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Abstract:
Whole-household migration potentially can alter the results of studies on income inequality based on panel data if it selects on household income. We model whole-household migration and its impacts on income inequality and poverty using a unique, nationally representative household panel data set from rural Mexico. Households that participate in whole-household migration and those who do not differ significantly in terms of observable characteristics; however, analyses of income and poverty based on the remaining sample are not necessarily biased. This finding is similar to those in previous research on the effects of attrition on panel data studies. We also analyze the changes in inequality and poverty due to whole-household migration and over time correcting for the effects of attrition. Our results support the migration diffusion hypothesis and underline the importance of paying attention to selective attrition in panel data studies on income distribution and poverty – especially in countries and regions with high migration rates.

Keywords: Attrition, panel data, income inequality, poverty, joint migration, Mexico

JEL classification: C23, O 15

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Introduction

The availability of panel data on individuals and households in developed countries has increased over the last forty years, contributing significantly to the quality of empirical research. Although panel data make it possible to study a range of socio-economic questions in a dynamic context, they also pose new challenges to empirical analysis due to attrition. Initial studies on attrition in longitudinal surveys focused on developed countries because of data availability (Fitzgerald et al. 1998). As more and more panel data become available for developing countries, it is critical to address attrition and attrition bias in development economics research, as well (Alderman et al., 2001; Thomas et al., 2001; Falaris, 2003; Maluccio, 2004; Baird et al., 2008).

A common form of attrition in developing countries is internal or international migration. Migration is a highly selective process, and its determinants and impacts on the income distribution in migrant sending communities have been rigorously studied in the economics literature, both theoretically and empirically (Adams, 1989; Taylor, 1992; Barham and Boucher, 1998; Adams et al., 2008; Acosta et al., 2008). Conflicting findings about the impacts of migration on income inequality and poverty may be explained by the way in which migration selects on individuals and households at different stages of the migration diffusion process (Stark et al. 1986). When migration is costly or risky, only better-off households can afford the costs and risks of sending members off as migrants. Nevertheless, poorer households can gain access to migrant labor markets as expanding networks of contacts with migrants decrease the costs and risks of migrating. Consistent with this view, a number of studies document that migrant remittances have an initially unequalizing income effect that becomes more equalizing as the incidence of migration increases (Stark et al., 1986; McKenzie and Rapoport, 2007). There has been little effort to study the impacts of migration and remittances on poverty.

Empirical research on migration and inequality mainly uses cross-sectional data and is concerned with split migration, that is, migration by individuals whose households remain in the migrant-sending area (Adams, 1989; Taylor, 1992; Barham and Boucher, 1998; Adams et al., 2008; Acosta et al., 2008; Taylor et al., 2008). Taylor (1992) and McKenzie and Rapoport (2007) are exceptions in that they use panel data, but they too study only split migration and do not investigate the effects of whole-household (i.e., joint) migration on income inequality.

Migration may alter inequality simply by removing some households from the income distribution. For example, if migration selects on whole households disproportionately from the extremes (middle) of the village income distribution, it will tend to decrease (increase) the village Gini coefficient over time, other things being equal. Moreover, if whole-household migration occurs in stages, remittances may be observed before the last household members emigrate, creating a spurious correlation between remittances and inequality. For example, it might appear that remittances increase (decrease) inequality if entire households that once received remittances disappear from the extremes (middle) of the income distribution.

We use panel data from the nationally representative Mexican National Rural Household Surveys (ENHRUM I and II)[1] to investigate how whole households are selected into migration and what this selection process implies for panel studies of income equality and poverty in migrant sending communities. While panel data make it possible to deal with most of the problems of empirical research based on cross-sectional data (McKenzie and Sasin, 2007), they also open up the possibility of biased results if attrition is ignored. No study, to our knowledge, has considered how whole-household migration may influence inequality and poverty in migrant-sending areas.

1. Attrition in panel data

The main problem with attrition in panel data stems form non-random attrition, which distorts the survey design, hence the representativeness of the data. If attrition were purely random, the results based on the remaining observations would still be unbiased and consistent. However, attrition may be selectively related to the outcome variables of interest; thus, special attention should be given to ensuring that the results of studies based on the remaining sample are unbiased and consistent (Fitzgerald et al., 1998).

Fitzgerald et al. (1998) classify attrition problems into two categories: selection on unobservables and selection on observables. Selection on unobservables occurs when there are unobserved variables that are correlated with both attrition and the outcome variable. The most widely used method to deal with this type of selection is the Heckman (1979) selection model, which relies on the existence of at least one variable correlated with attrition but not the outcome, except through attrition. Finding such a variable for models of attrition may be more difficult than in other applications, because most variables that affect attrition are also likely to enter the outcome equation (Fitzgeral et al., 1998). Data on the quality of the interview or interviewer characteristics may be candidates for exclusion restrictions as employed by Maluccio (2004) and Baird et al. (2008); however, such data are not always available.

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[1] ENHRUM is the Spanish acronym for Encuesta Nacional a Hogares Rurales de México.

Selection on observables occurs when selection depends on an observed variable that is also correlated with the outcome variable of interest, y. A common example of such a variable is a lagged outcome variable (y_{t-1}),as when starting income levels affect both attrition and later income levels. Selection on observables can be addressed with inverse probability weighting, which unlike a Heckman selection model does not require exclusion restrictions (Wooldridge, 2002).

Empirical panel data studies have mostly been based on data from developed countries that can meet the cost and infrastructure requirements of collecting large scale panel data. One of the longest running panel data sets used in empirical economics research is the Michigan Panel Study of Income Dynamics (PSID), which followed 4,800 families from 1968 to 1989 with annual surveys and covered 26,800 individuals in 1989. PSID provided information for a wide range of socio-economic characteristics but had an attrition rate of 50% by 1989. The high attrition rate motivated significant contributions to the literature on the study of panel data with attrition (Fitzgerald et al., 1998; Lillard and Panis, 1998).[2] Most research in this literature concludes that, though prevalent, attrition does not cause significant bias in statistical models estimated using panel data in rich countries.

