research questions and of dealing with the methodological challenges. Section 4 contains our empirical findings and section 5 concludes.

2. Methodological issues: Controlling for omitted variable bias to mitigate endogeneity and selection bias

In our paper, two important decisions related to migration will be studied: the decision to migrate and the decision to send remittances. Ideally, one would compare migrants and remittance senders with a counterfactual of non-migrating individuals and non-remittance receiving households. In general, the existence of a good counterfactual would allow us to compute average treatment effects quite easily since simple two-sample t-tests could be performed. Good counterfactuals also allow the computation of the 'true' marginal impact of an impact factor (e.g. remittances) by including an interaction term between the treatment indicator and the relevant impact factor. However, in most cases, it is not feasible to find a counterfactual that is sufficiently similar in all relevant aspects to the treatment group. Indeed, most studies suffer from self-selection into treatment in one form or the other. This implies that the treatment and control groups are affected by selection bias[2]. If the treatment and control groups (counterfactual) are dissimilar, this

[2] Adams (2011) mentions a few empirical strategies available to overcome selection bias: (1) randomized experiments, (2) construction of a counterfactual situation, and (3) multi-stage regressions that split simultaneous decisions into different stages, such as the two-stage Heckman model or multi-stage regressions that correct for omitted variable bias and selection bias. The feasibility of each method depends largely on data availability.

shortcoming must be ‘corrected’ when setting up the model [3]. As this paper also aims at analyzing the impact of remittances (average treatment effect) on household welfare, having a good counterfactual is essential.

When constructing a counterfactual, it is possible to control for differences in observable factors. However, migrant and non-migrant individuals/households often differ in their unobservable and non-measurable characteristics, such as talents, abilities, aspiration of household members, household cohesion, household solidarity, organizational talent of a household, family values, etc. These variables are usually ignored or omitted even though they are sometimes the most important determinants of household decisions. Whenever such unobservable characteristics are correlated with the explanatory variables on the right-hand side of the regression equation, regression results become biased (omitted variable bias). The omitted variable problem is closely related to the endogeneity/simultaneity problem or, in other words, omitted variables can lead to endogeneity.

In terms of endogeneity, either decisions or variables might be endogenous. The migration decision might be driven by poor employment opportunities at home, but migration itself might also weaken the job market in the country of origin (brain drain) and lead to more migration. Poverty might be an additional driver of migration (will to survive) while migration might also reduce poverty through remittances. Or, poverty might impede migration (lack of resources) and migration might increase poverty (loss of an important household member that was responsible for all strategic decisions). The use of panel data that include observations on the same household over two or more time periods could eliminate the bias that arises from it. With panel data at hand, one could use internal instruments (one could use simple lags of variables or more sophisticated lag structures). However, panel data are rare for household surveys. With these restrictions, much of the work revolves around finding relevant and exogenous instrumental variables (external instruments) to control for omitted variable bias beforehand.

To account for omitted variable bias, we modify a method utilized by Rosenbaum and Rubin (1983) (see Wooldridge, 2002, p. 618, formula 18.24). This method that was originally used to

[3] The Heckman two-stage model is often used to mitigate this problem. In Heckman’s model it is assumed that the probability of an event (e.g. receipt of remittances) is triggered by one (or more) specific observables and quantifiable variable(s) that are not responsible for the main outcome (e.g. per capita income of the poor). The difficulty here arises in specifying an exogenous variable (exclusion variable) that causes the occurrence of an event, but has no direct impact on the dependent variable in the second stage equation. Such a variable can be difficult to identify in most cross-sectional data.

compute average treatment effects. To this end, we always run two-stage regressions.[4] We do so when analyzing the likelihood of migrating, the likelihood of receiving remittances, and the impact of remittances on welfare, i.e. when dealing with all research questions. In the first stage, we always run a probit regression that is related to the main equation. This way, we obtain propensity scores for the first-stage that will serve as a control for omitted variables in the second stage, which contains our regression of interest. The difference between individual and average propensity scores of the pre-stage becomes our proxy variable for omitted variables, measuring the deviation between individual and average propensity scores. The fact that an individual or household is above or below the average propensity score can thus be considered as a proxy of being different from the average in a variety of characteristics that might also be unobservable or unquantifiable. In the second stage, this 'construct' of a proxy variable then enters the micro-econometric equation of interest. By using a proxy variable for omitted variables, we can mitigate the omitted variable bias and reduce endogeneity.

Generally,[5] we argue that omitted variables bias must be addressed first (before the main regressions are run) since omitted variable bias leads to endogeneity and selection bias problems. Our approach to deal with omitted variable bias and endogeneity in an 'integrated way' is based on multi-stage regressions but differs from the Heckman approach in that controlling for omitted variables takes place both in the first-stage regressions (probit regressions) and in the second-stage regressions (main regressions). This improves both the probit and the main regressions. The procedure is described in section 3.[6]

---

[4] Our procedure is similar to Heckman's in that we also obtain a correction measure in the first stage. However, we do not need an exclusion restriction as required in Heckman's two-stage procedure since both first and second stage refer to situations that use the same dataset but are not related to the same decision problem. For example, we run a probit on the likelihood to be employed (in the first stage) and run a probit on the likelihood to migrate (in the second stage). Our correction measure (obtained from the first stage) is very intuitive as it compares an individual/household with the average individual/household.

[5] Reliable results on the economic impact of remittances require overcoming at least three econometric challenges as explained by Adams (2011): simultaneity in the decision-making process by households, selection bias, and omitted variable bias.

[6] In the first stage, we tackle the omitted variable problem by constructing a proxy variable based on propensity scores since the omitted variable bias will most likely burden the regression with endogeneity and selection bias problems. In contrast to Heckman, we control for omitted variable bias (endogeneity and selection bias) by including differences of individual propensity scores from sample-average propensity scores signaling that an individual is different from the average. This proxy variable is obtained from a first-stage regression which is easier to model than a Heckman first-stage regression and then included as an omitted variable and selection bias control in the second stage (in the main equation).

