ECONOMIC RECORD

THE ECONOMIC SOCIETY OF AUSTRALIA

THE ECONOMIC RECORD, VOL. 88, NO. 282, SEPTEMBER, 2012, 425–439

Assessing the Poverty Impacts of Migrants' Remittances Using Propensity Score Matching: The Case of Tonga*

ELIANA V. JIMENEZ-SOTO
School of Population Health, University of Queensland, Herston, Queensland, Australia

RICHARD P. C. BROWN
School of Economics, University of Queensland, St. Lucia, Queensland, Australia

We estimate the impacts of remittances on poverty in Tonga, a poor Pacific island country highly dependent on migrants' remittances. Using household survey data, we apply Propensity Score Matching (PSM) to estimate without-remittances incomes of migrant households from which counterfactual poverty rates are derived. We compare these with poverty rates from observed income including remittances to gauge their effects on poverty. We find that remittances reduce the incidence of poverty by 31 per cent and depth of poverty by 49 per cent. The results are robust both to alternative specifications of the PSM model and to use of an alternative counterfactual income estimation method.

I Introduction

Remittances have the potential to play an important development role by providing households in low-income countries with much needed social protection. Formal systems of social protection face severe obstacles in developing countries, where they tend to overstretch fiscal and institutional capacities of governments and cannot easily be extended to those in the informal sector (Guhan, 1994; Holzmann & Jorgensen, 2000; Norton, 2002). As a result, households in developing countries have traditionally relied on informal systems of social protection to provide for adequate levels of welfare in the face of otherwise uninsured risks (Deaton, 1997).

In many countries of the South Pacific, the ability of social networks to provide financial support in times of need has come under increasing stress (Abbott & Pollard, 2004; ADB, 2004; UNDP, 2006). Not only are family networks within a community exposed to common, covariate risks impacting similarly on different members of the network and eroding its capacity to provide co-insurance (Morduch & Sharma, 2001), but high population growth rates and youth unemployment are also placing social networks under enormous pressure (Duncan *et al.*, 2006). Tonga is no exception as evidenced by the 2006 Nuku'alofa riots.

International migrants' remittances, unlike within-country internal transfers, are not as sus-

* The authors wish to acknowledge the important contributions and suggestions of Gareth Leeves, Chris O'Donnell, Prasada Rao, two anonymous referees and the editors of *Economic Record*. We also thank the World Bank for permission to use the survey data on which the empirical analysis is based.

JEL classifications: F22, F24, I32, O15

Correspondence: Richard P.C. Brown, School of Economics, University of Queensland, Brisbane, St. Lucia, Queensland 4072, Australia. Email: r.brown@economics.uq.edu.au

doi: 10.1111/j.1475-4932.2012.00824.x

ceptible to covariate risks and are therefore potentially better providers of social protection in the face of adverse economic shocks or natural disasters impacting on the migrant's household in the country of origin. Furthermore, in many developing countries, including Tonga, socio-cultural institutions encourage migrants to use their remittances to fulfil their extended family and kinship obligations in times of need (Brown, 1997; Brown & Jimenez, 2011). The extent to which poor households have access to international migration opportunities will determine the extent to which remittances can contribute to the alleviation of poverty in the migrants' country of origin.

Findings from recent empirical literature on the impacts of migrants' remittances indicate that in most instances remittances reduce poverty in the recipient country (Adams, 1989, 2006, 2011; Barham & Boucher, 1998; Rodriguez, 1998; Lopez-Cordoba, 2004; Adams & Page, 2005; Yang & Martinez, 2006; Hobbs & Jameson, 2012). However, in some instances it was found that the income gains from remittances were not sufficient to offset the estimated losses from migration, resulting in an overall increase in poverty (Adams, 2006; Acosta *et al.*, 2007).

The main purpose of this article is to estimate the effects of remittances on poverty in Tonga, a small Polynesian island country, with a population of around 100,000. In the absence of significant domestic economic growth and the collapse of a small-scale manufacturing economy, international migration and remittances have been of considerable significance for the last 40–50 years (Connell & Brown, 2005). So substantial has international migration become that the domestically resident population of Tonga has scarcely grown in recent decades, and there are now at least as many ethnic Tongans living overseas as at home. As many as 60 per cent of all households in Tonga have at least one overseas migrant, and 90 per cent of households receive remittances, with Tonga now considered as a 'mature' migration country (World Bank, 2006, chapter 3). The Tongan experience therefore provides a suitable case for investigation of the potential poverty, alleviating impacts of remittances in a highly vulnerable developing economy with widespread access to international migration.

In this article, we apply the method of Propensity Score Matching (PSM) to estimate the treatment effects of migration and remittances on poverty using a dataset compiled by the authors from a customised household survey in Tonga. Our earlier study (Brown & Jimenez, 2008) followed a strand of the existing migration literature and applied Heckman self-selection and naïve models to estimate the effects of remittances on household income and the associated measures of welfare (Adams, 2006). This procedure did not incorporate the stochastic term in the predictions, which might have biased the results reported in Brown and Jimenez. Moreover, doubts have been raised concerning the validity of the results from Heckman self-selection models given their strong normality and homoskedasticity assumptions (Deaton, 1997). Therefore, following recent developments in the economics literature on program and policy evaluation (or 'treatment effects'), our preferred approach in this article is to employ PSM methods, which control for self-selection based on observables without relying on such strong distributional assumptions. We find that remittances have a strong impact on poverty reduction, in terms of both the extent and depth of poverty in Tonga. In addition, to examine the extent to which our counterfactual estimates of poverty are sensitive to the choice of methodology, we also compare our results with those obtained from the 'next best choice', that is stochastic imputation with Heckman self-selection models (Barham & Boucher, 1998; Acosta *et al.*, 2007). Our findings suggest that the estimated poverty-reducing impacts of remittances are robust and consistent across different model specifications. The rest of this article is organised as follows: Section II discusses the PSM methodological approach in estimating migrant households' counterfactual income. Section III discusses the empirical analysis, including appropriate sensitivity testing. Section IV presents and discusses the resulting poverty measures in the observed and counterfactual scenarios and in Section V conclusions are presented.

