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Migration, remittances, and inequality: estimating the net effects of migration on income distribution

Bradford Barham *, Stephen Boucher [1]

Department of Agricultural and Applied Economics, University of Wisconsin-Madison, Madison, WI 53706, USA

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Abstract

This paper examines the net effects of migration and remittances on income distribution. Potential home earnings of migrants are imputed, as are the earnings of non-migrants in migrant households, in order to construct no-migration counterfactuals to compare with the observed income distribution including remittances. The earnings functions used to impute migrant home earnings are estimated from observations on non-migrants in a selection-corrected estimation framework which incorporates migration choice and labor-force participation decisions. For a sample of households in Bluefields, Nicaragua, migration and remittances increase income inequality when compared with the no-migration counterfactual. © 1998 Elsevier Science B.V.

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1. Introduction

The remittances of money and goods by migrants to their communities of origin can have important impacts on the distribution of household income and welfare.

* Corresponding author. E-mail: barham@aae.wisc.edu.

[1] E-mail: boucher@aae.wisc.edu.

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This is especially the case in developing economies, where household earnings are low, inequality is often pervasive, and domestic or international migration of family members can provide a major source of income through the remittance of wage earnings. Recent empirical work (Stark et al., 1986; Stark, 1988; Taylor, 1992; Adams, 1989; Oberai and Sing, 1980; and Lipton, 1980) suggests that migration and remittances can either increase or decrease the inequality of household income distribution.

Differences in both method and empirical context can account for these ambiguous results. This paper examines two key sources of methodological variation: (1) the specific economic question being asked and (2) the econometric or statistical techniques used to generate estimates of income and income distributions. [2] Variation in the economic question under investigation arises, because remittances can be treated, in effect, as an exogenous transfer by migrants or as a potential substitute for home earnings. When treated as an exogenous transfer, the economic question is how remittances, in total or on the margin, affect the observed income distribution in the receiving community. When treated as a potential substitute for home earnings, the economic question becomes how the observed income distribution compares to a counterfactual scenario without migration and remittances but including an imputation for home earnings of erstwhile migrants. This latter treatment is, in our view, the more interesting economic question, because it compares income distributions in the community with and without migration and remittances.

The importance of econometric or statistical techniques in accounting for the ambiguity in results is potentially relevant to both treatments of remittances. However, when remittances are viewed as an exogenous transfer, econometric issues arise only if the inequality analysis attempts to incorporate the indirect effects of remittances on the other income sources of receiving households, such as farm income for a credit constrained household (Taylor, 1992). Otherwise, the relevant comparisons of observed income distribution do not require econometric estimations. When remittances are viewed as a substitute for home earnings by the migrants, the counterfactual scenario of no migration requires generating an estimate for what migrants might have earned if they had stayed home. In addition, the loss of remittance income and the return of migrants to the sending household might affect the participation decisions and earnings outcomes of other household members. Thus, counterfactual earnings estimates for both migrants and other members of their households need to be constructed from observed earnings data, and the econometric approach used to generate those estimates takes center stage.

[2] A third source of methodological variation, the measure of inequality can also be important (Stark, 1988). As in Stark et al., the Gini coefficient is used here as a summary measure. Additional attention is given, however, to hypothesis testing when the test statistic is the Gini coefficient.

The unique contribution of this paper is that it develops counterfactual scenarios of no migration and remittances using an econometric approach and imputation process that allow appropriate counterfactual distributions of household income to be constructed and statistically compared to the observed household income distribution with migration and remittances. The parameters of the earnings equation are estimated in an econometric model of double-selection, where the two selection rules model the choice of migration and the choice of labor force participation by non-migrants. [3] The model specification also partially incorporates the potential endogeneity of labor participation decisions within the household. Parameter estimates are used to construct two counterfactual scenarios: one that simply replaces remittance flows in observed household incomes with imputed values of migrants' home earnings; and a second that also allows for the potential effects of the return of migrants on the participation decisions and earnings outcomes of other family members. General equilibrium effects of a wholesale return of migrants and the loss of remittance transfers on labor, product, and other markets are not explicitly modelled because of limitations in data. [4]

The article is organized as follows. Section 2 provides a succinct review of alternative methods for assessing the effects of migration and remittances on inequality, and locates this paper's contribution. Section 3 introduces the migration and remittance data, which were collected in Bluefields, Nicaragua in 1991. Section 4 presents inequality outcomes using the remittance-as-a-transfer approach, which involves decomposing the Gini coefficient into the relevant income sources. This exercise shows that remittances appear to reduce inequality in the observed income distribution. Section 5 develops the econometric model of individual earnings with double selection and discusses the resulting parameter estimates. Section 6 constructs individual earnings imputations for the no-migration counterfactuals, using a simulation procedure to generate error draws to recover the unobserved components of earnings and of participation choices. Section 7 compares the observed income distribution and the remittance-as-a-transfer result with the two counterfactual distributions, and decomposes the Gini coefficient for one of the two counterfactuals. These comparisons show that, when treated as a substitute for home earnings, migration and remittances increase inequality rather than decrease it. Section 8 concludes.

[3] There is a well-known basis for self-selection inherent to migration and earnings outcomes (Nakosteen and Zimmer, 1980; Tunali, 1985; Taylor, 1987; and Hoddinott, 1994).

[4] See Taylor (1995) for a first effort at a village-level general equilibrium model for treating the impacts of migration and remittances on the local economy. One of the unique aspects of Taylor's recent work is that it attempts to capture the potential for rather poorly integrated local factor markets (especially credit-risk markets) and the accompanying effects of remittances on helping to relax the resulting constraints. This general equilibrium analysis does not, however, explicitly address the measurement of household income inequality.