The availability of panel data in developing countries started in the late 1980s with the World Bank LSMS project. Nowadays more and more countries and international organizations are involved in medium- to large-scale panel data projects, and the literature on attrition on panel data is expanding to developing countries (Alderman et al., 2001; Thomas et al., 2001; Falaris, 2003; Maluccio, 2004; Baird et al., 2008; Fuwa, 2011). Most of this literature agrees with the finding of panel data studies from developed countries that, while attriters and non-attriters may significantly differ from each other, empirical analyses based on the non-attriting sample are not necessarily biased due to non-random attrition.

Alderman et al. (2001) describe attrition in the Indonesia Family Life Survey (IFLS), which tracks households that move. They conclude that attrition is correlated with household size, expenditure, and migration behavior. Thomas et al. (2001) analyze attrition in panel surveys from three developing countries (Bolivia, Kenya and South Africa) and conclude that attrition is related to some household characteristics. It does not, however, significantly affect the estimated coefficients of these variables in

2 For more research on the topic see The Journal of Human Resources Special Issue on Attrition in Longitudinal Surveys, Vol. 33, No. 2, Spring, 1998.

analyzing various outcomes of interest (e.g. child development, family planning, and reproductive behavior).

Falaris (2003) conducts a detailed study of attrition in three different LSMS data sets from three countries (Peru, Cote d'Ivoire and Vietnam). He estimates a number of outcome equations (i.e. schooling, labor force participation, fertility and wages) and concludes that using data reduced by attrition would not result in biased coefficients in most of the cases. Maluccio (2004) analyzes attrition in the Kwazulu Natal Income Dynamics Study and concludes that only a few parameters in the household expenditure function based on the reduced sample are estimated with bias. Baird et al. (2008) analyze attrition (among other data quality issues) using the Kenya Life Panel Survey, Round 1, and conclude that attrition did not select individuals in any way related to their main outcome of interest, i.e., randomized de-worming intervention. This result, however, is primarily due to the great effort the survey organizers invested in tracking the individuals who moved, internally and internationally. A comparison between movers and stayers shows that these two groups differ significantly from each other along some observable characteristics.

Fuwa (2011) provides the most recent study on attrition in panel data in developing countries focusing on household relocation in the rural Philippines. While the main conclusion in this study agrees with the previous findings in the literature, it presents evidence of selective migration. This paper emphasizes the importance of paying special attention to different types of migrants in studies of well-being that employ panel data.

These studies underline the importance of understanding the effects of attrition on outcome variables of interest and controlling for its effects in statistical analyses based on data from less developed countries, especially in migration prone areas. Although most find that attrition is correlated with migration behavior and incomes, none explicitly analyze the effects of whole-household migration on income inequality and poverty. These studies' focus is on whether or not attrition biases parameter estimates related to micro behavior in the non-attriting population. Income inequality and poverty, however, are aggregate outcomes that may be affected more directly by the selective removal of individuals or households.

The question of how migration affects income distribution over time is inherently subject to the problem of selection on observables if some households leave the sample and migrate between the different rounds of data collection. The migration diffusion hypothesis suggests that household income is closely related to migration decisions. Pioneer migrant households are likely to be from the upper part of the income distribution; however, as migration spreads and the costs and risks of migration decrease, poorer households may also be able to afford migration (Stark et al., 1986). At the extreme, whole households may migrate for reasons related to their income, a case of selection on observables. We present a stylized model of whole-household migration in the next section, before analyzing whole-household migration as a case of selection on observables in the ENHRUM data and demonstrating its effects on the study of inequality and poverty.

2. Modeling whole-household migration

Most contemporary research on migration in low and medium income countries assumes that, rather than being entirely the domain of individuals, migration decisions take place within a larger context—typically the household, which potentially consists of individuals with diverse preferences and differential access to income. Continuing interactions between migrants and rural households, including migrant remittances, underpin this assumption. A wealth of econometric studies find that household as well as individual characteristics significantly explain migration by individual family members, and migration has important feedbacks on the economies of the households and communities migrants leave behind (Massey, et al., 2005; Taylor and Martin, 2001).

Viewed from this perspective, the migration of whole households can be modeled as an extreme outcome in which it is optimal for all household members to migrate. In the simplest household migration model, a household allocates its family members' time to migration (*m*) and non-migration (*0*) activities in order to maximize household welfare or utility, subject to a household budget constraint represented by the sum of individual family members' net contributions to household income, y_i:

$$\max U(C,L)$$
$$\textit{subject to } C \leq \sum_i y_i$$

Under the usual assumptions of household models (Singh, Squire and Strauss, 1986; Taylor and Adelman, 2003), the logic of maximizing utility implies maximizing income. This is always the case in a separable or recursive model, which implies well functioning markets. In the imperfect market environment characterizing most migrant-sending areas, utility maximization does not necessarily imply full income maximization; for example, there may be tradeoffs between production and leisure or between income activities and subsistence production (see Taylor and Adelman, 2003). If households are risk averse and lack access to income insurance, there also may be a tradeoff between expected income and risk (Rosenzweig and Binswanger, 1994, provide a textbook example of risk-expected return tradeoffs and their welfare implications). Timing and liquidity constraints may create tradeoffs between consumption and production (e.g., feeding family members at planting time, versus spending scarce liquidity on fertilizer that would improve crop yields). All of these considerations add complexity to the model, usually causing the separability of production and consumption to break down. Moreover, all potentially may be affected by migration. A considerable amount of theoretical and empirical research over the past three decades explores potential positive effects of migration on production, as remittances (or the promise to remit in the event of adverse income shocks) loosen investment and risk constraints, or the negative effects, if substitutes for the migrants' lost labor are not available (e.g., see Taylor and Martin, 2001 and reprinted articles in Stark, 1991).