II *Methodology*

In estimating the effects of international migrants' remittances on the income of recipient households, a number of important methodological issues and challenges are widely acknowledged in the economics literature. First, remittances cannot be treated simply as an exogenous addition to the income of the recipient household, given that this ignores both what the migrant would have earned had migration not occurred, and the possible effects that the absence of the migrant and the subsequent inflow of remittances could have on the activities and earnings of those remaining.[1] For this reason, a major methodological challenge addressed in recent remittances research is the estimation of counterfactual income of migrant households, from which the poverty impacts of remittances can be assessed.

Second, as it cannot be assumed that those who migrate are randomly selected and therefore share the characteristics of non-migrants, using non-migrant household earnings to estimate migrant households' counterfactual earnings requires appropriate self-selection testing and, where required, adjustment for self-selection bias in the earnings estimations. For this reason, another important methodological challenge is to employ appropriate methods to allow for possible self-selection bias in deriving estimates of migrants' counterfactual income from the observed earnings of non-migrants.

Third, it is usually, and most often implicitly, assumed that only migrant households have access to international remittances (e.g. Adams, 2006). Parameter estimates from non-migrant households are then used to estimate the counterfactual income of migrant households. However, the customised Tongan survey, which focused on the households' migration status, showed that households without migrants also received remittances.[2] It is therefore necessary also to test whether remittances received by non-migrant households have an impact on their other sources of income.

These challenges have given rise to a number of innovative methods for estimating the poverty impacts of migration and remittances when the researcher is limited to a single, cross-sectional dataset as in our case. The alternative approaches can be grouped into two broad categories: those that rely on models using instrumental variables (IVs) for migration and remittances to estimate cross-regional comparisons of observed poverty rates; and those that rely on the comparison of poverty rates using observed 'with migration and remittances' household incomes, and estimated counterfactual household incomes in a hypothetical 'without migration and remittances' scenario. The studies in the first category focus mainly on estimating the effects of cross-regional variations in migration and remittances (instrumented) on regional-level poverty rates (Lopez-Cordoba, 2004; Adams & Page, 2005), or the exploitation of a natural experiment to instrument remittances (Yang & Martinez, 2006). In the absence of natural experiments and datasets with a sufficiently large number of regional-level observations, the analyst needs to rely on the second form of analysis where the main challenge is to estimate what the households' income would have been in a hypothetical without-migration-and-remittances scenario. The resulting measures of poverty derived from the estimated counterfactual incomes are then compared with the poverty measures based on the households' observed income, including remittances.

The counterfactual income approach was first used in the migration and remittances literature by Adams (1989) and subsequently refined by Barham and Boucher (1998). To estimate counterfactual household income, Barham and Boucher first tested for self-selection of non-migrant households using a Heckman self-selection model, and then estimated a mean regression of incomes for non-migrant households from the second-stage, OLS equation. The resulting parameters were then used to predict the counterfactual incomes for migrant households. However, they also added a stochastic term component to predicted incomes drawn randomly from the empirical distribution of residuals obtained in fitting the income regression to their sample. Although the error term is drawn randomly, the procedure was replicated one thousand times to derive their bootstrap predictions. A potential problem with using Heckman self-selection models is that if the strong normality assumptions do not hold, results may be compromised, and even when normality holds, issues concerning heteroske-

[1] See Brown and Leeves (2011) for an analysis of the combined effects of migration and remittances in Fiji and Tonga on the earnings of migrant households from other sources.

[2] The 'household' was defined broadly in terms of as those 'eating from the same pot' and migrant household members were those currently living abroad, who either resided with the household before leaving, or who would reside with the household if they were to return. Non-migrant households could be receiving remittances from extended family members not treated as members of the household, or friends or distant relatives.

dasticity could also introduce bias to the results (Deaton, 1997).

Such limitations of the Heckman self-selection models have prompted, in other strands of the literature in which counterfactual outcomes are estimated, the adoption of alternative methods with less restrictive distributional assumptions. One such method, appropriate for analysis using non-experimental data, as in our case, is Propensity Score Matching. The PSM estimators have a long tradition in the evaluation literature, which has devoted considerable attention to the methodological complexities involved in estimating the '*Average Treatment Effects*' of social programs.[3] The contemporary literature on Average Treatment Effects is built upon a counterfactual where each individual has an outcome with and without treatment (Wooldridge, 2010). The objective is usually to assess the causal effect of a treatment (migration in our case), on a particular outcome (household income in our case), experienced by those affected by the treatment, after correcting for non-random selection of participants (Ravallion, 2008). However, the non-treatment outcome of the treated group is not observable. Therefore, in the absence of natural experiments, which could generate a control group with the same observables and unobservables as the treated observations, non-experimental estimators are required to solve the non-random selection problem and to estimate the counterfactual outcome for the treated group in the hypothetical absence of treatment (Winship & Morgan, 1999).