2. Alternative methods for measuring the effects of remittances on inequality

The seminal works of Stark et al. (1986), Stark (1988) examine the effect of remittances on the size distribution of household income in the receiving community. They use a Gini decomposition framework to identify the contributions of each income source to the Gini coefficient, as shown in Eq. (1) and described below.

$$G_0 = \sum_{k=1}^{K} R_k G_k S_k. \tag{1}$$

For a given population of households, the left-hand-side variable, G_0, is the Gini coefficient of total income. The three right-hand-side terms are as follows: $R_k = \mathrm{cov}[y_k, F(y_o)]/\mathrm{cov}[y_k, F(y_k)]$, the Gini correlation of income component k (e.g., remittances) with total income y_o, where $F(y_o)$ is the cumulative distribution of total income and $F(y_k)$ is the cumulative distribution of income component k; G_k is the Gini coefficient corresponding to income component k, e.g., the inequality of remittances; and, S_k is the share of component k in total household income.

Stark et al. then use this decomposition framework to compare the effects of remittances on household income distribution in two ways. First, they omit the remittance component of household income from the summation in Eq. (1) and compare the resulting Gini with the observed Gini. Although this approach provides a direct measure of how remittances contribute to income distribution in the receiving community, it does not address the economic issue of what the migrants would be contributing to their families if they had not migrated. The other way Eq. (1) is used is to derive an expression for the marginal effect of a change in remittances on income distribution (see Stark et al., 1986 for this comparative static exercise). This marginal effect approach allows for the potentially useful analysis of how policy choices and other economic factors that directly influence remittances on the margin (e.g., by altering the transaction costs of transfers) would change income distribution outcomes associated with remittances.

A notable feature of the Stark et al. approach is that remittances are treated as an exogenous income source. Adams (1989) introduces, and this article extends, an alternative approach that treats remittances as a substitute for home earnings. The benefit of this approach is that it compares the observed household income distribution with an economically interesting counterfactual income distribution-one without migration. [5] The challenge is in the econometrics of devising representa-

[5] Stark (1988) (p. 310) identifies this approach when they write, "estimates of the migrant's net contributions to household income need to take into account the full opportunity cost of migration, including the income the migrants would have contributed to their households had they not migrated."

tive income imputations for the counterfactual and in constructing representative income distributions.

Econometrically, Adams (1989) estimates a household income function, based on aggregate factors of production, for non-migrant households. He, then, applies the coefficient estimates and the endowment bundles of migrant households (without migration and remittances) to impute their earnings under a no migration scenario. The econometric model does not control for the (individual or household) selection problem involved in the original migration decision; thus, in effect, it treats migrant and non-migrant observations as if they were drawn randomly rather than self-selected from the population. Moreover, the household level earnings estimation suppresses differences in expected home earnings of migrants that could arise from variations in their observed and unobserved individual characteristics.

As noted above, this paper estimates individual earnings equations in a double-selection model involving migration choices and non-migrants' labor force participation decisions. It also incorporates the potential intrahousehold endogeneity of participation decisions by examining the effect of remittances, the number of adults in a household, and the earnings of the head of household on participation decisions by non-migrants. In this fashion, the econometric model developed below draws on Taylor (1992), in that it explores feedback effects of remittances on other income sources.

The other statistical innovation of this paper is in the effort taken to construct an appropriate income distribution. The variance of a counterfactual household income distribution based only on the conditional expectation of individual's earnings would be artificially reduced since it would not incorporate the variation due to the unobserved components of individuals' labor force participation decision and earnings. The structure of the econometric model permits the identification of the joint probability distribution of the unobserved terms, from which random draws are taken and incorporated into the income imputations. This process makes the Gini coefficient for the counterfactual a random variable. Thus, meaningful statistical comparisons of counterfactual Ginis with the observed Gini require estimates of means and standard errors or confidence intervals for these test statistics. The means and 95% confidence intervals are constructed using a simulation method discussed below. [6]

[6] Another sources of variance in the Gini coefficient are not addressed in the analysis. It concerns the fact that most Gini measures are constructed from samples rather than populations. Sandstrom et al. (1985), Sandstrom (1988), and Yitzhaki (1991) examine different methods for estimating sample variances for Ginis. In this paper, the sampling distribution of the observed outcome is treated as if the sample distribution was degenerate or a population.

3. Data from Bluefields, Nicaragua

The empirics are based on a data-set collected in 1991 in Bluefields, Nicaragua, an Atlantic Coast Port with a long history of international migration. Surveys were conducted with 152 households selected randomly in three neighborhoods of Bluefields, Nicaragua, which were known to be migrant-sending areas. About 15% of the total number of households in each neighborhood were included. Respondents were asked about household demographics, formal and informal labor market participation of household members, non-wage activities, and wage earnings for individuals 15 and over residing in Bluefields. Demographic and remittance (cash and in-kind) data were also collected on individuals that previously resided in the sample households but at the time of the interview were residing either elsewhere within Nicaragua or abroad. Foreign earnings of migrants were not known by the Bluefields households. This precluded modelling the migration decision in a full mover–stayer specification as developed in Nakosteen and Zimmer (1980) or Tunali (1985).

The summary household and migrant statistics presented in Table 1 show that migration is widespread and that remittances are a major component in household income. Just over 57% of households interviewed had at least one member

Table 1
Summary statistics of sample households, migrants, and non-migrants

Variable	Sample statistic
Household level	
Mean number of adults per household	3.4
Share of households with at least one migrant	57.2%
Average number of international migrants per migrant household	1.9
Share of households with at least one remitting migrant	33.3%
Share of migrant remittances in total household income (all households)	9.9%
Share of migrant remittances in total household income (receiving households)	36.7%
Migrant level	
Age	38.3
Sex (female = 100, male = 0)	34.0
Years of formal schooling	8.9
Ethnicity (creole = 100, mestizo = 0)	85.9
Yearly remittances per migrant	US$223
Non-migrant level	
Labor force participation rates[a]	
Males	56.6%
Females	35.6%
Quarterly individual earnings (US$)	
Males	244.1
Females	104.4

[a] Measured as the percentage of months during 1990 that an individual was either employed for a wage or self-employed in market production.

abroad.[7] Remittances represent about 10% of total household income for all households.[8] However, for Bluefields' households that received remittances during 1990, remittances represented about 37% of total household income. Migrants were, on average, more educated, more likely to be male, and creole.[9] Labor force participation among adults in Bluefields was only 44.5%, reflecting the town's economic fragility in 1990, after a decade of revolutionary and counter-revolutionary activity in Nicaragua, and, it seems, the port town's dependence on foreign transfers.