Family member *i*'s contribution to household utility depends on her migration status. If family members are sorted between migration and non-migration activities so as to maximize household welfare, then household utility, U, is the higher of u_{0i}, the utility if person *i* does not migrate, and u_{mi}, utility if the person migrates. Then:

$$U = \begin{cases} u_{mi} \ \mathit{if} \ u_{mi} > u_{0i} \\ u_{0i} \ \mathit{otherwise} \end{cases} \tag{1}$$

The switching migration regime depicted in (1) is not trivial, because the departure of any individual family member may influence the net income contributions and other determinants of the utility of other family members, both as migrants and non-migrants. Thus, even in the simplest separable household model, (1) represents a complex simultaneous equation system in which the explanatory variables include the migration and income outcomes of all other family members. One can simplify the model considerably by considering its reduced form, in which utility with and without migration depends on a vector of variables, *x*, that explain household utility in each migration regime, including household demographics, assets, and the human capital of each family member. In the simplest case, household utility is a linear function of these explanatory variables; that is,

$$u_{mi} = \alpha_m + \beta_m x + \varepsilon_{mi} \ \ \mathit{and} \ \ u_{0i} = \alpha_0 + \beta_0 x + \varepsilon_{0i} \quad \mathit{for} \ \ i = 1, ..., I \ \ \mathit{members}$$

where ε_{mi} and ε_{0i} are stochastic errors. Migration by person *i* is observed, then, if

$$u_{mi} > u_{0i}$$

implying

$$\alpha_m + \beta_m x + \varepsilon_{mi} > \alpha_0 + \beta_0 x + \varepsilon_{0i}$$

The probability of whole-household migration, then, is given by:

$$\begin{aligned} &P(\varepsilon_{0i} - \varepsilon_{mi} < \alpha_m - \alpha_0 + (\beta_m - \beta_0)x) \quad for\ \ all\ \ i\ \ in\ \ the\ \ household \\ &= F(\alpha_m - \alpha_0 + (\beta_m - \beta_0)x) \end{aligned} \tag{2}$$

This probability can be modeled empirically using a probit regression under the assumption that the errors are approximately normally distributed as $(0, \sigma_m^2)$ and $(0, \sigma_0^2)$, respectively. The mirror image of this probit regression, i.e., predicting the probability of non-attrition, corresponds to the first step in correcting further analyses (e.g., on income inequality or poverty) using inverse probability weights as in Wooldridge (2002). Before analyzing the changes in income inequality and poverty in rural Mexico between 2002 and 2007, we discuss the extent of attrition (whole-household migration) in the ENHRUM panel and test whether it appears to be non-randomly correlated with these outcomes.

3. Whole-household migration in ENHRUM data

3.1. Data

ENHRUM I and ENHRUM II surveys were conducted at the beginning of 2003 and 2008, respectively, and the original sample covers 1,765 households in 5 regions, 14 states and 80 communities. INEGI, Mexico's national information and census office, designed the survey frame to provide a nationally and regionally representative sample of Mexico's rural population.[3] The original sample is representative of more than 80 percent of the population in rural Mexico.[4]

Although the ENHRUM sample was designed to be representative of rural Mexico's population, this representativeness may not be guaranteed in the panel if attrition is significant and non-random. During the second round of data collection, the surveyors were instructed to locate and re-interview the households in the first panel as best as they could; however, this was not possible when all members of a household migrated and could not be tracked. If whole-household migration is correlated with income, analyzing changes in the income distribution and poverty without paying attention to attrition may result in inconsistent estimates.

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[3] INEGI is the Spanish acronym for Instituto Nacional de Estadística, Geografía e Informática.

[4] The survey covers communities that have between 500 and 2,500 inhabitants. For reasons of cost and tractability, communities with fewer than 500 inhabitants were not included in the survey.

There were 212 cases of whole-household migration between the two survey years, representing 12% of the base-year sample. This is at the lower end of attrition rates in panel data from developing countries, which range from 6% to 50% (Alderman et al., 2001). Table 1 shows the distribution of the households that left the sample after 2003 across five census regions defined by INEGI. The two highest attrition regions are those bordering the United States: almost 45 percent of attrition cases are in the Northeast and 17 percent in the Northwest. The West Central region is the highest international migrant-sending region in Mexico; 41% of households in this region had at least one migrant in the U.S. in 2002; however, the incidence of whole-household migration from this region is less than that of the South-Southeast, which has the lowest migration incidence of all regions (9.8% of households there had at least one U.S. migrant in 2002).

Table 1. Number of households that attrited and percentages across regions

Region	Observations	Percentage
South-Southeast	33	15.57
Central	14	6.60
West Central	32	15.09
Northwest	37	17.45
Northeast	96	45.28
Total	**212**	**100.00**

Table 2 compares the averages of total per capita income, income sources, household and village characteristics of the households that migrated wholly between 2002 and 2007 (attriters) and those that did not (non-attriters). Although total per capita income is not significantly different between these groups, there are some significant differences in income sources. Attriters have significantly higher per capita livestock and transfer income, as well as lower average per capita income from farm wages. The differences between the two groups in terms of other income sources are not statistically significant.

Attriter households have significantly smaller household sizes and their heads are significantly more likely to be younger than 30 years and older than 60 years old. It is interesting to note that attriters have significantly smaller proportions of their total land under irrigation and are less likely to have ejido plots. It appears that tenure security may still be an important variable in households' migration decisions in spite of the wide-ranging land certification program (PROCEDE), which reformed the ejido system in 1992. Other household characteristics, i.e., average age of the household head, average schooling, and average land owned do not differ significantly between the two groups.

Attriters also differ significantly from non-attriters with regard to their village characteristics. They come from villages where a larger share of households had US migrants and smaller share had internal migrants, suggesting that most of the attriters may have moved to the US if migrant networks decrease the costs and risks of migration as suggested by theory. The average attriter is more likely to come from a village with a secondary school and clinic.