The PSM estimators have been developed to correct for non-random selection and to pair each treated observation (migrant households) with a similar control observation (non-migrant households) on the basis of their propensity scores, and to interpret the outcome of the control observation as the counterfactual outcome of the treated observation in the absence of treatment. Matching on the basis of the propensity score would enable migrants to be compared to non-migrants who are similar in terms of their observed characteristics, thereby correcting for self-selection of migrants, conditional on those observables. In this article, we extend the PSM approach to analysis of the impacts of international migration and the subsequent remittances on the incidence and depth of poverty in Tonga.

The PSM methodology applied here consists of the following steps: First, we estimate a probit regression model of the treatment variable, that is, the household engaging in international migration. Second, the parameters of the estimated probit model are used to calculate the propensity score, that is, the predicted probability to migrate for each household, based on the observed characteristics included in the model. Third, using the estimated propensity score, each migrant household is matched with the nearest non-migrant household, using the 'nearest neighbor' matching procedure with replacement.[4] Fourth, once a migrant household has been matched with the nearest non-migrant household, the observed income of the latter is imputed to the former.[5] Fifth, tests for 'balance' and 'common support' are undertaken.

We should note that the use of PSM estimators to correct for self-selection relies on the assumption that there exists a set of observable conditioning variables (X), for which the non-migration outcome (Y_0) is independent of migration status (M), that is, $Y_0 \perp M|X$. In other words, PSM assumes that there is a set of observable conditioning variables that captures all the relevant differences between the treated and the control groups so that the non-treatment outcome is independent of treatment status, conditional on those characteristics (Smith & Todd, 2005; Wooldridge, 2010). This is a potential limitation of extending the PSM methodology to estimate migrants' counterfactual income, for it

[3] See Becker and Ichino (2002), Dehejia and Wahba (2002), Heckman *et al.* (1996, 1997), LaLonde (1986), Ravallion (2005), Rosenbaum and Rubin (1983), Smith and Todd (2005), Winship and Morgan (1999).

[4] Although it needs to be acknowledged that matching with replacement could affect the variance of the estimates, the alternative approach of not allowing replacement during matching suffers more serious defects; it usually results in many treated observations being matched with control observations that have very different propensity scores; and, the results depend on the sorting order of the data. Subsequently, we also test the robustness of the results to the number of matching observations; migrant households are re-matched using the 'two nearest neighbours' procedure.

[5] When applying the 'two nearest neighbours' procedure, the imputed income of the migrant household is given by the mean income of the two nearest matching observations.

is conceivable that unobservables, such as an entrepreneurial predisposition of household members, could be correlated with the migration decision. As discussed below, a relatively large number of covariates have been used to minimise this potential bias. In addition, with a view to examining the extent to which our results are dependent on the choice of PSM as the method to estimate counterfactual income, we also compare our results with those obtained from the stochastic imputation method, traditionally used in the migration and remittances literature.

III Econometric Estimations

(i) The Data

The data are from a sample of 500 households in Tonga, surveyed in the first half of 2005.[6] Table 1 shows the composition of the sample in terms of whether the household had a migrant or not and whether it received remittances or not, in the preceding year.[7] As expected, an extremely high proportion of households had at least one migrant (58.2 per cent) and almost all of these received remittances.[8] Although the high incidence of remitting migrants was to be expected from previous knowledge of remittances and migration networks in the region, what was not expected was the high proportion of households (78.5 per cent) without a migrant that had also received remittances, despite the use of a broad definition of household. In total, almost 90 per cent of households received remittances.

TABLE 1
Composition of Tongan Sample

	Migrant	Non-Migrant	Total
Remittances	284 (56.8%)	164 (32.8%)	448 (89.6%)
No-Remittances	7 (1.4%)	45 (9.0%)	52 (10.4%)
Total (%)	291 (58.2%)	209 (41.8%)	500 (100.0%)

TABLE 2
Mean Per Capita Income and Remittances by Migration Status (All Values in US$ 2004; Standard Deviations in Parentheses)

	Migrant	Non-Migrant
Remittances		
Income/Capita	1651.7 (4,397,7)	865.4 (706.8)
Remittances/Capita	987.7 (1,967.6)	332.9 (421.9)
No-Remittances		
Income/Capita	6,431.0* (14,342.7)	1,242.7 (992.5)
Remittances/Capita	—	—
Total		
Income/Capita	1,766.7 (4,864.8)	946.6 (790.0)
Remittances/Capita	963.9 (1,949.6)	261.2 (397.9)

Notes: *As there are only seven households in this category, this value should be treated with due caution.

The summary statistics in Table 2 show the mean incomes and remittances of households in each of the four categories, indicating that although households with migrants enjoy considerably higher mean incomes (excluding remittances), the variability of their income is also much greater.[9] However, it can also be observed that as expected, average remittances received are substantially larger for households with overseas migrants.

The observation about non-migrant households receiving remittances is important as counterfactual income estimation methods are based on the observed income of non-migrant households. It is usually assumed that only migrant households

[6] For details of the design of the survey instrument, selection of enumeration areas, sampling and survey administration, see World Bank (2006, chapter 3, Appendix C).

[7] In this study, remittances are defined broadly to include cash transferred both formally through the financial system and informally, hand-carried, as well as remittances in kind (e.g. goods sent or carried by the migrant), as well as payments such as airfares, made by the migrant on behalf of the recipient household.