3. Methodology for tackling the research questions

3.1. Who emigrates and why?

The traditional literature on migration looks at the drivers of migration, usually labeled as migration push factors (the factors that make you leave the country of origin) and pull factors (the factors that make the host country attractive) (Bodvarsson and van den Berg, 2013; Kondo, 2017). Mansoor and Quilin (2006) identify economic and demographic push factors (poverty, unemployment, low wages, high fertility rates, lack of basic health services and education, etc.); political push factors (conflict, insecurity, violence, poor governance, corruption, human rights abuses), and social and cultural push factors (discrimination based on ethnicity, gender, religion, political orientation, sexual orientation) that characterize the source countries of origin.

In terms of the pull factors, the authors differentiate between economic pull factors (prospects of higher wages, potential for improved standard of living, potential for personal or professional development; political pull factors (safety and security, political freedom); and social and cultural pull factors (family reunification, networks in host countries, absence of discrimination). If the benefits of migration outweigh the economic and non-economic (political, cultural, personal etc.) costs of migration, migration takes place.

The 'push and pull' literature mixes macro-level migration determinants with micro-level migration determinants. This may seem problematic at first but is justified by the complexity of migration decisions. These decisions take into account that individuals' migration decisions are triggered by opportunities: income and wage differentials, differentials in health services, and educational opportunities which are very often determined at the macro level. However, it should also be noted that people's aspirations (mostly determined by the past and current socioeconomic status of the individual himself/herself, his/her family and his/her friends and peer groups) and capabilities (mostly determined by genes and the environment) are at the heart of migration decisions (De Haas, 2011). It must be acknowledged that people's aspirations and capabilities are hard to observe. These limitations make the econometric work more difficult but we include proxies (control functions) for some of these variables to account for these factors.

Model

We model the decision to migrate of individual *i* in household *j* by means of a binary response model. M is a dichotomous variable where M=1 if the individual migrates and M=0 otherwise.

$$P(M = 1 / W) = \Phi(W\ \alpha) \qquad (1)$$

P is the probability. α is a vector of unknown parameters. W is a vector of explanatory variables, such as characteristics of the individual (age, gender, education, employment status, type of job), characteristics of the household to which the individual belongs (household size, dependency ratio, education of household head) and characteristics of the environment or region in which the individual lives ("département"[7], urban or rural area, rate of unemployment). Here, we should note that the survey data does not include all the explanatory variables needed for a comprehensive model. As such, we face some modeling limitations and controlling for omitted variables becomes even more important. Because the dataset contains insufficient information on the host countries, the focus will be on push factors, i.e. the circumstances that drive people out of Haiti.

We choose a probit approach to model the likelihood[8] for migration π_{ij}, where

$$\pi_{ij\_mig} = \Phi(w_{ij}^{'}\alpha) = E(m_{ij})\,. \qquad (2)$$

π_{ij_mig} is the probability of migration of individual *i* in household *j* which corresponds to his/her expected value of (out)migration ($E(m_{ij})$). m_{ij} is a binary (1, 0) variable and follows a binomial distribution $m_{ij} \sim B(1;\pi_{ij\_mig})$. α is the parameter vector to be estimated. $w_{ij}^{'}$ is the vector of explanatory variables and Φ is the cumulative distribution function of the standard normal

[7] Administrative division of Haiti

[8] π_{ij} could be computed by means of a linear binary model which could have probabilities beyond the [0;1] interval and is therefore not desirable; by a logit model that works with a logistic function.

distribution. An estimation of the model (estimation of the vector α) yields individual propensity scores for migration that are used to predict the migration probability for each individual.

The above equation does not yet address the omitted variable bias which is related to selection bias and that arises given that individuals that migrate might have different unquantifiable and/or unobservable characteristics compared to those that do not migrate. As mentioned in section 2, if these omitted variables are correlated with our other explanatory variables (e.g. education, level of deprivation, poverty status etc.), our estimates will be biased and inconsistent. Therefore, our improved binary response model/probability model includes a control for omitted variables.

$$\pi^{*}_{ij\_mig} = w^{'}_{ij}\alpha + (\hat{\pi}_{ij\_employed} - av\hat{\pi}_{employed})\ \chi_1 \qquad (3)$$

Equation (3) represents our preferred model. The second term on the right-hand side of the equation represents our control for omitted variable bias (OVBC). A similar adjustment has been proposed by Wooldridge (2002, p. 618) in a different context, namely to compute proper average treatment effects. Our preferred control for omitted variables consists of $\hat{\pi}_{ij\_employed}$ (it reflects the individual propensity of being employed) and $av\hat{\pi}_{employed}$ (the average propensity of being employed). The difference between the individual propensity and its average captures the impact of individual characteristics deviating from the average. The term $(\hat{\pi}_{ij\_employed} - av\hat{\pi}_{employed})$ results from a pre-stage probit estimation[9] of being employed.

χ_1 captures the impact of omitted variables on the likelihood to emigrate. We have also included the propensity of being poor, using $(\hat{\pi}_{ij\_poor} - av\hat{\pi}_{poor})$ as a measure for omitted individual differences. This alternative measure has also been statistically significant in capturing differences among individuals.. The results changed only slightly (results are available upon request).