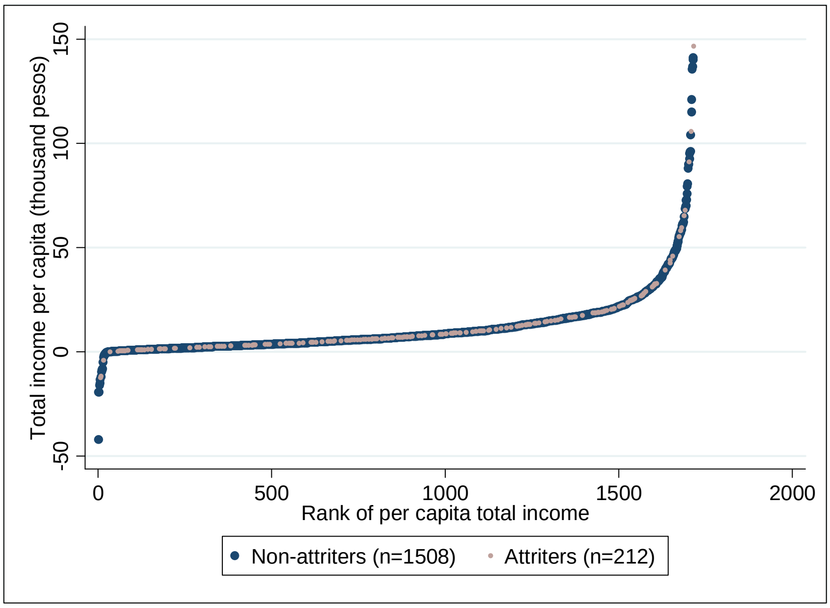
Table 2. Income household and village characteristics by attrition status

	Variable	**Non-attriters**	**Attriters**	**Signif.**
Income Variables	Total income	11,785.94	13,870.47	
	US remittances	1,025.42	1,517.78	
	MX remittances	217.47	325.19	
	Crop income	1,719.19	1,683.09	
	Livestock income	392.24	1,449.56	**
	Farm wages	1,472.09	966.40	**
	Non-farm wages	4,236.47	4,804.05	
	Off-farm income	1,651.59	1,405.75	
	Transfer income	1,071.48	1,718.65	**
Household Characteristics	Household size	4.66	3.35	***
	Number of adults	3.04	2.23	***
	Number of children	1.63	1.13	***
	Age of head	49.49	48.92	
	Young head (<30 yrs.)	0.09	0.18	***
	Old head (>60 yrs.)	0.24	0.31	**
	Avg. household education	5.42	5.20	
	Area owned	3.68	2.94	
	Irrigated area as % of total	0.11	0.08	*
	Ejido Dummy	0.37	0.23	***
Village Characteristics	Village US migrant netw.	23.18	28.00	***
	Village MX migrant netw.	39.07	31.19	***
	Secondary school	0.68	0.74	*
	Clinic	0.61	0.69	**
	Observations	**1508**	**212**	

Note: *, ** and *** indicate that the difference between groups is significant at the 10%, 5% and 1% levels respectively.

How attrition affects income inequality depends critically on where the attriters stood in the base-year income distribution. The average per capita income rank of attriters in the whole sample is significantly higher than that of non-attriters (920 vs. 853); however this difference is significant only at the 10 per cent level. Figure 1 shows the per capita total income ranks for both groups in 2002. Attriters are not concentrated at the top nor bottom of the total-income distribution but are distributed all along the income spectrum. This makes it difficult to assess ex ante how their disappearance in the second panel might affect income inequality, poverty, and the changes in both over time. For this, a theoretical and empirical model of attrition is needed.

Figure 1. Rank of per capita total income (in 000's) by attrition group



The distribution of the incomes of attriters and non-attriters may be different in regions at different stages of their migration diffusion curves. The West Central region has had the highest international migration incidence, followed by the Northeast, Central and Northwest regions (Taylor et al. 2008). Although the South-Southeast region has the lowest international migration incidence, it has the highest internal migration incidence and has also been recording the highest increase rates of international migration (Arslan and Taylor, 2010).

Table 3 shows the average incomes and income ranks for attriters and non-attriters by region. Attriters have higher per capita income than non-attriters in all regions except the Northwest and Northeast, though this difference is not statistically significant. Attriters also have a higher ranking on the regional income scale as compared to non-attriters except in the Northeast. These observations provide some understanding for the differences between attriters and non-attriters, however, they are only based on unconditional means. We model the attrition behavior using a multivariate probit model in the next section.

Table 3. Average income and income ranks by attrition group

	Average income		Income rank	
Region	**Non-attriters**	**Attriters**	**Non-attriters**	**Attriters**
South-Southeast	5,963.8	7,632.7	182.1	198.0
Central	8,203.2	11,065.9	175.5	188.5
West Central	11,780.5	13,703.4	172.3	169.1
Northwest	18,730.5	17,171.5	162.5	175.5
Northeast	16,570.3	15,207.1	169.4	161.2
Total	**11,785.9**	**13,870.5**	**172.8**	**172.4**

3.2. Empirical model of attrition in ENHRUM

We use the ENHRUM panel data to estimate a probit regression corresponding to equation (2). The vector of explanatory variables includes physical, human and migration capital, as well as community variables from the ENHRUM community surveys. All explanatory variables are created using data from ENHRUM I, prior to the attrition period. Physical capital variables include the assets measured by a composite index of household assets (except land) and dwelling characteristics, the amount of land owned by the household, the percentage of irrigated land, a dummy variable indicating households that have ejido land, and a dummy variable indicating households that have wage income.[5] Human capital variables include the number of adults and children, indicators of whether the household head is younger than 30 or older than 60 years old, and the average years of education in the household. Migration capital is measures at two levels: household and village. The household variable is the number of migrants in the US and in other parts of Mexico. The village variable is defined as the percentage of households in the village with at least one migrant in the US or in other parts of Mexico, respectively. Finally, the community variables include indicators of the existence of a secondary school and a clinic in the community.