4. Migration, remittances and inequality in Bluefields: the two Gini methods

Observed income distribution in the sample, including remittances, generates a Gini coefficient of 0.43, while the home earnings of non-migrants generate a Gini of 0.47. When the comparison is done using household income per adult equivalent,[10] the home earnings' Gini is 0.50, and the observed Gini is 0.46. In other words, household income in the absence of remittances is nearly 10% more unequal than it is with remittances in both cases. Essentially the same magnitude of inequality reduction is obtained in Stark et al. (1986) and Taylor (1992).[11]

The Gini decomposition figures for household income in the sample are shown in Table 2. The two components of household income are remittance and home earnings. The Gini coefficient of remittances (G) is lower than that of non-remittance income (0.39 vs. 0.47), and the correlation of remittances with total income (R) is much lower than that of non-remittance income with total income (0.58 vs. 0.96). These two factors combine to give remittances a strong inequality reducing effect, even though the share of remittances (S) is only 10% of overall income. The last column in Table 2 reports the percent change in the Gini coefficient for a percent change in remittances or in income from other sources. For home earnings, a 1% increase in remittances would reduce the Gini coefficient by about 5%.[12]

[7] Only 2% of all migrants were internal and their net remittances were zero.

[8] Remittances were 33 and 40% of total household income in the Mexican villages studied in Stark et al. (1986), Stark (1988), and 12.5% in the rural Egyptian villages studied in Adams (1989).

[9] Creoles are English-speaking, African–Nicaraguans, descendants of slaves brought to the Atlantic Coast by the English in the seventeenth and eighteenth centuries. Mestizos speak primarily Spanish and are descendants of Central American indians and the colonizing Spanish.

[10] Household members over the age of 12 are counted as 1. Under the age of 12, they are counted as 0.5.

[11] Stark et al. (1986) report on two Mexican villages. With the inclusion of remittance income, the Gini coefficient declines from 0.43 to 0.40 in one village and from 0.53 to 0.46 in the other. In Taylor (1992), the decline in the Gini is from 0.52 to 0.48.

[12] In Stark (1988), the results across the two villages are ambiguous. In Taylor (1992), the marginal change in the Gini associated with remittances is positive, indicating an increase in inequality.

Table 2
Gini decomposition

Income source	Share in total household income (S)	Gini coefficient for income source (G)	Gini correlation with total income rank (R)	Contribution to Gini of total income (SGR)	% share in Gini of total income (SRG/G)	% change in Gini of total income from 1% change in income
Migrant remittances	0.099	0.39	0.58	0.02	5%	−5%
Home earnings	0.901	0.47	0.96	0.41	95%	5%
Total income	1.00	0.43	1.00	0.43	100%	–

5. An econometric model of home earnings with double selection

The analysis now turns to how income distributions would compare when remittances are treated as a substitute for home earnings. This requires constructing individual income estimates in the absence of migration, i.e., predicting what migrants might earn in Bluefields and how the 'return' of migrants could impact the decisions of other family members regarding labor force participation and work intensity. Because migrants' home earnings are unobservable, and because migrants may represent a non-randomly chosen subset of the overall sample, any point estimate of the conditional mean of migrants' home earnings requires invoking additional assumptions. One possible approach is to treat non-migrants as a random draw from the population, in effect the approach taken by Adams (1989). Under this assumption, a mean regression of earnings for non-migrants who work could be run, and expected earnings for migrants could be 'fitted' using the parameter estimates. This approach becomes problematic if migrants and non-migrants differ systematically in their expected earnings, because the regression estimates will be biased. Empirical research noted above has, indeed, found evidence of selection in the migration choice.

A common means of 'correcting' for the bias associated with systematic differences between groups is to impose a specific probability distribution structure on the model which explicitly incorporates the selection rule(s). That is the modelling strategy adopted here. We follow Tunali (1985) in extending the specification of Heckman (1976, 1979) to include two selection criteria: the migration choice and the labor force participation decision. The latter is motivated by the fact that participation rates are very low in Bluefields, which indicates that the subsample of labor force participants may be non-randomly selected. The model is specified as follows:

$$Y_{1i}* = \beta_1' X_{1i} + U_{1i}; \quad \text{not migrate selection rule} \tag{2.1}$$

$$Y_{2i}* = \beta_2' X_{2i} + U_{2i}; \quad \text{participate selection rule} \tag{2.2}$$

$$Y_{3i} = \beta_3' X_{3i} + \sigma_3 U_{3i}; \quad \text{earnings equation.} \tag{2.3}$$

In Eqs. (2.1), (2.2) and (2.3), the X_{ji}'s are $K_j \times 1$ vectors of explanatory variables, β_j's are $K_j \times 1$ vectors of unknown coefficients, σ_3 is an unknown scale parameter, and the U_{mi}'s are the unobserved terms with zero means and the following correlation matrix:

$$\Sigma = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix}.$$

The selection variables, $Y_{1i}*$ and $Y_{2i}*$, representing the 'propensity' to not migrate (or stay) and the propensity to participate in the labor market, are not observed. Only the sign is observed, i.e., whether or not an individual migrates and whether or not an individual participates in the labor market in Bluefields. Thus, the variance of the unobserved terms in the selection equations cannot be estimated and are set to one. The binary variables D_1 and D_2 are the observed outcomes of the selection rules and allow classification of the sample following:

$$D_1 = \begin{cases} 1 \text{ if } Y_1 * > 0 \\ 0 \text{ if } Y_1 * \leq 0 \end{cases} \tag{3}$$

$$D_2 = \begin{cases} 1 \text{ if } Y_2 * > 0 \\ 0 \text{ if } Y_2 * \leq 0 \end{cases} \tag{4}$$

With full information regarding labor market and earnings outcomes, four possible outcomes can occur as a result of the two selection rules. In the model estimated below, there are only three observed outcomes [(1. $D_1 = 1$); (2. $D_1 = 0$, $D_2 = 1$); (3. $D_1 = 0$, $D_2 = 0$)], because the data do not provide information on migrants' labor force participation status.