After having estimated α and χ_1 an improved propensity score $\hat{\pi}^{*}_{ij\_mig}$ can be computed as:

[9] In this respect we borrow from Heckman's idea of applying a two-stage procedure. In the first stage Heckman uses a probit (to contstruct a selection term based on propensities of the first stage) to control for selection bias in the second stage.

$$\hat{\pi}^{*}_{ij\_mig} = w'_{ij}\hat{\alpha} + (\hat{\pi}_{ij\_employed} - av\hat{\pi}_{employed})\ \hat{\chi}_1\ . \qquad (4)$$

Based on equation (4), we compute the migration probabilities $\hat{\pi}_{ij\_mig}$ for all 17,327 individuals *i*. We then pick in each household *j* the individual with the highest migration probability $\max(\hat{\pi}_{ij\_mig})$ as this person will leave first and label it as the household's migration probability $\hat{\pi}_{j\_mig}$ (in our case, 4,930 households). This migration probability will then be used as a control in further estimations at the household level, i.e. it will enter other regressions at later stages.

Following Bertoli and Marchetta (2014), we include in the w-vector a set of exogenous variables (gender of migrant; partnership status; gender of household head; age of household head; employment status of household head; household size; share of dependent household members over all household members; geographical factors, such as departments). The expected effect of those variables is described in Acosta et al. (2007) and Hentschel et al. (2000). In addition, we include two potentially endogenous variables (education of household head and poverty status). These variables are supposed to capture self-selection into migration. We expect more years of education to have a positive effect on migration due to potentially higher returns to education in the host country. In terms of poverty, a migration-reducing effect results if poverty restricts available funds to travel to and settle down in the host country. Or, a migration-promoting effect results if the migrant's household views migration as a necessity and is able to borrow to finance travel and accommodation costs abroad. We omit household assets or an asset index for the household since these variables are highly correlated with poverty status and/or education.

3.2. Which households are more likely to receive remittances?

In the Haitian case, migrants usually do not take their families along but leave them behind. The left-behind households have the following income sources: remittances, assistance from emergency aid (if negatively affected by the earthquake), and work. Haitian households of all income strata have at least some access to remittances from migrant workers (who mostly migrated to the Dominican Republic or to the US).[10] We observe the following distribution of remittances in Haiti looking at different income quantiles: 17% of the poorest 1%, 17% of the poorest 10%, 22% of the richest 10%, and 27% of the richest 1% receive remittances. Remittances account for 39% of household income in the poorest decile and to 17% in the richest decile.

More information on the welfare impact of remittances (in terms of per capita expenditures) on households in Haiti and their distributional impact will be obtained by regression analysis on the mean and quantile regressions (see sections 3.3/4.3 and sections 3.4/4.4).

Model

We model the incidence of receiving remittances using the following probability model:

$$P(R = 1 / Z) = \Phi(Z\ \beta) \tag{5}$$

P is the probability. R is a dichotomous variable where R=1 if the household receives remittances and R=0 otherwise. Z is a vector of explanatory variables, such as characteristics of the household (household size, dependency ratio, education of household head) and characteristics of the environment or region the individual lives in (department, urban or rural area, rate of unemployment). β is a vector of unknown parameters, and Φ is the cumulative distribution function of the standard normal distribution. Estimation of the model yields the likelihood that a household receives remittances.

We obtain the expected value of receiving remittances, by using the following equation at the household level:

$$E(r_j) = z_j^{'}\beta = \pi_{j\_remit} = \Phi(z_{ij}^{'}\beta) \tag{6}$$

[10] In contrast to a study on Liberian migrants who migrated with their entire families to Ghana and lived in a refugee camp there (Omato, 2011), Haitian households mainly stayed in Haiti (if they were affected by the earthquake they lived in a camp or stayed with relatives) and received remittances from relatives and friends who worked abroad.

where r_j indicates whether a household *j* receives remittances or not; $r_j=1$ if it receives remittances, $r_j=0$ otherwise and follows a binomial distribution $r_j \sim B(1;\pi_{j\_remit})$; z_j is a vector of factors that characterize household *j* and their environment; β is a vector of unknown parameters ; π_{j_remit} is the estimated probability that a household j receives remittances.

Similarly, as we did when estimating the probability of migration, we chose a control function approach that deals with the omitted variable problem which is related to selection bias (households that receive remittances might have other unquantifiable and/or unobservable characteristics than households that do not receive remittances). If the omitted variables are correlated with other explanatory variables (e.g. level of education, level of deprivation; poverty status etc.), our estimates will be biased and inconsistent.

After having estimated β and χ_2, we compute an improved propensity score for receiving remittances $\pi^*_{j\_remit}$. Our control function uses the distance between the estimated propensity of household *j* to migrate ($\hat{\pi}_{j\_mig}$) and the estimated average propensity of all households ($av\hat{\pi}_{mig}$) to migrate as proxies for omitted variable bias (obtained from the probit for migration in an earlier step). Hence, χ_2 captures the impact of being different compared to the average household on the likelihood of receiving remittances. Thus, the improved estimation equation reads as follows:

$$\pi^*_{j\_remit} = z_j^{'}\beta + (\hat{\pi}_{j\_mig} - av\hat{\pi}_{mig})\ \chi_2) \qquad (7)$$

3.3. Does the fact that a household receives remittances improve household welfare (expenditures) in Haiti? What is the average treatment effect in the whole sample (ATE) and on the treated (ATET) in absolute and in relative terms?

The distributional impact of remittances on the households left behind is an issue that deserves empirical clarification since the outcome that richer households benefit more from remittances is as plausible as the result that poor households might benefit more ex ante. A pro-rich effect is to be expected when richer households have more financial means to finance the travel of the emigrants to richer (maybe farther away) destinations and find decent accommodation in areas with good job opportunities. Hence, they are likely to find better paid jobs and to send relatively high amounts of remittances back home. However, it is also plausible to assume that members from poorer households are forced to leave their homes due to family pressure, and to send large amounts of money back to their families (initially to pay back the loan, and then to assist their families by supplementing their income). In addition, a very strong family glue in poor households might lead to the feeling of being obliged to help and hence, lead to higher financial support from emigrants as the receipt of remittances could be the only viable instrument to survive or to make one's way out of poverty. Up to now, absolute effects have been addressed. Yet it might be interesting to learn about the relative effects of remittances in Haiti. Hence, we also calculate the relative effects.