[5] The asset index is created using Principal Components Analysis based on information on household's ownership of a house, their dwelling's characteristics (e.g. number of rooms, availability of running water, electricity and phone line) and the values of business assets, farm and home machinery, and livestock.

Table 4 reports the results of the probit regressions for attrition. The aforementioned differences between regions in terms of their migration experiences may result in differences in the way explanatory variables affect attrition. Some of the regional dummies in the regression for the whole sample (first column) are significant. We also run a separate regression for each of the 5 regions to test whether their attrition processes differ beyond a simple shift. The standard errors are clustered at the village level to control for potential error correlation across households within a village.

Per capita total income is not significantly correlated with the probability that a household migrates. More asset holdings are negatively correlated with attrition only in the Northwest region, and land holdings are negatively correlated with attrition only in the South-Southeast region. The share of the land area that is irrigated, however, affects attrition positively in this region. Most of the human capital variables are consistently significant both nationwide and regionally. The number of adults and children significantly reduce the probability of whole-household migration, and having a household head that is younger than 30 years old increases it significantly. The average education of all household members does not significantly affect attrition in the whole sample. In the Northwest region, however, households with higher average education are more likely to attrit.

Only international migrant networks affect attrition significantly. Larger US migrant networks increase the probability of whole-household migration slightly in the whole sample. This effect mainly reflects the linkages between whole-household migration and US migrant networks in the West Central and Northwest regions. Although we do not have data on where the attriters have migrated to in ENHRUM surveys, these results suggest that the attriters are more likely to have migrated to the US than to other parts of Mexico at least in these regions. The effect of US migrant networks is not significant in other regions. Community variables do not affect attrition significantly in the whole sample; however, attriters are more likely to come from villages that have a clinic in the South-Southeast region.

Table 5. **Probit results for attrition equations (marginal effects reported)**

	Probit			IV Probit (Bootstrapped)		
p(attrition)	**Household migrants**	**Village networks**	**Both**	**Household migrants**	**Village networks**	**Both**
Asset index	-0.006	-0.009	-0.008	-0.011	-0.008	-0.006
Wage D	-0.034*	-0.033*	-0.032*	-0.033	-0.033*	-0.058
Land (ha.)	-0.001	0.000	0.000	-0.001	-0.001	-0.001
% irrigated	0.008	0.013	0.012	0.011	0.011	0.023
Ejido D.	-0.043**	-0.043**	-0.042**	-0.044***	-0.043***	-0.048**
Adults	-0.032***	-0.032***	-0.031***	-0.033***	-0.031***	-0.036***
Children	-0.010*	-0.010**	-0.010*	-0.01	-0.010*	-0.017
Head <30	0.069**	0.068**	0.072**	0.063	0.068**	0.024
Head>60	0.023	0.03	0.025	0.036	0.027	0.09
Average educ.	0.000	0.000	0.000	0.000	0.000	-0.004
Secondary school	0.005	0.005	0.005	0.005	0.004	0.005
Clinic	0.014	0.005	0.005	0.009	0.009	0.015
Central	-0.053**	-0.058***	-0.058***	-0.056***	-0.057***	-0.049*
West Central	0.006	-0.02	-0.021	-0.01	-0.012	0.007
Northwest	0.032	0.005	0.005	0.02	0.017	0.018
Northeast	0.154***	0.104**	0.104**	0.124**	0.126*	0.123
HH US Migs.	0.001		-0.001	0.018		-0.021
Hh MX Migs.	0.003		0.006	-0.012		-0.066
Vil US mig. %		0.000	0.000		0.000	0.000
Vil MX mig. %		-0.001	-0.001*		0.000	0.001
Observations	**1720**	**1720**	**1720**	**1720**	**1720**	**1720**

The attrition regressions above may be subject to endogeneity bias due to the migrant network variables. If there is an unobserved variable (e.g., a weather shock) that is both correlated with the village migrant networks in the base year and attrition, then the error terms in the simple probit regressions will be correlated with the explanatory variables, resulting in biased estimated coefficients. We ran the same probit regressions using instruments for the potentially endogenous village network variables.[6] We use data on GDP per capita in the destination states (both in the US and Mexico) to construct instruments for village networks similar to those in Orrenius et al. (2009). Our IVs are weighted averages of GDP growth in migrant destination states over the 5 years following the first round of the survey. We use the share of migrants from each village (*v*) in each state (*j* and *k*) in 2002 as weights, where *j* and *k* are indices for all states in the US and Mexico, respectively, to create the IVs as follows:[7]

$$\begin{aligned} IV_{v,US} &= \sum_{j=1}^{51} Share\,Migs_{vj} \times GDPgrowth_j^{02-06} \\ IV_{v,MX} &= \sum_{k=1}^{32} Share\,Migs_{vk} \times GDPgrowth_k^{02-06} \end{aligned} \tag{3}$$

We argue that the changes in the GDP of the states where migrants of a village started out in 2002 affect whole-household migration only through their influence on migration networks. We report the results of the attrition regressions using these instruments in Table 6. These regressions are carried out using the `divprob` command in Stata 10. This program does not provide detailed diagnostics for instrumental validity; therefore we also run the regressions with a linear probability model (LPM) using two-step GMM estimation with robust standard errors (`ivreg2` with `gmm2s` option in Stata 10, as explained in Baum et al., 2007) in order to test for instrumental validity. The results of these tests are reported in appendix Tables A1 and A2.[8] Table A1 reports the coefficients of the IVs in the first step regressions, indicating that the IVs are rightly correlated with the endogenous variables. We reject under- and weak identification and fail to reject the hypothesis that the orthogonality conditions are valid (Table A2). Moreover, the Wald test results reported at the bottom of Table 6 show that the error terms of the first step regressions do not contain extra variation that is correlated with attrition; hence, the IVs are

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[6] The income variable can also be potentially endogenous for similar reasons. We ran both sets of regressions (without and with IVs) excluding the per capita income variable that treats the remaining physical capital variables as a reduced form indicator of wealth. The coefficients of the non-IV regressions showed some difference from the results in Table 5, however, all coefficients were virtually the same after instrumenting for the network variables. Therefore, we present the results that include the income variable following the the literature on attrition in panel data (Thomas et al., 2001; Maluccio, 2004).