With this structure, the regression function for the equation of interest, the earnings equation is:

$$E(Y_{3i}|X_{3i}, D_1, D_2) = \boldsymbol{\beta}_3' \boldsymbol{X}_{3i} + \sigma_3 E(U_{3i}|X_{3i}, D_1, D_2); \tag{5}$$

If $E(U_{3i}|X_{3i}, D_1, D_2) \neq 0$, then a linear regression of Y_3 on $\boldsymbol{X}_3$ will result in biased parameter estimates. In order to generate unbiased estimates of the elements of $\boldsymbol{\beta}_3$, additional information regarding the conditional distribution of the unobserved term, U_{3i}, is required. The additional structure imposed here is the form of the joint distribution of the three unobserved terms. Assume $(U_{1i}, U_{2i}, U_{3i}) \sim N(0, \Sigma)$, independent of the observation and of the covariates. [13] For an individual, however, the unobserved terms may be correlated.

Because no observations are available on foreign earnings by migrants, earnings, Y_3, are observed only when $Y_1 * > 0$ and $Y_2 * > 0$. Then, for this subsample, the conditional expectation of Y_3 is:

$$\begin{aligned} &E(Y_3|X_3, U_1 > -\boldsymbol{\beta}_1'\boldsymbol{X}_1, U_2 > -\boldsymbol{\beta}_2'\boldsymbol{X}_2) \\ &\quad = \boldsymbol{\beta}_3'\boldsymbol{X}_3 + \sigma_3 E(U_3|U_1 > -\boldsymbol{\beta}_1'\boldsymbol{X}_1, U_2 > -\boldsymbol{\beta}_2'\boldsymbol{X}_2). \end{aligned} \tag{6}$$

[13] It should be noted that the distributional assumptions invoked in order to obtain identification have been criticized. For example, Goldberger (1983) shows that the estimates will be very different if the normality assumption is violated. One other concern about the error structure assumed in this model is that the Ui's among household members are probably not independent. For simplicity sake, we choose to ignore the complications of constructing the ensuing econometric analysis with correlated error terms among household members, but this would be an area for further methodological innovation.

As shown in Tunali (1985), the multivariate normal structure allows the derivation of an expression for the conditional expectation of the disturbance, U_3:

$$E(U_3|U_1 > -\boldsymbol{\beta}_1' X_1, U_2 > -\boldsymbol{\beta}_2' X_2) = \rho_{13}\lambda_1 + \rho_{23}\lambda_2; \tag{7}$$

where the two λ terms are the analogues to the single selection inverse Mill's ratio. With these results, the conditional expectation in Eq. (6) becomes:

$$E(Y_3|X_3, U_1 > -\boldsymbol{\beta}_1 X_1, U_2 > -\boldsymbol{\beta}_2' X_2) = \boldsymbol{\beta}_3 X_3 + \theta_1\lambda_1 + \theta_2\lambda_2;$$
$$\text{where } \theta_1 = \sigma_3\rho_{13}, \text{ and } \theta_2 = \sigma_3\rho_{23}. \tag{8}$$

The estimation is conducted in two steps. First, data on the outcomes of the two selection rules are used to obtain the likelihood function for the bivariate probit. Letting $F(.)$ and $G(.,.;.)$ denote respectively the univariate and bivariate standard normal cumulative density functions, this likelihood function is:

$$L = \prod_{D_1=0} F(-\boldsymbol{\beta}_1' X_1) * \prod_{\substack{D_1=1 \\ D_2=2}} G(\boldsymbol{\beta}_1' X_1, -\boldsymbol{\beta}_2' X_2; -\rho_{12})$$
$$\times * \prod_{\substack{D_1=1 \\ D_2=1}} G(\boldsymbol{\beta}_1' X_1, \boldsymbol{\beta}_2' X_2; \rho_{12}) \tag{9}$$

The first term of the likelihood function corresponds to migrants; the second term to non-migrants who do not participate in the local labor force; and the third non-migrants who do participate. Maximum likelihood estimation of Eq. (9) yields consistent estimates of $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\rho}_{12}$.

These parameter estimates are used to construct $\hat{\lambda}_1$ and $\hat{\lambda}_2$ for each individual. These can then be inserted into Eq. (8) to yield the selection corrected earnings equation:

$$Y_3 = \boldsymbol{\beta}_3' X_3 + \theta_1\lambda_1 + \theta_2\lambda_2 + \sigma_3\nu_3; \; E(\nu_3|D_1 = 1, D_2 = 1) = 0. \tag{10}$$

Eq. (10) is fit by ordinary least squares regression of Y_3 on X_3 and the constructed variables $\hat{\lambda}_1$ and $\hat{\lambda}_2$ for those individuals who are both non-migrants and who work. [14] Finally, estimates of the correlation coefficients, ρ_{12} and ρ_{13}, are obtained by solving the equations for θ_1 and θ_2 given in Eq. (8).

5.1. Variable description

Names and definitions of the variables used in the bivariate probit are reported in Table 3, while summary statistics of these variables are found in the text table

[14] Tunali (1985) (p. 170) shows that the parameter estimates are consistent, however the estimates of the standard errors are inconsistent. This inconsistency results from: $\text{var}(Y_3|Y_1^* > 0, Y_2^* > 0) = \sigma_3^2 \text{var}(V_3|Y_1^* > 0, Y_2^* > 0) \neq \sigma_3^2 = \text{var}(U_3)$. Tunali (1985) (p. 195–202) provides an expression for the corrected asymptotic covariance matrix and unbiased estimator of σ_3, which are used in the estimation procedure carried out in LIMDEP (Greene, 1991).