Related to our research question, there are survey-based studies on the poverty impact of remittances for Mexico (Taylor et al., 2005), Ghana (Adams, 2006; Adams et al. 2008), the Philippines (Yang and Martínez, 2006), Nepal (Lokshin et al., 2010), Guatemala (Adams and Cuecuecha, 2010a and 2010b) and Ecuador (Bertoli and Marchetta, 2014). Adams (2011) offers a comprehensive literature review of the economic impact of international remittances using household surveys. In these studies, selection bias has been addressed using various methods, such as the Heckman correction for selection bias (Heckman, 1979) or the Lee method (Lee, 1983), which is a follow-on to the Heckman method. All in all, the authors find a poverty–reducing effect of remittances.

Model

The main equation to measure the welfare impact of remittances uses 'per capita expenditures of the household', y_j, as dependent variable. On the right-hand side of equation (8), we include our dichotomous variable r_j (receipt of remittances), as well as other control variables x_j.The novelty here is to include two additional controls for omitted variable bias: a) We use x_j deviations from their mean levels to control for the fact that household *j* is different from the average household in one or several characteristics, captured by the vector $(x_j - \bar{x})$. b) We also utilize households' deviations of propensity scores (for the receipt of remittances) from their mean values. To tackle selection bias, we include the respective deviations from the mean value of the control group.

Hence, the estimation equation reads as follows:

$$y_j = c + r_j\theta + x_j^{'}\xi + r_j(x_j - \bar{x})'\varsigma + r_j(\hat{p} - av\hat{p})\chi_3 + u_j \quad , \tag{8}$$

where r_j is dichotomous (0, 1) and equals 1 for treatment (receipt of remittances); c is a constant; θ captures the average treatment effect (ATE); $x_j^{'}$ is a vector of household characteristics; ξ is a vector of unknown parameters; ς measures the impact of deviations in observable variables from the average (represented by the vector $(x_j - \overline{x})$); χ_3 measures the impact of observable and unobservable factors that influence the propensity score; $(\hat{p} - av\hat{p})$ stands for the deviation between a household's propensity to receive remittances and the average propensity (to receive remittances); and u_j is an i.i.d. error term.

To answer the question of whether poor households benefit from receiving remittances or not, we rank households from the poorest to the richest, form quantiles τ, and estimate the following quantile regressions $Q_{Y_j/RHS_j}(\tau)$ where Y_j represents the dependent variable and RHS_j represents all right-hand side variables:

$$Q_{Y_j/RHS_j}(\tau) = c + r_j\theta_\tau + x_j^{'}\xi_\tau + r_j(x_j - \overline{x})'\varsigma_\tau + r_j(\hat{p} - av\hat{p})\chi_{3\tau} + u_j \,. \tag{9}$$

θ_τ captures the average treatment effect in quantile τ; $\chi_{3\tau}$ captures the left-out variable effect in quantile τ, and $b_\tau = \arg\min_{b\in\mathbb{R}^k}$ with $b_\tau = (\theta_\tau, \xi_\tau, \varsigma_\tau, \chi_{3\tau})$. The ATE, captured by θ (regression on the mean) and θ_τ (quantile regression) respectively, measures the impact of the receipt of remittances on per capita expenditures.

We use characteristics of the household to explain per capita household expenditures, such as the head of household's gender and age, the share of dependent household members, hours worked, and department in which the household is located and sector in which the household works. In addition, we control for the impact resulting from the household's deviations from the average household.

3.4. What is the impact of a higher volume of remittances on per capita expenditures in different population strata?

At this stage, we are interested in the specific impact of remittances in Haiti, in terms of their marginal (direct and indirect) impact on per capita expenditure not only for the average household but also for households belonging to different expenditure strata, i. e. poor, intermediate, and rich households. If there was no indirect impact, the total impact could be easily computed by adding remittances to the original expenditures. However, given that remittances do have an indirect impact[11], it can only be captured and computed by an econometric model.

Model

$$y_j = c + rv_j\kappa + x_j^{'}\psi + r_j(x_j - \bar{x})'\lambda + r_j(\hat{p} - av\hat{p})\chi_4 + u_j \quad (11)$$

rv_j is the volume of remittances that household *j* receives. κ is the impact (marginal effect) of a one unit increase in remittances on per capita household income. ψ captures the marginal impact of changes in the x-vector, λ captures the marginal impact of deviations of the variables x from their mean values and χ_4 captures the impact of omitted variables on per capita expenditure.

The quantile regression of the above regression is of the following form:

$$Q_{Y_j/RHS_j}(\tau) = c_\tau + rv_j\kappa_\tau + x_j^{'}\psi_\tau + r_j(x_j - \bar{x})'\lambda_\tau + r_j(\hat{p} - av\hat{p})\chi_{4\tau} + u_j\,. \quad (12)$$

κ_τ, ψ_τ, λ_τ and $\chi_{4\tau}$ stand for the above mentioned regression coefficients in quantile τ.

3.5. Data used

We use data from ECVMAS 2012, a living conditions survey covering 23,555 individuals and 4,930 households. The survey has two main objectives, to provide data to assess poverty and living conditions in the country, and to analyze the impact of the January 2010 earthquake on the economic situation of Haitian households. The survey also contains data on labor force participation and unemployment. The sample is a two-stage stratified cluster sample with a total of 500 clusters or sections d'énumération (SDE) and is designed to be representative at the level of the ten départements as well as nationally. In addition, a separate stratum was created to represent the population living in internally displaced persons camps.[12]

[11] The indirect channels of remittances are e.g. their impact on labor force participation and their impact on consumption and investment behavior of the ones left behind. The indirect influences of remittances can increase or reduce the direct impact of remittances on income.