[8] The percentage for Tonga is considerably higher than the 75 per cent found in the 2001 *Household Income and Expenditure Survey*. The most likely explanation for the difference is that the HIES used a rather general question about cash remittances only, whereas this questionnaire asks numerous questions with cross-checks to assist the respondent in recalling transfers that might not have been considered remittances, such as in-kind transfers, and bills paid on behalf of the household. The 91 per cent figure is also very similar to what was observed in a similar survey over a decade earlier (Brown, 1995).

[9] Income includes estimates of subsistence income derived from the survey data (see World Bank, 2006, chapter 3).

have access to international remittances (Adams, 2006).[10] With there being four categories of household: (i) migrant households receiving remittances; (ii) migrant households not receiving remittances; (iii) non-migrant households receiving remittances; and (iv) non-migrant households not receiving remittances, the question then arises as to which non-migrant category to use when estimating migrant household income; (iii), (iv) or the two combined?

The small size of the sample, and in particular the sub-sample of non-migrant households not receiving remittances (45), does not allow us to estimate counterfactual income of migrants from the sub-sample of households with neither migrants nor remittances. Instead, we use all non-migrant households irrespective of whether they receive remittances or not. As this implies treatment of remittances to non-migrant households as exogenous additions to their income, it becomes necessary to test for possible effects on non-migrant households' income. Clearly, there is no opportunity cost in the form of forgone migrants' income, but it is possible that remittances received by non-migrant households have indirect effects on their observed income from other sources. This hypothesis was formally tested by regressing the natural log of household income on remittances for non-migrant households using instrumental variable techniques. It was found that remittances have no statistically significant effect on income of non-migrant households.[11] It is therefore considered reasonable to use the observed income of non-migrant households (excluding remittances) to estimate the counterfactual non-remittances income of migrant households.

(ii) Counterfactual Income Estimation using PSM

Using the sample data, the sequence of steps to estimate counterfactual income applying the PSM method (described in Section II) was followed.[12] For the matching estimators to exhibit least potential bias, it is important that: (i) both the treatment (migrant) and the control group (non-migrant) are located in the same markets; (ii) the outcome variable is measured in an identical manner for both the treated and the control groups; and (iii) the dataset includes a relatively large number of observable variables that would capture the 'non-ignorable' determinants of treatment (LaLonde, 1986; Heckman *et al.*, 1996, 1997; Smith & Todd, 2005).[13] In our case, both the migrant and the non-migrant groups are obviously located in the same markets and were administered the same household questionnaire, satisfying conditions (i) and (ii). However, given that we use a cross-sectional dataset, the choice of exogenous observable variables is restricted, indicating that condition (iii) could be violated. To address this, two specifications of the PSM model were estimated, one with and one without additional community-level migration variables. The two sets of results were then compared in relation to the two criteria of 'balance' and 'common support' which constitutes an integral part of the PSM procedures.

In the first step, a probit migration equation is used to estimate the probability that the household is a migrant household. We estimate the probit model as follows:

$$P(M_1 = 1) = \Phi(\beta_0 + \beta_1 Z + \varepsilon) \qquad (1)$$

where: M_1 represents the propensity to be a migrant household; Φ is the cumulative density function for the standard normal distribution; and, Z is the vector of household and individual migrant characteristics, which defines our 'base model'. We also estimated an extended model with an additional vector of community variables, consisting of: the average maximum length of absence of migrants from households in the respective community; and, the average amount of annual remittances received by households in the community.[14] The inclusion of these community migration variables serves as a robustness check, allowing us to gauge the extent to which the results are sensitive to the choice of variables. The definitions and summary statistics of the variables used to estimate the model are presented in Tables A1 and A2 respectively. The

[10] Adams *et al.* (2008) also find a significant number of non-migrant households in receipt of remittances.

[11] Results available from authors on request.

[12] We used the '*psmatch2*' procedure in STATA developed by Leuven and Sianesi (2003).

[13] Indeed, the larger the number of covariates included, the more relevant differences between the treated and the control groups that would be captured.

[14] These community-level variables were constructed from the household survey data, treating households in each primary sampling unit as the 'communities', but always excluding the observation from the household in question.

regression results for both models are shown in Table A3.

Each of the subsequent steps of the PSM procedure was accordingly performed using both sets of probit results, with and without community-level conditioning variables. Following the PSM procedure outlined previously, the estimated coefficients from the two probit models were then used to calculate, for each household, the predicted probability of it being a migrant household, and then each migrant household was matched with the nearest non-migrant household, using the 'nearest neighbor' matching procedure, with replacement.[15] The robustness of the results to use of the alternative 'two nearest neighbours' matching rule was also tested, and found to have a negligible effect. (Results available from authors on request.) Once the counterfactual income of the migrant household has been estimated by imputing to the observed income of the nearest non-migrant household, we test and compare the two sets of PSM results for 'balance' and 'common support' after matching, and then test the robustness of the preferred specification estimates to alternative matching rules.

The problem of 'imbalance' can occur when assignment of treatment is not random, and large differences in the distribution of characteristics between the treated (migrant) and the control (non-migrant) groups can be expected. An important part of the PSM procedure is to achieve balance in the distribution of observables between the two groups such that the distribution of observable covariates is approximately the same for both groups after matching (Lee, 2006; Ravallion, 2008). Common balancing checks used are the reduction in the absolute 'standardized bias',[16] the reduction in the pseudo R^2 in probit models predicting treatment before and after matching, and *t*-tests for equality of means. However, Imai *et al.* (2008) have shown that results from the *t*-tests are sensitive to sample size and can be misleading. Therefore, we use only the first two balancing checks, these results being independent of sample size. The relevant data for the standardised bias check are shown in Table 3a and a more detailed analysis of covariate balance in Table 3b.