Table 3
Variable definitions

AGE	Age in years
AGESQ1	(Age squared)/100
EDUC0	Dummy for education: equals 1 if illiterate, 0 otherwise
EDUC1	Dummy for education: equals 1 if had some primary schooling, 0 otherwise
EDUC2	Dummy for education: equals 1 if completed primary and/or had some secondary schooling, 0 otherwise
EDUC3[a]	Dummy for education: equals 1 if completed secondary and/or had some post-secondary schooling, 0 otherwise
CREOLE	Dummy for ethnicity: equals 1 if creole, 0 if mestizo
HOH	Dummy for head of household: equals 1 if individual is the household head, 0 otherwise
CHILDREN	The number of children under 6 years old in the household
CONTINUE	Dummy for in school: equals 1 if individual was enrolled in school at the time of the interview, 0 otherwise
ADULTS	The number of adults (over 16 years old) in the household
REM1	(1992) Remittance income/10
DYHOH1	(Income of household head)/10. Equals 0 for household heads
CHILD	Dummy indicating individual is child of the household head
SIBLING	Dummy indicating individual is sibling of household head
PARENT	Dummy indicating individual is parent of household head
SPOUSE[a]	Dummy indicating individual is spouse of household head
OTHER[a]	Dummy indicating individual has no relation to household head
WEALTH1	Value of (house + property + financial assets)/10
WELTHSQ1	(Wealth1)2/100

[a]Indicates dummy variable excluded from the regression.

in the appendix. The regressors can be grouped conceptually into two categories, traditional human capital characteristics and family structure characteristics. The second group is included in order to reflect the possibility that the migration and labor force participation decisions may depend on an individual's position in the household or known earnings of other household members. These family structure characteristics may be especially important in Bluefields, where extended families frequently reside in the same household, and where labor market participation rates are quite low, 35% for women and 57% for men and where working men on average earn 40% more than working women. Variables reflecting position in the household include categorical variables indicating the relationship to the household head, and the number of adults and children under 6 years old in the household.

The probability of migration is assumed to depend on an individual's age and position in the household, access to information regarding foreign labor market conditions, access to migration networks, and the human capital characteristics which influence the ratio of expected earnings abroad to expected earnings at home. [15] Relative to the depressed labor market of Bluefields, returns to education are likely to be greater abroad. This leads to the expectation that those individuals with higher levels of education would be more likely to migrate. Older individuals are also expected to have a higher probability of migration; however, very old and very young adults may be unlikely to migrate in both cases for a variety of reasons. Thus, age squared is included as a regressor. Since creoles have a longer tradition of migration, stronger migration networks, and speak English as a native language, they are expected to be more likely to migrate than mestizos. Individuals outside the immediate family (household head and spouse) are expected to be more likely to migrate because they have less immediate responsibility for child rearing and income provision. Finally, since there is a significant initial cost in financing most migration, individuals from households with more wealth are anticipated to have a higher probability of migration than those from low wealth households. The wealth squared term captures the possibility that wealthier households may be less likely to sacrifice personal dislocation for the economic gains of migration. [16]

In terms of individual decisions to participate in the local labor market, much of the same logic applies. More distant relatives are expected to be less likely to participate, because they have less immediate responsibility for household provi-

[15] Ideally, information on migrants' earnings abroad would also be available. Then a full mover–stayer structural model could be estimated as in Nakosteen and Zimmer (1980) and Tunali (1985). However, since migrant income is not known, the estimated migration decision here is of reduced form.

[16] A referee correctly notes a potential endogeneity problem with the wealth variable given the potential feedback effects of earlier migration on wealth.

sioning. The presence of young children may have contradictory effects. For men, it is likely to provide an incentive to work more since there are additional household costs. Women, however, are more likely to have the bulk of child rearing responsibilities, so the presence of young children may reduce their probability of participation. Higher numbers of adults is likely to reduce the need for other adults to work, although the presence of other adults to help with child rearing may allow women a greater possibility of working. Other sources of income are expected to have a negative effect on the probability of working. Thus, the level of remittances to a household would be negatively correlated with the probability of individual labor force participation. The income of the head of household is also included as a determinant of the probability of working for other adult household members. [17] Finally, the variables included in the earnings regression attempt to capture human capital characteristics with variables for age, education, and ethnicity, as well as the effect on intensity of labor effort attributable to the number of adults in the household.

5.2. Estimation results

Results of the bivariate probit estimation using maximum likelihood, run separately for men and women, are presented in Table 4. Most of the coefficients have the expected sign. Recall that the dependent variable in the migration decision takes value 1 if an individual does not migrate and 0 if she does. In both probits, AGE and AGESQ1 are significant at the 5% level with an inverse quadratic structure, indicating that the probability of migration and labor force participation first increase and then decrease with age. Lower levels of education are associated with lower probabilities of working, relative to the highest education category which was omitted. However, only EDUC1 is significant at the 5% level for women. As expected, lower levels of education are also negatively correlated with migration.

The coefficient on the head of household variable is positive and significant for men at the 5% level in the participation equation but not significantly different from zero in the migration equation. For women, this variable is not significantly different from zero in either equation. The number of adults in the household and other income sources are significant determinants of labor force participation for women. For men, the negative coefficient on wealth and the positive coefficient on

[17] This assumption is fairly common in models of female labor force participation (see Smith, 1980 and Pong, 1991), and in effect assumes that the definition of head of household is invariant and culturally defined as opposed to endogenously determined by something like an individual's earnings contribution.