[12] For more details on sampling, see the technical report "2012 Enquête sur les Conditions de Vie de Ménage Après le Séisme Sample Selection and Weighting".

ECVMAS 2012 includes a chapter on remittances received by the household (Questionnaire Part A, Chapter R). It captures information on the amount, frequency, and origin of remittances, divided by remittances received from other households living in Haiti, permanent residents in other countries, temporary residents living abroad, and students living abroad. It is not possible to track the exact country of origin of remittances. The chapter also includes a question on the relationship between the receiving household and the person sending remittances. However, it does not provide information on gender, age or education of the sender and thus, is not suitable for creating a counterfactual in a scenario of no migration and no remittances.

4. Empirical findings

4.1. Results on the likelihood to migrate

The models presented in Table 1 are estimated via the eprobit (extended probit regression) command in STATA that controls for endogeneity or endogenous selection into treatment (models 1, 2 and 5) or via the probit command with extensions (models 3 and 4). More specifically, models 3 and 4 are estimated by a probit command, including an omitted variable control/endogeneity control which is inserted 'by hand'. Clearly endogenous variables are instrumented one after the other (due to computational issues) in Table 1, model 1 and 2. The education of the household head is instrumented by a variable on the socio-economic background of the head and a rural-urban dummy. Poverty is instrumented by a rural-urban dummy and the labor market participation of the head. Model 5 depicts a model that controls for selection bias.

All models show very similar results and have their 'pros' and 'cons'. For computational reasons, a combination of endogeneity control, omitted variable control and selection bias control in STATA has not been not feasible. M**odels 3 and 4**, which control for omitted variable bias (triggering endogeneity and selection bias issues), are our preferred models. These models reflect the fact that an individual's characteristics can differ from the 'average' individual. This possibility is captured by an indicator variable that measures the deviation between the individual's propensity of being poor (model 3) or being employed (model 4) from the average propensity of being poor (model 3) or employed (model 4) suggesting that this deviation might be due to a bunch of characteristics that cannot all be included in the model. Models 3 and 4 of Table 1 show that these indicator variables are significant at the 99% confidence level and hence, are important determinants of the migration decision. The control variables imply that individuals who have a *higher propensity of being poor* than the average are *less likely* to migrate, whereas individuals who have a *higher propensity of being employed* are *more likely to migrate*.

Table 1 Probit for the Probability of Migration

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Male	0.17***	0.17***	0.17***	0.18***	0.17***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Steady partner	0.26***	0.26***	0.26***	0.26***	0.28***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
HHhead female	0.18***	0.17***	0.18***	0.21***	0.21***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Age of head	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HHhead works	-0.05	-0.03	-0.07		selection
	(0.10)	(0.10)	(0.10)		variable
Education of head	0.31***	0.24***	0.26***	0.28***	0.27***
	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
HHsize	-0.03***	-0.02**	-0.03***	-0.03***	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of dependent HH members	-0.03	0.05	-0.01	0.02	-0.01
	(0.13)	(0.13)	(0.13)	(0.07)	(0.12)
Being poor; OVBC (*omitted var. bias control, effect captured by* χ_1*, eq. 3 deviation in: propensity of being poor)*		-0.45***	*-0.33*** (χ_1)*		
		(0.16)	*(0.16)*		
Being employed; OVBC, effect captured by χ_1*, eq.3*: *deviation in propensity of being employed*				1.33*** *(χ_1)*	
				(0.22)	
Department dummy	yes	yes	yes	yes	yes
Estimation tech.	eprobit (IV edu)	eprobit (IV poor)	probit by hand (OVBC)	probit by hand (OVBC)	eprobit (endogenous selection)
Obs.	17,807	17,807	17,807	17,327	17,357

Note: Standard errors are in parentheses; ***, **, and * stands for 1%, 5% and 10% significance; n.s. =not significant.

Moreover, the regression results related to the migration decision in **Table 1** show that being male and having a steady partner lead to a higher propensity to migrate. The propensity to migrate also increases if the household head is female and also increases with greater education of the household head. In contrast, the propensity to migrate decreases with household size. Poor individuals or individuals with a higher-than-average propensity of being poor are significantly less likely to emigrate than richer individuals. This suggests that some financial means are needed to enable household members to go abroad (e.g. to buy a bus ticket to go to the Dominican Republic or to buy a flight ticket to go to the US). Individuals with a higher likelihood of being employed at home are more likely to migrate, suggesting that they are more proactive and/or more willing to compromise and/or more adaptive. Regression coefficients also show that individuals who come from the Northeast or the Southeast (living closer to the Dominican Republic border), are more likely to emigrate.[13]

4.2. Results on the likelihood to receive remittances

Table 2 contains models 1-4, which differ in their estimation techniques. For models 1 and 2, we use the probit command and for models 3 and 4, we use the eprobit command in Stata. In models 2-4, we control for omitted variable bias. To this end, we include the deviation of the household's propensity to migrate from the average household propensity to migrate which covers not only differences in observables but also differences in unobservable characteristics.

Model 1 is the benchmark model in which all variables are treated as exogenous. It does not include a control for omitted variables. Model 2 uses model 1's estimation technique but includes a control for omitted variable bias. In model 3, annual per capita expenditures, which represents household welfare, are treated as endogenous. This variable is instrumented by the household head's labor force participation and a rural-urban dummy. In model 4, we treat selection into treatment as endogenous. For computational reasons, a combination of model 3 and 4 is not possible.