These tables show that covariate balance is improved after matching both with and without the community-level conditioning variables included. However, the reduction in the standardised bias achieved is substantially larger when community-level variables are included. Similarly, in relation to the Pseudo R^2 balance criterion, it can be seen from Table 4 that the value is also substantially lower after matching, indicating that the observed characteristics in the model explain very little of the variation of observed propensity scores in the sample.

Biases could also result if the propensity scores of a substantial number of migrant households lie outside the boundaries of the distribution of propensity scores for non-migrant households, that is 'failure of common support' (Ravallion, 2008). If the characteristics of migrant households are substantially different to those of non-migrant households, using the observed income of the latter to impute counterfactual income of the former could not be justified. We follow the common practice in application of the PSM method to base the estimation of counterfactual income only on those observations with common support (Ravallion).[17] The common support statistics are shown in Table 5.

These show that when community control variables are included, the number of households off common support increases from 8 to 22, but it is reassuring that this still leaves over 97 per cent of the sample on common support. The 22 observations not on common support are dropped from the sample when estimating counterfactual incomes applying the PSM method with community controls.[18]

[15] Although matching with replacement could affect the variance of the estimates, the alternative approach of no replacement suffers more serious defects as it usually results in many treated observations being matched with control observations that have very different propensity scores, and the results depend on the sorting order of the data (Smith & Todd, 2005).

[16] Measured as the difference of the sample means in the treated and non-treated groups scaled by the square root of the average variances in the original samples (Rosenbaum & Rubin, 1985).

[17] However, we also tested for any resulting sample bias as a consequence of dropping those observations without common support. The results were very similar. Available from the authors on request.

[18] A more stringent test would be to impose common support by dropping a certain percentage of treated observations at which the propensity scores density of the untreated observations is the lowest. The sample was trimmed at 5 and 10 per cent. Reassuringly, the poverty estimations did not change substantially. Results available from the authors on request.

TABLE 3
(a) Summary Statistics for Absolute Standardised Bias Before and After Matching. (b) Covariate Statistics for Absolute Standardised Bias Before and After Matching

	Without Community Controls*		With Community Controls**	
	Before match	After match	Before match	After match
(a)				
Mean Bias	34.86	8.51	38.66	4.99
Median Bias	24.23	7.6	31.7	3.88
SD of Bias	24.61	6.37	24.87	2.96
Minimum Bias	5.63	0.46	5.63	1.83
Maximum Bias	84.75	18.30	83.30	9.38
Explanatory vars.	11	11	12	12

Variable	Sample	Without Community Controls*	With Community Controls**
(b)			
HH Size	Before match	84.80	83.3
	After match	1.4	−2.7
HH Dependency Ratio	Before match	−60.70	−60.70
	After match	7.4	8.8
Female HH Head	Before match	24.20	24.20
	After match	7.6	1.8
Age of HH Head	Before match	51.80	51.80
	After match	−3.7	2.2
Square Age of HH Head	Before match	50.30	50.30
	After match	−1.9	4.30
Urban	Before match	19.00	19.00
	After match	0.5	−8.9
Outer-island	Before match	−22.20	−22.20
	After match	−13.1	9.4
Adult Education	Before match	39.10	39.10
	After match	8.6	−2.6
Interaction Female, Education	Before match	15.40	15.40
	After match	17.3	4.3
Own Agricultural Land	Before match	5.60	5.60
	After match	−18.3	−3.0
Interaction Outer-island, Ag. Land	Before match	−10.40	
	After match	−13.80	
Av. Community Maximum Length of Stay	Before match	—	72.70
	After match	—	8.4
Av. Community Remittances Received	Before match	—	19.70
	After match	—	−3.50

Notes: $*n = 500$; $**n = 478$ observations on common support

IV Poverty Measures with Observed and Counterfactual Income

(i) PSM-Derived Poverty Measures

In this section, we report the estimated impacts of remittances on both the extent and depth of poverty using the standard *Poverty Headcount Ratio* and *Poverty Gap Ratio* respectively. The former measures the *extent* of poverty in terms of the percentage below the poverty line, whereas the gap ratio measures the *depth* of poverty; i.e. it measures, for those in poverty, the mean difference between their income level and the poverty line, expressed as a percentage of the poverty line. In the with-migration-and-remittances scenario observed income (including remittances) of both migrant and non-migrant households are used to calculate the poverty

TABLE 4
Pseudo R^2 Balance Statistics Before and After Matching

	Without Community Controls		With Community Controls	
	Before match	After match	Before match	After match
Pseudo R^2	0.30	0.02	0.36	0.01
LR Chi^2	20.57	17.31	247.7	6.41
P-value	0.000	0.10	0.00	0.894

TABLE 5
PSM Tests of Common Support With and Without Community Controls

	Off Common Support	On Common Support	Total
Without Community Controls			
Non-Migrant HH	0	209	209
Migrant HH	8	283	291
Total	8	492	500
With Community Controls			
Non-Migrant HH	0	209	209
Migrant HH	22	269	291
Total	22	478	500

indicators. In the counterfactual scenarios, the indicators are re-calculated using observed income (excluding remittances) for non-migrant households and our PSM-imputed income (excluding remittances) for migrant households.[19]

To calculate poverty rates, an estimated threshold poverty-level of income for the household, expressed on a per capita basis, is required. As there is no official household-level poverty line for Tonga, we estimate the poverty line as the median of the required adult-equivalent per capita income in the sample. An adult-equivalent per capita poverty line of U$879 (2004 prices) was thereby derived. This procedure follows an important strand of the poverty measurement literature that uses survey

[19] The estimations of per capita income in the counterfactual scenarios include all household members including migrants and non-migrants, whereas in the observed, with-migration scenario migrants are not included.