Table 4
Estimation results of bivariate probit

Variable	Log-likelihood = −244.13		Log-likelihood = −248.68	
	Men		Women	
	Coefficient	Asymptotic T-ratio	Coefficient	Asymptotic T-ratio
Labor force participation decision (1 = Participate, 0 = Not Participate)				
Constant	−0.496	−0.547	−1.674	−1.908[a]
Age	0.0903	2.128[b]	0.147	3.577[b]
Agesq1	−0.107	−2.293[b]	−0.161	−3.861[b]
Educ0	−0.0275	−0.045	−0.505	−0.846
Educ1	−0.0875	−0.217	−0.560	−2.167[b]
Educ2	−0.220	−0.623	−0.272	−1.101
Creole	−0.395	−1.224	−0.631	−3.055[b]
Hoh	1.099	3.022[b]	0.339	1.198
Child	0.049	0.181	0.270	1.103
Children	0.162	1.465	0.038	0.536
Continue	−0.987	−2.641[b]	−0.396	−1.116
Adults	−0.127	−1.566	−0.171	−3.076[b]
Rem1	−0.013	−1.675	−0.010	−1.749[a]
Dyhoh1	−0.295	−0.678	−0.008	−3.018[b]
Migration decision (1 = Not Migrate, 0 = Migrate)				
Constant	8.398	4.111[b]	6.288	2.927[b]
Age	−0.212	−4.379[b]	−0.096	−2.431[b]
Agesq1	0.267	4.201[b]	0.103	2.260[b]
Creole	−0.771	−3.249[b]	−0.697	−2.657[b]
Children	0.199	2.340[b]	0.281	2.499[b]
Adults	−0.239	−4.188[b]	−0.252	−3.771[b]
Educ0	0.854	1.236	3.857	0.00
Educ1	0.568	2.301[b]	0.676	2.269[b]
Educ2	0.601	2.584[b]	0.433	1.603
Hoh	−0.059	−0.183	0.647	1.050
Child	−0.122	−0.423	−0.567	−2.141[b]
Sibling	−0.996	−2.610[b]	−1.744	−5.222[b]
Parent	−0.063	−0.046	−1.196	−1.918
Wealth1	−0.985	−1.752[a]	−0.616	−0.968
Welthsq1	0.076	1.847[a]	0.047	0.983
$\rho 12$	−0.150	−0.254	0.374	0.884

[a]Significant at the 10% level.
[b]Significant at the 5% level.

wealth squared suggests that the highest probability of migration is among men from households in the middle of the wealth distribution.

Table 5 presents results of the OLS estimation of the earnings equations, both with and without the selection correction terms. The human capital coefficients have the expected signs, although the large standard errors on the coefficients for

Table 5
Parameter estimates of earnings equations

Variable	Men ($n = 125$)		Women ($n = 106$)	
	Coefficient estimate		Coefficient estimate	
	With correction	Without correction	With correction	Without correction
Constant	4.110 (5.584)[b]	3.812 (7.797)[b]	2.539 (2.036)[b]	3.388 (4.445)
Age	0.056 (1.831)[a]	.068 (3.286)[b]	0.098 (1.906)[a]	0.065 (2.124)[b]
Agesq1	−0.061 (−1.809)[a]	−0.0735 (−3.495)[b]	−0.108 (−1.815)[a]	−0.070 (−2.095)[b]
Ed	0.128 (2.263)[b]	0.124 (2.214)[b]	0.085 (1.242)	0.089 (1.372)
Edsq1	−0.061 (−1.433)	−0.053 (−1.307)	0.011 (0.253)	0.002 (0.005)
Creole	0.021 (0.128)	0.066 (0.523)	−0.277 (−1.185)	−0.183 (−1.298)
Adults	−0.055 (−1.547)	−0.043 (−1.503)	0.013 (0.226)	0.025 (0.662)
Hoh	0.436 (2.006)[b]	0.470 (3.073)[b]	0.131 (0.543)	0.060 (0.348)
λ1	−0.088 (−0.278)	NA	0.310 (0.731)	NA
λ2	0.233 (0.622)	NA	−0.268 (−0.491)	NA
R2	0.319	0.303	0.206	0.191

[a]Significant at the 10% level.
[b]Significant at the 5% level, T-statistics are in parentheses.

women reflect relatively imprecise estimates. The two selection coefficients are small and statistically insignificant for men and women. Both the relatively large standard errors on the selection coefficients and the fact that the other coefficient estimates are quite similar in the two specifications suggest, at least under the structural assumptions of trivariate normality, that the subsample of non-migrant labor force participants is randomly selected from the population. Under the assumptions imposed, the bias resulting from estimating via OLS without selection controls would be small.

6. Earnings imputations for the no-migration counterfactuals

This section takes the next step in constructing the Gini coefficient for household income by imputing individual earnings in the no-migration counterfactuals. Imputed individual incomes, $Y_{cf}*$, are constructed from two components, as depicted in Eq. (11):

$$Y_{cf}* = y_3 * D_2 * \tag{11}$$

The first component, y_3*, is an individual's potential earnings in Bluefields. The second component, D_2*, is a binary value indicator representing the discrete outcome of the labor force participation decision for that individual. Each of these two components is, in turn, the sum of an observed and unobserved component, as shown in Eqs. (12) and (13):

$$y_3 = \hat{\beta}_3' x_3 * + \hat{\sigma}_3 U_3 *, \tag{12}$$

$$D_2 * = \begin{cases} 1 \text{ if } \hat{\beta}_2' x_2 * + U_2 * > 0 \\ 0 \text{ if } \hat{\beta}_2' x_2 * + U_2 * \leq 0 \end{cases} \tag{13}$$

The observed components of $y_3 *$ and $D_2 *$ are the product of the parameter estimates, $\hat{\beta}_j$, and the updated regressors, $\boldsymbol{x}_j *$, which accommodate the changes in household structure and loss of remittances in the no migration counterfactuals. The unobserved components are $U_2 *$ and $U_3 *$, which have both systematic and unsystematic variation as discussed shortly.

Using just $\hat{\beta}_j x_j *$ for the imputations would be inappropriate for two reasons. First, as shown in Section 5, if there is a systematic relationship between the migration and participation decisions and earnings outcomes which is not accounted for by the observed characteristics, then the $\hat{\beta}_j' x_j *$ would give biased conditional estimates. Second, excluding the unobserved component of individual potential earnings or participation decisions from the imputation would artificially reduce the variance in household income. Therefore, the unobserved components —$U_2 *$ and $U_3 *$—are included in the imputation of individual incomes in order to construct appropriate household income distribution measures, which reflect both the systematic correlation in migration, participation, and earnings outcomes and the unsystematic variation which contributes to the underlying income distribution.