[13] Results available upon request

The regression results presented in **Table 2 (model 3, best model)** show that the likelihood of a household to receive remittances has about 'zero' correlation with the welfare level of the household (in terms of per capita expenditures). This implies that richer households are not more likely to receive remittances than poorer households. Moreover, the likelihood to receive remittances is positively related to the number of adults in the household and negatively related to the number of children, i.e. households with many children are less likely to receive remittances, perhaps because many children require the presence of adult household members. In contrast, households that were affected by the big earthquake or had to move to a camp because of the earthquake do not consistently show a significant change in their likelihood of receiving remittances. Interestingly, households that are more likely to have a migrant family member than the average household, i.e. households that are more likely to sacrifice someone (to do without the migrant's presence or help) are also more likely to be rewarded , in terms of receiving remittances.

Table 2 Probability of receiving remittances

	(1)	**(2)**	**(3)**	**(4)**
Number of adults in HH	0.12***	0.12***	0.11***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
# of children under 18 in main HH	-0.07***	-0.07***	-0.06***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Lived in a camp after earthquake	-0.07	-0.04	-0.10*	-0.01
	(0.05)	(0.05)	(0.05)	(0.06)
Affected by earthquake	0.14	0.15*	0.15*	0.11
	(0.09)	(0.09)	(0.09)	(0.10)
Deviation from mean propensity to migrate		3.94***	3.55***	3.99***
[OVBC omitted var bias control, effect captured by χ_2, eq. 6]		(0.60)	(0.60)	(0.66)
Per capita expenditures, proxy for wealth	0.00***	0.00***	0.00*(IV)	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-1.05***	-1.02***	-1.19***	-1.28***

	(0.05)	(0.06)	(0.07)	(0.06)
Estimation technique	probit (all RHS exogenous)	probit by hand (OVBC; all RHS exogenous)	eprobit by hand (OVBC; pcexp endogenous)	eprobit by hand (OVBC; selection endogenous)
Obs	4,930	4,930	4,930	4,930

Note: Standard errors are in parentheses; ***, **, and * stands for 1%, 5% and 10% significance; n.s. =not significant; estimations include omitted variable bias control (OVBC).

4.3. Results on the impact of remittances on welfare (the average treatment effect)

Table 3 contains a bundle of average treatment effects (ATEs): the unrefined ATE, which corresponds to the θ coefficient in eq. 8 and eq. 9 ; the refined ATE(x) controlling for changes in x-variables and the refined average treatment effect on the treated (ATET(x)).controlling for changes in x-variables in the group of remittances-receiving households. All treatment effects are converted into USD and computed based on the formulas outlined in Wooldridge (2002, p. 613). The computations are based on eq. 8 (regression on the mean) and eq. 9 (quantile regression). We obtain specific ATE(x) and ATET(x) for each household. To show comprehensible effects, we compute the average of the regression on the mean and quantile-averages for the quantile regressions.

The bottom panel of Table 3 features average per capita expenditures in 2012 that amount to 948 USD (equivalent to 41,712 Haitian gourdes) and the corresponding per capita expenditure for the following quantiles of per capita expenditure: 1%, 10%, 25%, 50%, 75%, 90%, and 99% which are needed for the computation of the relative treatment effects.[14]

The left-hand side panel of Table 3 shows the results, controlling for omitted variable bias (OVBC) by adding the $r_j(\hat{p} - av\hat{p})\chi_{3(\tau)}$ term which contains propensities for receiving remittances from a first-stage regression. The right-hand side panel of Table 3 shows the results without OVBC. We can see that the results in the left and the right panel differ substantially. Without OVBC (right panel) there is severe overestimation (triple the value) of the impact of remittances

[14] The exchange rate was about 44 Haitian gourdes (HTG) for one US dollar in 2012.

on the mean, an underestimation of the impact in the poorer quantiles, and an overestimation of the impact starting in the 75% quantile. Hence, we concentrate on the results of the left-hand panel, with OVBC.

The left-hand panel shows that the average treatment effects (ATE, ATE(x), and ATET(x)) increase in absolute terms from the poorest 1% to the 75% quantile. From the 90% quantile onwards, they start to decline and for the richest 1% they are insignificant. ATEx and ATETx show the treatment effect controlling for differences in the observables. One would usually expect the receipt of remittances to have a higher expenditure-impact on the treated. This is indeed the case for the richer 50% (and onwards) but not the case for poorer quantiles (up to the 25% quantile).

Table 3 Average treatment effects (ATEs) and average treatment effects on the treated (ATET) in USD in different quantiles of per capita household expenditures

Dependent variable: Per capita expenditures (welfare)								
	Omitted variable bias control [OVBC] (eq. 8 and 9 with correction term)				**No omitted variable bias control (eq. 8 and 9 without correction term)**			
Mean or quantiles	$\hat{ATE}$ (US$)	$\hat{ATE}x$ (US$)	$\hat{ATET}x$ (US$)	Relative* $\hat{ATET}x$ %	$\hat{ATE}$ **(US$)**	$\hat{ATE}x$ **(US$)**	$\hat{ATET}x$ **(US$)**	**Relative** $\hat{ATET}x$ **%**
Mean (eq.7)	110***	110***	121***	13%	356***	356***	**368*** **	39%
Q1% (eq. 8)	151***	120***	67***	59%	101***	56***	**41*** **	36%
Q10% (eq. 8)	189***	156***	122***	47%	156***	117***	**92*** **	36%
Q25% (eq. 8)	228***	206***	179***	43%	231***	202***	**177*** **	42%
Q50% (eq. 8)	268***	292***	311***	45%	304***	257***	**224*** **	32%
Q75% (eq. 8)	307***	328***	350***	30%	489***	451***	**427*** **	37%
Q90% (eq. 8)	200***	222***	246***	13%	539***	525***	**532*** **	29%
Q99% (eq. 8)	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	**n.s.**	n.s.