TABLE 6
Poverty Indicators With and Without Remittances: Reported and Counterfactual Income Estimates (2004)

Poverty Measure	Reported Income Including Remittances	PSM Counterfactual Income Without Remittances†
Poverty Headcount Ratio (%)	32.7	47.4
Poverty Gap Ratio (%)	11.6	22.7
Observations	(n = 500)	(n = 478)

Note: † with community controls and on common support.

data on '*the minimum required income*' to calculate poverty lines (Hagenaars & van Praag, 1985; Hagenaars & de Vos, 1988; Ravallion, 1998; Pradhan & Ravallion, 2000). This methodology has been found to produce sensible results when compared to 'objective' methodologies that rely on the researchers' own judgment of population welfare and addresses some of the shortcomings of international poverty rates (Deaton, 2001). Table 6 compares the poverty rates with migration and remittances calculated from observed household income with the poverty rates using the PSM-derived counterfactual income estimates (without remittances).

These results show that migration and remittances have a substantial impact on both the extent and depth of poverty in Tonga. The *Poverty Headcount Ratio* is estimated to decrease from 47.4 per cent in the counterfactual scenario to 32.7 per cent in the observed, with-migration-and-remittances scenario; a 31 per cent reduction of the poverty rate. The depth of poverty as measured by the *Poverty Gap Ratio* is estimated to decrease from 22.7 per cent in the counterfactual scenario to 11.6 per cent in the observed scenario; a 49 per cent reduction in the depth of poverty for those below the poverty line.

(ii) Sensitivity to Alternative Counterfactual Income Estimation Method

As previously discussed, we are also interested in examining the extent to which our results are dependent on the choice of PSM as the method to estimate counterfactual income. Accordingly, in this section, we compare our PSM-derived results with those obtained from the stochastic imputation method traditionally used in the migration and remittances literature and first applied by Barham and Boucher (1998) with individual survey data from Nicaragua. Following their procedure (see Section II), we begin by testing for self-selection, estimating two regression models of the natural log of income for *non-migrant* households, one with a self-selection control and one without. Formally, the following models for non-migrant households are estimated:

$$Y = \beta_0 + \beta_1 Z + \beta_2 \lambda + \upsilon \quad (2)$$

$$Y = \beta_0 + \beta_1 Z + \upsilon \quad (3)$$

where Y represents the natural log of household income from all sources (excluding remittances), which is a function of characteristics of the household and individual household members (Z). In Equation (2), λ is the selection control variable (the Inverse Mills Ratio) derived from the probit migration model reported in Table A4. In both equations, υ is the stochastic error term. Both sets of regression results are reported in Table 7.[20]

The purpose of the comparison is to ascertain whether the OLS estimates without selection controls Equation (3) would be biased, by comparing the coefficient estimates of the two models and the statistical significance of the selection variable coefficient λ in Equation (2). If evidence of self-selection is found, to estimate household income, a Heckman two-step self-selection model should be used.

It can be seen that the coefficient on the selection variable (λ) is small and not statistically significant, indicating that the sub-sample of non-migrant households can be considered a random selection from the population. This is reinforced by the finding that the estimated coefficients in the two models are very similar. This can be explained by historical migration patterns in Tonga where migration flows have been particularly substantial since the 1960s, with just over half of all ethnic Tongans now living outside the country and over 58 per cent of households having at least one migrant abroad (Table 1). Although relatively more skilled and wealthier households might have dominated the early migration waves, the long history of migration from Tonga, as well as the widespread access to international remittances suggests a lowering of migration costs, hence facilitating migration for the poor. A wider range of migration opportunities is also available to Tongans, including the New Zealand lotto system, skilled migration and family reunion visas in most destination countries (Lee, 2003).

On the basis of these findings and following Barham and Boucher (1998) and Acosta *et al.* (2007), we first calculate migrant households'

[20] Definitions of variables and descriptive statistics are shown in Tables A1 and A2 respectively.

TABLE 7
Non-Migrant Household Income Regression Results (Dependent Variable: Natural Log of Household Income)

	With Selection control		Without Selection control	
Variable	Coefficient	z-stat	Coefficient	z-stat
Log Household Size	0.42	0.75	0.50	0.99
Log Household Size^2	−0.05	−0.32	0.08	0.40
Dependency Ratio	0.84**	1.96	−0.08	−0.21
Female Head	−1.02*	−1.70	−0.86*	−1.76
HH Head Age	0.11**	1.93	0.08*	1.74
HH Head Age^2	−0.00**	−2.14	−0.00*	−1.91
Urban	0.53**	2.27	0.53*	1.64
Outer-Island	0.33	0.69	0.18	0.43
Tertiary Educated	0.11	0.94	0.21***	2.59
Female Head and Tertiary Educated	1.11**	2.36	1.07**	2.27
Agricultural Land	0.08	0.32	0.09	0.35
Outer-Island and Agricultural Land	0.26	0.70	0.29	0.88
Selection control variable (λ)	0.80	1.47	—	
Constant	4.08***	2.61	4.79***	3.42
Wald Chi^2(12)	127.38		146.26	
Probability > Chi^2	0.00		0.00	
R-Squared	—		0.19	
Adjusted R-Squared	—		0.14	
Observations (Uncensored)	500 (209)		209	