The estimation procedure identifies the parameters of the trivariate normal density function which describes the joint distribution of U_1, U_2, and U_3 in the population. By restricting the relevant range of the population distribution, the observed outcomes of the selection rules truncate the joint density function for each individual. Denoting $h(U;\hat{\Sigma})$ as the estimated standard trivariate normal density function, the truncated density functions $\phi(U,D_l,D_2)$ for migrants, non-migrant/non-participants, and non-migrant/participants are given in Eqs. (14a), (14b) and (14c), respectively:

$$\phi(U|D_1=0) = \begin{cases} \dfrac{h(\underline{U};\hat{\Sigma})}{F(-\hat{\beta}_1' X_1 *)} & \text{if } U_1 \leq -\hat{\beta}_1 X_1 *, \\ 0 & \text{otherwise} \end{cases} \tag{14a}$$

$$\phi(U|D_1=1,D_2=0)$$
$$= \begin{cases} \dfrac{h(\underline{U};\hat{\Sigma})}{G(\hat{\beta}_1' X_1 *, -\hat{\beta}_2' X_2 *; \hat{\rho}_{12})} & \text{if } U_1 > -\hat{\beta}_1' X_1 * \text{ and } U_2 \leq -\hat{\beta}_2' X_2 * \\ 0 & \text{otherwise} \end{cases} \tag{14b}$$

$$\phi(U|D_1=1,D_2=1) \times \begin{cases} \dfrac{h(\underline{U};\hat{\Sigma})}{G\left(\hat{\beta}_1 X_1 *, \hat{\beta}_2 X_2 *; \hat{\rho}_{12}\right)} & \text{if } U_1 > -\hat{\beta}_1 X_1 * \text{ and } U_2 > -\hat{\beta}_2 X_2 * \\ 0 & \text{otherwise} \end{cases} \tag{14c}$$

Random draws from these truncated density functions are taken and added to the observed components in Eqs. (12) and (13) to complete the imputation exercise. Because the unobserved components for each individual are generated from random draws, the income imputation exercise is replicated 1000 times. In each iteration, mean household income and the Gini coefficient are computed. The 95% confidence intervals are constructed by reporting the 25th and 975th elements of the vector of means and Ginis arranged in ascending order. Constructing the simulated distribution of the Gini coefficients and mean household income allows a meaningful comparison of the counterfactual household income distribution with the observed household income distribution.

As mentioned above, two no-migration counterfactuals are constructed. In the first, remittances are set to zero, home earnings estimates are imputed only for migrants (using Eqs. (12), (13) and (14a)), and these estimates are then added to the observed earnings of non-migrants to construct household income estimates. Thus, the first counterfactual considers only the direct income effects of the return of migrants, and omits the potential indirect effects of their return on the labor participation decisions and earnings outcomes of other family members. In the second no-migration counterfactual, these indirect effects are incorporated by imputing earnings of non-migrants in migrant households in a manner that allows for adjustments to occur for both the loss of remittance income and the addition of more potential labor force participants. [18]

Individual imputation outcomes of labor participation and incomes in Counterfactual 2 are presented in Table 6, and compared with the observed results for non-migrants. In the sample, the observed labor force participation rate was 44%; about 38% for non-migrants from households with migrants and 54% for non-migrants from households without migrants. A commensurate 40% gap is evident in average incomes of individuals in these two cohorts, which suggests that differences in labor force participation rates fully explain the lower earnings observed for non-migrants from households with migrants. This is also reasonably consistent with the rather compressed wage structure in Bluefields.

In Counterfactual 2, the imputed home-labor-force participation rate is 46% for erstwhile migrants and 35% for non-migrants from migrant households. Thus, the

[18] In neither counterfactual are earnings imputed for non-migrants from households without migrants. Observed earnings are used for these individuals in the income distribution analyses.

Table 6
Labor force participation and earnings: observed and imputed values

Observed	Labor market participation rates	Individual earnings (US$)
Non-migrants from		
Migrant households ($n = 304$)	37.8% (32.2–43.4)[a]	137.1 (107.0–167.2)
Non-migrant households ($n = 215$)	54.0% (47.2–60.8)	201.8 (158.7–249.9)
All ($n = 519$)	44.5% (40.1–48.6)	163.9 (138.7–189.1)
Imputed counterfactual II		
Migrants ($n = 167$)	46.3% (40.1–52.7)[b]	146.2 (120.0–174.4)
Non-migrants from migrant households ($n = 304$)	35.1% (32.6–37.5)	114.6 (99.7–130.7)

[a]These confidence intervals reflect the variation across individuals in the observed cohort of non-migrants.
[b]These confidence intervals reflect the variation of the cohort means which result from each of the iterations done in the Monte Carlo simulation procedure.

labor force participation rate of migrants is imputed to be nearly identical to the observed sample average of 44%, while that of non-migrants from households with migrants is imputed to decline from 38 to 35% with the return of other working age adults. The imputed quarterly incomes for these two cohorts are US$146 and US$115, respectively, which is considerably lower than the observed sample average of US$164 and the US$202 average for non-migrants from households without migrants. Overall, this counterfactual exercise yields a 25% increase in the labor force and a slightly larger than 25% increase in employment levels in the home market. This is accompanied by only a 9% increase in household incomes and a decline in the levels of household income per capita. Therefore, incorporating into the counterfactual the potential for variation in individual earnings estimates and for intrahousehold adjustments in labor force participation may help to reduce some of the distortion caused by not accounting explicitly for general equilibrium feedback effects of lost remittance flows and increased labor supply.

7. Gini coefficients and household incomes in the no-migration counterfactuals

The imputed earnings estimates allow the construction of Table 7 which compares the estimated means and 95% confidence intervals for the Gini coefficients and average household income in the two counterfactuals with those of the observed outcome with remittances and the 'no remittance' approach of Stark et al. (1986). Table 7 also includes these comparisons for households in per adult equivalent terms.

Table 7
Gini coefficients and income comparisons: observed vs. no remittances and no migration scenarios

Income per household	No remittances	Observed outcome with remittances	No-migration counterfactual scenario 1	No-migration counterfactual scenario 2
Gini coefficient 95% conf. interval	0.47 na	0.43 na	0.40 (0.38, 0.42)	0.38 (0.36, 0.40)
Mean income conf. interval 95%	560.0	621.1 na	717.1 (689.1, 748.3)	675.2 (634.1, 719.1)
Income per adult equivalent				
Gini coefficient 95% conf. interval	0.50 na	0.46 na	0.44 (0.42, 0.46)	0.44 (0.41, 0.46)
Mean income 95% conf. interval	127.2 na	141.0 na	137.5 (132.1, 143.8)	132.4 (125.4, 140.5)

Note first that the two no-migration counterfactuals produce Gini coefficients that are lower than the Gini for the observed income distribution with migration and remittances. In both counterfactuals, these differences from the observed Gini are statistically significant at the 5% level. [19] In the first counterfactual, the Gini coefficient declines to 0.40, a 7.5% drop from 0.43 in the observed distribution. In the second counterfactual, the Gini coefficient falls to 0.38, representing a 12% decline from the Gini for the status quo. When similar comparisons are made for household income in per adult equivalent terms, the Gini coefficient decline is smaller. It falls from 0.46 in the observed outcome to 0.44 in the two counterfactuals.