Notes: Controls (x): Gender of HHhead, age of head, HHsize, share of dependent HHmembers, hours worked; departments; sectors of work; x-deviations from their mean values.

Control for omitted variable bias [OVBC]:

HH propensity to receive remittances-average propensity to receive remittances (for receiving HH) $\hat{\theta} = A\hat{T}E$;

$A\hat{T}Ex = \hat{\theta} + (x - \overline{x})\hat{\varsigma}$ quantile-average over all HH in this quantile;

$AT\hat{E}Tx = \hat{\theta} + (\sum_{j=1}^{J} r_j)^{-1} * [\sum_{j=1}^{J} r_j (x - \overline{x}) * \hat{\varsigma}]$ quantile-average over remittances-receiving HH in this quantile;

* as percentage of either mean or quantile income; mean dependent variable/mean per capita expenditures in US$: 948 (US$);

Per capita expenditure per quantile in US$: Q1%: 114; Q10%: 257; Q25%: 417; Q50%: 691; Q75%: 1,151; Q90%: 1,823; Q99%: 4,469

Extreme poverty line: US$346; moderate poverty line: US$680; HTG1=$44 (2012); obs.: 4,930

This could mean that in these poorer quantiles, a substantial part of the increase in expenditures must be due to specific observables (x). For example, it might be that remittance-receiving households (treatment group) have more education and that this explains a substantial part of the increase in per capita expenditures. Relative ATETs (as a ratio of per capita expenditure) are highest for the poorest 1% and then start to decline. They are insignificant for the richest 1%. Hence, in relative terms, the poorest 1% benefits most and much more than the other quantiles. The ATE in the poorest 1% group is more than half (59%) of the usual per capita expenditure in this quantile. In the 10%, 25%, and 50% quantiles, about 47%, 43% and 45% of per capita expenditures can be financed by remittances respectively. The 25% well-to-do households and the 10% richest households finance between 30% and 13% of their per capita expenditures with remittances, respectively.

In annual money terms, ATET(x) are increasing up to the 75% quantile. They are 67 USD, 122 USD, and 179 USD in the poorest 1%, 10%, and 25% strata respectively. They are highest for the 50% (311 USD) and the 75% (350 USD) and then decreasing again. The ATETs are non-significant in the richest 1% quantile.

Individuals in the poorest 1% and the poorest 10% groups belong to the extreme poor with per capita expenditures below 346 USD (extreme poverty line) according to the poverty lines that have been computed by the World Bank for 2012 (see bottom panel of Table 3). Table 3 shows that remittances cannot lift the poorest 1% out of extreme poverty. However, the poorest 10% make it out of extreme poverty thanks to remittances. The poorest 25% are considered moderately poor as they have expenditures higher than 346 USD and lower than 680 USD. Thanks to remittances, they come closer to the poverty line for moderately poor households but still remain moderately poor.

4.4. Results on the impact of remittances on welfare (marginal effects)

The results in Table 4 show that per capita expenditures across all quantiles significantly increase with an increase in remittances. Table 4 shows the marginal effects with OVBC on the left-hand side of the panel and the results without OVBC on the right-hand side. On average, a one-dollar increase in remittances increases per capita expenditures by 0.80 dollars under OVBC and by 1.68 dollars without OVBC.

In **Table 4**, on the left-hand side, we observe that a one-dollar increase in remittances benefits higher per capita expenditure strata more than the other strata. More specifically, one more dollar of remittances increases expenditures by about 0.3 dollars, 0.4 dollars, 0.8 dollars, 0.9 dollars, 1.1 dollars and 1.0 dollar in the 1%, 10%, 25%, 50%, 75%, and 90% quantiles respectively. One explanation for this trend is that poorer households must use part of the remittances to pay back loans whereas better-off households can use remittances as collateral when borrowing or complement remittances with savings for larger purchases.

Moreover, it is worthwhile to note that the marginal effects estimated with OVBC are mostly substantially lower than those estimated without OVBC (Table 4, right-hand side). In general, the marginal effects under OVBC seem to be much more plausible.

Table 4 The marginal effect of remittances received, at the mean and by quantile

Dependent variable: Per capita expenditures (welfare)		
	Omitted variable bias control [OVBC]; eq. 11 and 12	No omitted variable bias control; eq. 11 and 12
	Marginal effect (1)x	Marginal effect (2)
Regression on the mean	0.80*** [9.22]	1.68*** [19.39]
Q1%	0.34*** [6.32]	0.31*** [3.64]
Q10%	0.44*** [5.08]	0.63*** [5.27]
Q25%	0.82*** [9.58]	1.00*** [12.45]
Q50%	0.93*** [8.42]	1.42*** [13.71]

Q75%	1.09*** [6.68]	2.04*** [10.04]
Q90%	0.97** [2.67]	2.72*** [7.19]
Q99%	n.s.	n.s.

Controls (x):
Gender of HHhead, age of head, HHsize, share of dependent HHmembers, hours worked; departments; sectors of work; for receiving HH: x-deviations from their mean values
Control for omitted variables, OVBC (left panel of Table 4):
HH propensity to receive remittances - average propensity to receive remittances (for receiving HH)

obs.: 4,930

Note: t-values in brackets; ***, **, and * stands for 1%, 5% and 10% significance. n.s. = not significant;

5. Conclusions

In this paper we analyzed factors that drive emigration using a sample of 17,807 individuals. At an individual level, certain features, such as being male and having a steady partnership, increase the propensity to migrate. A female household head and a more educated household head also increase the individual migration propensity. Coming from a poor household decreases the likelihood to emigrate.