Notes: Standard errors clustered at the community (PSU) level. ***Statistically significant at 1% level, **statistically significant at 5% level, *statistically significant at 10% level.

counterfactual income using a standard OLS model without a self-selection control. Then, applying the same bootstrapping method, we add a stochastic component to the predicted incomes. From this analysis, we derived an alternative set of counterfactual poverty estimates for our sample: a *Poverty Headcount Ratio* of 49.5 per cent and a *Poverty Gap Ratio* of 36.1 per cent. Comparing these with our preferred, PSM-derived estimates (see Table 6), we conclude that notwithstanding the expected differences in magnitude, they reinforce our conclusions that there is an unambiguously lower incidence and depth of poverty with migration and remittances.

V *Conclusions*

In the absence of experimental data, the estimation of counterfactual outcomes has been the subject of extensive methodological debate. In this article, we examine the use of PSM as an alternative method to estimate counterfactual income in the context of international migration and remittances, using household survey data from Tonga. We found that even after accounting for the forgone income of the households' migrants, the net improvement in income from remittances contributes substantially to poverty alleviation. In this study, we have also tested the sensitivity of findings to alternative methods and specifications for estimating counterfactual income in the hypothetical no-migration scenario. We found that our results were robust to alternative model specifications, showing a substantial reduction in both the incidence and depth of poverty with migration and remittances, after taking into account the opportunity costs of migration in terms of the estimated forgone income of migrant household members. These findings and the robustness of our results are also important in the context of the current migration policy debates in the region, as they show strong support for the potential poverty-alleviating role of increased migration opportunities for Pacific islanders to the two main destination countries, Australia and New Zealand.

It is important to acknowledge that none of the counterfactual income estimation methods available includes the general equilibrium effects of migration and remittances on the earnings of the communities at large, both migrant and non-migrant households. For this reason, there could be biases in the estimated counterfactual poverty rates, especially if they are used to assess the potential cost and benefits of a hypothetical no-migration scenario under which all migrants presently abroad are assumed to return home. The direction of the bias will depend primarily on what general equilibrium effects migration and remittances have had on both capital returns and labour returns for the skilled and the non-skilled population in each out-migration community. Further research would be required to examine these, which would require analysis of a complex array of factors, including the local institutional context in which labour and capital markets operate. Given that over 90 per cent of Tongan households receive remittances, the potential general equilibrium effects are unlikely to be negligible, and could well imply even higher poverty rates in the without-migration scenario, in which case our reported impacts on poverty alleviation should be considered as lower bound estimates.

Supporting Information

Additional supporting information may be found in the online version of this article:

DATA S1 *Datasets and Codes*

Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting materials supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

REFERENCES

Abbott, D. and Pollard, S. (2004), *Hardship and Poverty in the Pacific*. Asian Development Bank (ADB), Pacific Department, Manila.

Acosta, P., Fajnzylber, P. and Lopez, J. (2007), 'The Impact of Remittances on Poverty and Human Capital: Evidence from Latin American Household Surveys', in Ozden C. and Schiff, M. (eds), *International Migration, Economic Development and Policy*. The World Bank/Palgrave Macmillan, Washington, D.C.; 59–98.

Adams, R.H. (1989), 'Worker Remittances and Inequality in Rural Egypt', *Economic Development and Cultural Change*, **38**, 45–71.

Adams, R.H. (2006), 'Remittances, Poverty, and Investment in Guatemala', in Ozden, C. and Schiff, M. (eds), *International Migration, Remittances and the Brain Drain*. The World Bank/Palgrave Macmillan, Washington, D.C.; 53–80.

Adams, R.H. (2011), 'Evaluating the Economic Impact of International Remittances on Developing Countries Using Household Surveys: A Literature

Review', *Journal of Development Studies*, **47**(6), 829–845.

Adams, R.H. and Page, J. (2005), 'Do International Migration and Remittances Reduce Poverty in Developing Countries?', *World Development*, **33**, 1645–69.

Adams, R.H., Cuecuechca, A. and Page, J. (2008), 'Remittances, Consumption and Investment in Ghana', Policy Research Working Paper, *N*. 4515, Development Economics and Africa Division, The World Bank, Washington, D.C.

ADB (2004), *Priorities of the People*. Hardship in Tonga. Asian Development Bank, Manila.

Barham, B. and Boucher, S. (1998), 'Migration, Remittances, and Inequality: Estimating the Net Effects of Migration on Income Distribution', *Journal of Development Economics*, **55**, 307–31.

Becker, S. and Ichino, A. (2002), 'Estimation of Average Treatment Effects Based on Propensity Scores', *The Stata Journal*, **2**, 358–77.

Brown, R.P.C. (1995), 'Hidden Foreign Exchange Flows. Estimating Unofficial Remittances to Tonga and Western Samoa', *Asian and Pacific Migration Journal*, **4**, 35–68.

Brown, R.P.C. (1997), 'Estimating Remittance Functions for Pacific Island Migrants', *World Development*, **25**, 613–26.