[7] We thank Pia Orrenius for providing us with historical data on GDP, unemployment and other economic indicators for all US states. State level Mexican GDP data is obtained from INEGI: http://dgcnesyp.inegi.org.mx/cgi-win/bdieintsi.exe/NIVR150070#ARBOL

[8] We also tried using historical village level migration networks (in 1990) based on the migration histories of households as IVs. This experiment did not change the main results significantly; therefore we only report the results using the weighted GDP growth IVs, because we think that their exogeneity is more intuitive, besides being valid based on the diagnostic tests presented in the appendix Table A2.

exogenous to the attrition equation. Based on these test results, we conclude that our instrumental variables are reasonably valid.

After instrumenting, the coefficient on the US migrant network becomes insignificant in all instances where it was significant before (i.e., the whole sample, West Central and Northwest regions), indicating that there was an omitted variable in the error term that was positively correlated with the US network. The US migration network in the South-Southeast region, however, becomes significant after instrumenting, making this the only region where whole-household migration is significantly affected by US migrant networks. All other results in Table 6 are very similar to the un-instrumented results in Table 5. We find that attrition is significantly correlated mainly with the human capital variables and with land and asset ownership in some regions. Inasmuch as these variables are significantly correlated with income, analyses of outcome variables based on household income (e.g. inequality and poverty) without correcting for attrition may be biased.

Fitzgerald et al. (1998) suggest a formal test to identify whether attrition would introduce a significant bias in the analyses based on the remaining sample. This procedure includes estimating the outcome regression of interest (income and poverty in our case) using covariates from the first round, a dummy variable identifying whether the household attrited in the second round and the interactions of this dummy variable with all covariates. The test for attrition bias then is the joint significance test for all attrition interactions. If they are significant, this would mean that attriters had different behavioral patterns from non-attriters before leaving the sample, and hence, analyses of outcome variables based on non-attriting sample should be corrected for attrition.

We test for attrition bias as suggested by Fitzgerald et al. (1998) using both income and poverty regressions. We estimate the income regressions using Least Absolute Deviation (LAD) method because the total income is negative for 33 households and its distribution is right-skewed. After inspecting the data thoroughly, we decided that these are legitimate negative incomes rather than measurement or typographical errors. A common procedure to estimate skewed income regressions is to do a logarithmic transformation, which excludes negative incomes. LAD is another method to decrease the effect of outliers on the estimated coefficients. We chose the LAD specification in order to not to loose observations with negative incomes.

Table 7. FGT tests for attrition bias for income and poverty outcomes

	Income (IV-LAD)				Poverty (IV-probit)			
	Coeff.	Std.	[95% Conf. Interval]		Coeff.	Std.	[95% Conf. Interval]	
Attriter (A)	6,744.60	5,706.91	-5,237.23	16,632.47	-0.91	1.01	-2.65	1.18
A*Land	795.39	598.80	353.86	3,132.32	-0.02	0.04	-0.12	0.02
A*% irrigated	-1,179.20	4,569.24	-5,618.54	5,285.06	0.31	0.50	-0.67	1.44
A*Adults	-24.72	1,028.48	-2,009.21	1,947.46	0.07	0.13	-0.15	0.38
A*Children	-1,264.48	670.03	-2,531.30	-484.76	0.18	0.11	-0.14	0.38
A*Head age	-123.41	70.99	-225.82	8.79	0.01	0.01	-0.01	0.03
A*Avg. educ.	-9.95	363.60	-530.02	1,117.79	0.02	0.06	-0.08	0.13
A*Off-farm D.	-397.55	1,990.91	-3,359.90	2,486.48	-0.37	0.30	-0.89	0.42
A*US mig netw.	27.34	52.66	-26.87	140.46	0.01	0.01	0.00	0.03
A*MX mig netw.	-11.02	72.89	-127.53	98.45	0.00	0.01	-0.02	0.03
US mig. netw.	54.07	14.89	21.29	72.71	-0.01	0.00	-0.02	0.00
MX mig. netw.	-23.26	33.71	-102.83	30.59	0.00	0.01	-0.01	0.02
Land	76.06	45.62	11.65	140.07	-0.01	0.01	-0.02	0.00
% irrigated	1,734.58	823.43	223.51	3,194.87	-0.12	0.14	-0.33	0.26
Adults	-246.76	161.84	-559.28	29.22	0.05	0.03	-0.01	0.10
Children	-880.21	106.37	-1,093.41	-706.01	0.17	0.02	0.13	0.23
Head age	39.69	25.35	9.34	96.69	-0.01	0.00	-0.01	0.00
Average educ.	449.12	103.37	194.04	583.09	-0.05	0.02	-0.08	-0.01
Off-farm Dummy	2,814.23	444.34	2,143.89	3,400.22	-0.58	0.08	-0.71	-0.43
Central	911.91	517.67	110.35	1,965.54	-0.21	0.12	-0.41	0.05
West Central	977.02	986.94	-905.93	2,810.35	-0.34	0.19	-0.65	0.05
Northwest	5,059.51	1,044.18	3,441.16	7,166.74	-0.79	0.17	-1.10	-0.46
Northeast	988.49	1,222.91	-1,022.92	3,801.65	-0.26	0.24	-0.70	0.26
Constant	1,579.28	1,898.24	-2,874.87	4,998.41	0.98	0.48	0.12	1.95
p- value of the F-test for the significance of attrition interactions				0.62				0.76