Moreover, we investigate whether household wealth has an influence on the likelihood of receiving remittances on a sample of 4,930 households. Our findings show that this is not the case. Both poor and non-poor households are equally likely to receive remittances. Households with a larger number of adults and a smaller number of children are more likely to receive remittances as they are more likely to have a migrant. Unsurprisingly, households that have a larger than average propensity to have an emigrant are more likely to receive remittances.

In order to distinguish the effects of remittances on the poor and the rich we have run quantile regressions. Analyzing the effect of receiving remittances, compared to non-receivers, we find that richer quantiles have a higher ATE in absolute terms and hence, benefit the most in absolute terms. However, in relative terms (computing the share of per capita remittances with respect to per capita expenditures) the poorest and poor households benefit the most. Considering the marginal effect of remittances, remittances seem to benefit the wealthier quantiles more than the poorer quantiles.

As expected, OVBC matters and changes the results. A challenge in answering our research questions has been to account for endogeneity and omitted variable bias. To minimize omitted variable bias, we included a composite variable based on estimated propensities and their deviation from the mean. This instrument is supposed to also alleviate endogeneity. We have tackled the problem of selection bias by using the ‘endogenous selection’ command in eprobit in STATA and by including the deviations of the control variables from their respective means when studying the impact of remittances on household welfare.

References

Acosta, P., Fajnzylber, P. and López, H. (2007) The Impact of Remittances on Poverty and Human Capital: Evidence from Latin American Household Surveys. In C. Özden and Schiff, M. (eds.). International Migration, Economic Development and Policy (pp. 59-98). Washington D.C.: The World Bank.

Adams, Jr., R. (2006) Remittances and poverty in Ghana. World Bank Policy Research Working Paper 3838, World Bank, Washington, DC.

Adams, Jr., R., Cuecuecha, A. and Page, J. (2008) The impact of remittances on poverty and inequality in Ghana. World Bank Policy Research Working Paper 4732, World Bank, Washington, DC.

Adams, Jr., R. and Cuecuecha, A. (2010a) The economic impact of international remittances on poverty and household consumption and investment in Indonesia. World Bank Policy Research Working Paper 5433, World Bank, Washington, DC.

Adams, Jr., R. and Cuecuecha, A. (2010b) Remittances, household expenditure an investment in Guatemala. *World Development*, 38(11), pp. 1626–1641.

Adams, Jr., R. (2011) Evaluating the economic impact of international remittances on developing countries using household surveys: A literature review. Journal of Development Studies 47(6): 809-829.

Bertoli , S. and Marchetta; F. (2014) Migration, Remittances and Poverty in Ecuador. *The Journal of Development Studies* 50(8): 1067-1089.

Bodvarsson, Ö. B., Van den Berg, H. (2013) The Economics of Immigration. *Theory and Policy*. Springer: Heidelberg

De Haas, H. (2011) The determinants of international migration: Conceptualising policy, origin and destination effects. Working Paper 03/2011. International Migration Institute. University of Oxford.

Heckman, J. (1979) Sample selection bias as a specification error. *Econometrica.* **47** (1): 153–61.

Hentschel, J., Lanjouw, J.O., Lanjouw, P and Poggi, J. (2000) Combining Census and Survey Data to Trace the Spatial Dimensions of Poverty. A Case Study of Ecuador. *The World Bank Economic Review* 14: 147-165.

Kondo, K. (2017) The Economics of International Immigration. Springer: Heidelberg.

Lee, L. F. (1983) Generalized Econometric Models with Selectivity. *Econometrica* 51: 507-512.

Lokshin, M., Bontch-Osmolovski, M. and Glinskaya, E. (2010) Work-related migration and poverty reduction in Nepal. *Review of Development Economics* 14(2): 323–332.

Mansoor, A.and Quillin, B. (2006) *Migration and remittances : Eastern Europe and the Former Soviet Union (English).* Europe and Central Asia reports. Washington, DC: World Bank. http://documents.worldbank.org/curated/en/183131468024337798/Migration-and-remittances-Eastern-Europe-and-the-Former-Soviet-Union

McKenzie, D., Gibson, J. and Stillman, S. (2006) How important is selection? Experimental versus nonexperimental measures of the income gains from migration. World Bank Policy Research Working Paper 3906, World Bank, Washington, DC.

Omato, N. (2011) Who receives remittances? A case study of the distributional impact on Liberian refugees in Ghana. Centre for Development policy and Research. *Development Viewpoint 61*, *May 2011.*

Rao, P. (2006) Poverty Measurement Using the Expenditure Approach. Working Paper_August 2006_School of Economics. University of Queensland. Brisbane. Australia.

Rosenbaum, P.R. and Rubin, D.B. (1983) The Central Role of the propensity Score in Observational Studies for Causal Effects. *Biometrika* 70: 41-55.

Taylor, J.E., Mora, J., Adams, Jr., R. and Lopez-Feldman, A. (2005) Remittances, inequality and poverty: evidence from rural Mexico. Working Paper 05–003. Department of Agricultural Economics, University of California, Davis, CA.

UNICEF (2018) Migration Profiles. Accessed 10/17/2018. https://esa.un.org/miggmgprofiles/indicators/files/haiti.pdf

Wooldridge, J. M. (2002) Econometric Analysis of Cross Section and Panel Data. The MIT Press: Cambridge, Massachusetts.

World Bank (2005). Poverty Manual. Chap. 2. Revision of August 8, 2005. Accessed 10/17/2018. http://siteresources.worldbank.org/PGLP/Resources/PMch2.pdf

Yang, D. (2008) International migration, remittances and household investment: evidence from Philippine migrants' exchange rate shocks. *Economic Journal* 118(528): 591–630.

Yang, D. and Martinez, C. (2006) *Remittances and poverty in migrants home areas: evidence from the Philippines*, in: C. Ozden and M. Schiff (eds) International Migration, Remittances and the Brain Drain (Washington, DC: World Bank), pp. 81–121.