The Gini comparisons in Table 7 demonstrate the importance of choice of method on the conclusions reached. When remittances are considered as an exogenous transfer as they were in Section 4, they reduce income inequality. The Gini for household income falls from 0.47 to 0.43 when the 'exogenous' remittance component is included. In contrast, the counterfactual exercise of this section has shown that remittances, when considered as a substitute for home earnings, increase income inequality. The Gini for household income rises from 0.38 in the second no migration and remittance counterfactual to the observed Gini of 0.43.

This result can be further explored by comparing Table 8, a Gini decomposition of income distribution for Counterfactual 2, with Table 2, a Gini decomposition using the remittance as exogneous income source approach. First, in both cases, the Gini coefficient for income source (G) shows that the home earnings contributed by migrants is more equally distributed across households than is income contributed by non-migrants (e.g., in Table 8, G for home earnings imputed to migrants is 0.39 compared to 0.46 for non-migrants). Second, the share of household income (S) contributed by migrants is only 10% in the observed outcome of migration, compared with 24% the no-migration counterfactual. This is the key difference that drives the change in direction in the inequality outcome across the two methods. In the no-migration counterfactual, the effect of returning the migrants to Bluefields is to increase the earnings contributions of a group whose earnings are considerably more equally distributed in the population. Finally, the Gini correlation with total income rank (R) for migrants' home earning is only slightly different from non-migrants in the counterfactual (0.83 vs. 0.85), whereas it is considerably lower for remittances in the observed outcome (0.58 vs. 0.96). Thus, most of the reduction in inequality associated with the no migration counterfactual arises from the increased share of total income accounted for by a cohort whose income contributions are more equally distributed across households.

[19] The null hypothesis is that the counterfactual Gini's, GCF_1 and GCF_2, are equal to the observed Gini, G_0. The null is rejected if G_0 does not lie within the 95% confidence intervals for GCF_1 and GCF_2. The 95% confidence interval is constructed by taking the 25th and 975th element of the vector of 1000 simulated Ginis arranged in ascending order.

Table 8
Gini decomposition for counterfactual 2-no migration

Income source	Share in total household income (S)	Gini coefficient for income source (G)	Gini correlation with total income rank (R)	Contribution to Gini of total income (SGR)	% share in Gini of total income (SGR/G)
Migrant imputed home earnings	0.24 (0.20–0.27)	0.39 (0.36–0.42)	0.83 (0.61–1.0)	0.08	21
Non-migrant home earnings	0.76 (0.73–0.80)	0.46 (0.44–0.49)	0.85 (0.80–0.90)	0.30	79
Total income	1.00	0.38	1.00	0.38	100

As a final note, it may be disconcerting to some readers that average household income rises in the two counterfactuals, by more than 15% the first one and by nearly 10% in the second. These income figures would suggest the counter-intuitive finding that households are better off without migration, but such a conclusion would not account for the increased consumption demands placed on the household by the addition of return migrants. Indeed, comparisons of income per adult equivalent in the second counterfactual, where intrahousehold adjustments are allowed, reveals that per capita income falls by 6%, from an observed mean of US$141 per quarter to US$132 in the second counterfactual. Thus, household income adjusted for the number of adult equivalents gives the expected result that consumption opportunities are higher in the observed world of migration and remittances, even without accounting for the depressing economy-wide effects associated with a loss of remittance income.

8. Conclusion

This paper addressed the question of how migration and remittances impact the distribution of income. Income distributions under two counterfactuals of 'no migration' were compared with the observed distribution with migration and remittances. A selection-corrected earnings equation was estimated to control for the migration and labor force participation decisions in the observed earnings of non-migrants. The results were then used to impute participation decisions and earnings for migrants and non-migrants in migrant households. The study used data gathered in 1991 in Bluefields, Nicaragua, a port town with a long history of migration.

As in Stark et al. (1986), Stark (1988) and Taylor (1992), remittances reduce income inequality when the effects are measured as if remittances were an exogenous income source. However, when the observed income distribution is compared with two no-migration counterfactuals, where migration and remittances are treated as a substitute for home earnings, income inequality was found to be lower in the no-migration counterfactuals. In other words, the potential home earnings of migrants in Bluefields have a more equalizing effect than do remittances on income distribution. Whether this result would stand up to a fuller general equilibrium specification of this question is a topic for further research. Yet, the sensitivity of the inequality outcome to the choice of method suggests that future research should select the appropriate method for the comparison at hand.

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Appendix A. Descriptive statistics of regressors

Variable	Men (n = 324)		Women (n = 362)	
	Mean	Standard deviation	Mean	Standard deviation
Age	35.2	16.11	37.80	17.69
Agesq1	15.0	14.71	17.39	16.93
Educ0	0.046	0.21	0.052	0.22
Educ1	0.31	0.46	0.32	0.47
Educ2	0.40	0.49	0.31	0.46
Creole	0.73	0.44	0.72	0.45
Children	1.01	1.20	1.2	1.39
Continue	0.10	0.30	0.12	0.32
Adults	5.26	2.54	4.8	2.40
Rem 1	4.53	11.76	6.20	14.55
Dyhoh1	18.65	28.38	32.01	42.57
Hoh	0.28	0.45	0.17	0.38
Child	0.43	0.50	0.35	0.48
Sibling	0.083	0.28	0.074	0.26
Parent	0.025	0.16	0.055	0.22
Wealth1	5.85	1.95	5.91	1.99
Wealthsq1	38.0	25.92	38.88	26.34

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