We classify households as "poor" if their per capita income is below the per capita food poverty line publicized by the Mexican National Council for Social Development Policy Evaluation (CONEVAL).[9] Both income and poverty regressions are estimated using a two-step instrumental variables approach in order to account for the potential endogeneity of the migration network variables. The instrumental variables are the same as defined in equation (3) above, except that the GDP growth in

[9] CONEVAL is the Spanish acronym for El Consejo Nacional de Evaluación de la Política de Desarrollo Social. See www.coneval.gob.mx/contenido/med_pobreza/3488.xlsx for data on poverty lines.

destination states is for the 5 years preceding the first round of the survey rather than following it. This is because of the fact that the outcome variables in income and poverty regressions are expected to depend on historical networks, rather than networks after the first round as in the case of attrition. The results of these regressions for the whole sample are presented in Table 7. The standard errors are bootstrapped and the confidence intervals presented are bias corrected.

We fail to reject the hypothesis that the coefficients of attrition interactions jointly equal to zero in both income and poverty regressions. We conclude that attriters are not significantly different from non-attriters in terms of their income generating functions and their probabilities of being poor. We also conducted the same tests for each region separately, and similarly fail to reject the null hypothesis that attriters and non-attriters are not significantly differ from each other. This result is similar to most research in the attrition literature that concludes that although attriters and non-attriters may be significantly different from each other based on some observables, the analyses relying on the remaining sample in panel studies need not be biased (Alderman et al., 2001; Thomas et al., 2001; Falaris, 2003; Maluccio, 2004; Baird et al., 2008). Nonetheless, we pay special attention to attrition in our analyses of the changes in income distribution and poverty in the next section, in order to see the effects of whole-household migration on these outcomes in rural Mexico between 2002 and 2007.

4. Attrition and changes in inequality and poverty

The central question of this section is how the Gini coefficients, poverty indices and their change over time are affected by whole-household migration. Following Wooldridge (2002), we use inverse probability weighting to correct both inequality and poverty indices for attrition.

4.1. Attrition and inequality: We first calculate the Gini coefficients for both years using the whole sample available in each round. We then calculate the Gini coefficients in 2002 only for those households that remained in the sample to analyze how attrition affected the change over time in the income distribution (Table 8).

Table 8. Gini coefficients and changes in inequality

Region	2002 - Whole sample	2002 - Without attriters	2007	Change due to attrition	Change for non-attriters	Total change 02-07
South-Southeast	0.56	0.55	0.54	-0.002	-0.01	-0.02
Central	0.54	0.54	0.59	-0.001	0.05	0.05
West Central	0.56	0.55	0.57	-0.017	0.02	0.01
Northwest	0.50	0.51	0.54	0.017	0.03	0.04
Northeast	0.56	0.61	0.51	0.045	-0.10	-0.05
Total	**0.57**	**0.60**	**0.56**	**0.029**	**-0.04**	**-0.01**

For the whole sample, the Gini coefficient decreased by 0.04 points for the group of households that are in both samples. The initial impact of attrition was to increase inequality by 0.03 points for the 2002 sample. If we had ignored attrition, we would have concluded that the inequality had decreased less than it really did (0.01 points). The inequality increasing effect of attrition is biggest in the Northeast region, which has the highest attrition rate and has a high incidence of international migration. Northwest region is the next highest attrition region and it also saw inequality increase due to attrition. Attriters seem to come from the middle parts of the income distribution in these regions. Inequality decreased by 0.1 points over time for the remaining sample in the Northeast, while it increased by 0.03 points in the Northwest region.

In the South-Southeast, Central and West Central regions, attrition decreased income inequality. South-Southeast and Central were traditionally less migration intensive regions, whereas Western Central region has the highest migration intensity. The households that left the sample in the South-Southeast and Central regions had both higher average per capita incomes and were ranked higher in the regional income scale (Table 3), supporting the migration diffusion hypothesis. Although attrition decreased the Gini coefficient by a larger magnitude in Western Central region, attriters had more or less the same average income and income ranks as non-attriters in this region.

For the remaining sample in the South-Southeast region inequality decreased over time such that we would have overestimated the decrease, had we ignored the effect of attrition. Whereas ignoring attrition would not have an effect on the conclusion about the change in inequality over time in the Central region, it would have caused us to underestimate the increase in inequality in the West Central region given that attrition decreased it to begin with. These results demonstrate how the effect of ignoring attrition on the analyses of the changes in the income distribution depends on where households that left the sample stood in the first year of the survey.

4.2. Attrition and poverty: In the last part of the paper, we conduct a similar analysis in order to understand the effects of attrition on the changes in poverty over time. We use the food poverty line of CONEVAL mentioned above to calculate the Foster-Greer-Thorbecke (FGT) headcount index of poverty (Table 9). Around 30% of all households in the ENHRUM sample are considered poor based on this poverty index in both years. This ratio is the highest in the South-Southeast region and the lowest in the Northwest region with 62% and 20% of the households under the poverty line, respectively.

Table 9. FGT poverty headcount indices and changes in poverty

Region	2002 - Whole sample	2002 - Without attriters	2007	Change due to attrition	Change for non-attriters	Total change 02-07
South-Southeast	0.62	0.63	0.53	0.013	-0.10	-0.08
Central	0.51	0.50	0.46	-0.003	-0.04	-0.04
West Central	0.36	0.36	0.34	-0.001	-0.02	-0.02
Northwest	0.20	0.21	0.24	0.009	0.03	0.04
Northeast	0.21	0.23	0.20	0.022	-0.03	-0.01
Total	**0.30**	**0.34**	**0.31**	**0.038**	**-0.03**	**0.01**

In the sample as a whole, poverty headcount increased by 4 percentage points due to attrition indicating that mostly households above the poverty line engage in whole-household migration. Poverty decreased by 3 percentage points for the remaining sample. If the effect of attrition was ignored, we would have concluded that poverty had actually increased by 1 percentage point. Over the 5 years spanned by our data, poverty headcount ratios decreased by varying degrees in all regions except in the Northwest, with the biggest decreases recorded in the South-Southeast region (10 percentage points).

As in the case of inequality, the impact of attrition on poverty is the biggest in the Northeast region with an increase of 2 percentage points. Attrition increased poverty headcount in South-Southeast and Northwest regions as well, indicating that mostly non-poor households can afford whole-household migration in these three regions. In the Central and West Central regions, on the other hand, poverty headcount decreased slightly with attrition, suggesting that the costs (and risks) of migration are low enough to enable even some poor households to migrate wholly. Overall, the poverty headcount ratio in the remaining sample decreased by a larger magnitude compared to the changes due to attrition in all regions (except in the Northwest). We would have slightly underestimated this decrease in poverty in rural Mexico had we not accounted for attrition. In the Northwest region, on the other hand, we would have overestimated the increase in poverty given that attrition had increased the poverty headcount ratio to begin with.

5. Conclusions

Attrition in panel data may introduce bias in the analyses based on the remaining sample if attrition probabilities depend on the outcome variables of interest. We formally model whole-household migration and test whether households that participate in whole-household migration and those that do not differ significantly in terms of their income generating functions and poverty probabilities using panel data from rural Mexico. Using a novel set of instruments for migrant networks, we show that although these two groups differ from each other significantly along some human capital variables, their behavioral income generation coefficients do not differ significantly. These results are robust to different functional form specifications and instruments, and hold both nationally and regionally. We conclude that analyses of income and poverty based on panel data reduced by attrition need not be biased in the ENHRUM sample.

We also analyze the effects of attrition on the changes in income distribution and poverty in rural Mexico between 2002 and 2007. We find that attrition increased both inequality and poverty in the whole sample, with heterogeneous effects across regions. Attriters in the South-Southeast region come from the top of the income distribution, hence inequality decreases and poverty increases in the remaining sample due to attrition. The opposite happens in the northern regions that are also the most attrition prone areas, where attriters come from the lower and middle parts of the income distribution with an inequality increasing effect. Poverty also increases due to attrition in these regions, suggesting that households in the middle of the income distribution (above the poverty line) are more likely to engage in whole-household migration.

These results provide supporting evidence for the migration diffusion hypothesis from the point of whole-household migration. To our knowledge, there are no other studies in the literature that test this hypothesis for the case of whole-household migration, or that analyze the effects of attrition on income distribution and poverty. Our results also underline the importance of paying due attention to attrition in studies based on panel data from developing countries, especially in migration prone areas.

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APPENDIX:

Table A1. Coefficients of the excluded IVs and the R-squared of the first steps of the ivprobit

	All		South-SE		Central		West Central		Northwest		Northeast	
	Coef.	**p-val**	**Coef.**	**p-val**	**Coef.**	**p-val**	**Coef.**	**p-val**	**Coef.**	**p-val**	**Coef.**	**p-val**
Dep var: US migrant network												
Weighted MX state growth rate	39.69	0.33	672.18	0.00	-82.53	0.47	-868.09	0.00	-192.83	0.00	971.80	0.00
Weighted US state growth rate	864.14	0.00	1259.83	0.00	1108.65	0.00	-36.40	0.84	1339.97	0.00	-56.11	0.57
Adj. R-squared	0.72		0.76		0.88		0.78		0.82		0.89	
Dep var: MX migrant network												
Weighted MX state growth rate	477.33	0.00	371.36	0.00	2281.02	0.00	485.21	0.00	18.78	0.71	712.02	0.00
Weighted US state growth rate	20.43	0.62	-36.48	0.58	605.54	0.00	-585.31	0.00	-43.61	0.67	-27.20	0.67
Adj. R-squared	0.86		0.92		0.93		0.97		0.87		0.86	

Note: Coefficients of other right hand side variables are not reported. All control variables in table 6 are included in the first stage regressions as well.

Table A2. Instrumental Validity tests from 2-step GMM Linear Probability Models for attrition with robust SEs (Summary results for first-stage regressions of `ivreg2` routine in Stata)

		All	South-SE	Central	West Central	North-west*	North-east*
First stage regressions		P-val.	P-val.	P-val.	P-val.	P-val.	P-val.
US mig. network: F-test of joint significance for IVs		0.000	0.000	0.000	0.000	0.000	0.000
MX mig. network: F-test of joint significance for IVs		0.000	0.001	0.000	0.000	0.000	0.000
Underidentification test							
Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified)							
Ha: matrix has rank=K1 (identified)		P-val.	P-val.	P-val.	P-val.	P-val.	P-val.
Kleibergen-Paap rk LM statistic.	Chi-sq(1)=142.63	0.000	0.003	0.000	0.000	0.000	0.000
Kleibergen-Paap rk Wald statistic.	Chi-sq(1)=196.84	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification test							
Ho: equation is weakly identified							
Kleibergen-Paap Wald rk F statistic**		86.87	5.97	31.17	9.23	18.61	36.07
Weak-instrument-robust inference							
Tests of joint significance of endogenous regressors B1 in main equation							
Ho: B1=0 and overidentifying restrictions are valid		P-val	P-val	P-val	P-val	P-val	P-val
Anderson-Rubin Wald test.	F(2,1697)=0.69	0.795	0.095	0.773	0.915	0.744	0.998
Anderson-Rubin Wald test.	Chi-sq(2)=1.39	0.793	0.084	0.764	0.911	0.728	0.998
Stock-Wright LM S statistic.	Chi-sq(2)=1.38	0.794	0.091	0.767	0.912	0.730	0.998

Notes: * The regressions for Northeast and Northwest regions include village local migrant networks in 1990 as an additional IV to avoid underidentification otherwise.

** The critical values of the Kleibergen-Paap rk F Statistic are 4.58 and 7.03 for 15% and 10% maximal IV sizes, respectively.