Brown, R.P.C. and Jimenez, E. (2008), 'Estimating the Net Effects of Migration and Remittances on Poverty and Inequality Comparison of Fiji and Tonga', *Journal of International Development*, **20**, 547–71.

Brown, R.P.C. and Jimenez, E.V. (2011), 'Subjectively-Assessed Welfare and International Remittances: Evidence from Tonga', *Journal of Development Studies*, **47**(6), 829–45.

Brown, R.P.C. and Leeves, G. (2011), 'Impacts of International Migration and Remittances on Source Country Household Incomes in Small Island States: Fiji and Tonga', *Applied Economics*, **43** (27), 3965–76.

Connell, J. and Brown, R.P.C. (2005), *Remittances in the Pacific: An Overview*. Pacific Studies Series, Asian Development Bank, Manila.

Deaton, A. (1997), *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. Johns Hopkins University Press for the World Bank, Baltimore.

Deaton, A. (2001), 'Counting the World's Poor: Problems and Possible Solutions', *World Bank Research Observer*, **16**, 125–47.

Dehejia, R. and Wahba, S. (2002), 'Propensity Score Matching Methods for Nonexperimental Causal Studies', *The Review of Economics and Statistics*, **84**, 151–61.

Duncan, R., Booth, V., Zhang, G., Rao, M., Maheshwar, R. and Fakavae, T. (2006), 'The Young and Restless: The Challenge of Population Growth', in World Bank (ed.), *At Home and Away: Expanding Job Opportunities for Pacific Islanders through Labor Mobility*, The World Bank, Washington, D.C.; 29–45.

Guhan, S. (1994), 'Social Security Options for Developing Countries', *International Labour Review*, **133**, 35–53.

Hagenaars, A. and de Vos, K. (1988), 'The Definition and Measurement of Poverty', *The Journal of Human Resources*, **23**, 211–21.

Hagenaars, A. and van Praag, B. (1985), 'A Synthesis of Poverty Line Definitions', *Review of Income and Wealth*, **31**, 139–53.

Heckman, J., Ichimura, H., Smith, J. and Todd, P. (1996), 'Sources of Selection Bias in Evaluating Social Programs: An Interpretation of Conventional Measures and Evidence on the Effectiveness of Matching as a Program Evaluation Method', *Proceedings of the National Academy of Sciences*, **93**, 13416–20.

Heckman, J., Ichimura, H. and Todd, P. (1997), 'Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme', *Review of Economic Studies*, **64**, 605–54.

Hobbs, A.W. and Jameson, K.P. (2012), 'Measuring the Effect of Bi-Directional Migration Remittances on Poverty and Inequality in Nicaragua', *Applied Economics*, **44** (19), 2451–60.

Holzmann, R. and Jorgensen, S. (2000), *Social Risk Management: A New Conceptual Framework for Social Protection and Beyond*. The World Bank, Washington.

Imai, K., King, G. and Stuart, E.A. (2008), 'Misunderstandings between Experimentalists and Observationalists About Causal Inference', *Journal of the Royal Statistical Society*, **171** (2), 481–502.

LaLonde, R. (1986), 'Evaluating the Econometric Evaluations of Training Programs', *American Economic Review*, **76**, 604–20.

Lee, H. (2003), *Tongans Overseas. Between Two Shores*. University of Hawaii Press, Honolulu.

Lee, W. (2006), 'Propensity Score Matching and Variations on the Balancing Test', Unpublished Manuscript. Melbourne Institute of Applied Economic and Social Research, Melbourne.

Leuven, E. and Sianesi, B. (2003), 'PSMATCH2: STATA Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing'. Available from: http://ideas.repec.org/c/boc/bocode/s432001.html

Lopez-Cordoba, E. (2004), *Globalization, Migration and Development: The role of Mexican Migrant Remittances*. Inter-American Development Bank, Washington.

Massey, D. (1990), 'Social Structure, Household Strategies and the Cumulative Causation of Migration', *Population Index*, **56**, 3–26.

Massey, D., Goldring, L. and Durand, J. (1994), 'Continuities in Transnational Migration: An Analysis of Nineteen Mexican Communities', *American Journal of Sociology*, **99**, 1492–533.

Morduch, J. and Sharma, M. (2001), 'Strengthening Public Safety Nets: Can the Informal Sector Show the Way?', FDND Discussion Paper 122, International Food Policy Research Institute, Washington, DC.
Norton, A. (2002), 'Social Protection: Defining the Field of Action and Policy', *Development Policy Review*, **20**, 541–67.
Pradhan, M. and Ravallion, M. (2000), 'Measuring Poverty Using Qualitative Perceptions of Consumption Adequacy', *The Review of Economics and Statistics*, **82**, 462–71.
Ravallion, M. (1998), *Poverty Lines in Theory and Practice*. World Bank, Washington, D.C.
Ravallion, M. (2005), 'Evaluating Anti-Poverty Programs', World Bank Policy Research Paper 3625, World Bank, Washington.
Ravallion, M. (2008), 'Evaluating Anti-Poverty Programs', Ch.59 in Schultz, T.P. and Strauss J. (eds), *Handbooks in Economics, Development Economics Volume 4*. North Holland/Elsevier, Oxford and Amsterdam; 3787–846.
Rodriguez, E. (1998), 'International Migration and Income Distribution in the Philippines', *Economic Development and Cultural Change*, **46**, 329–50.
Rosenbaum, P. and Rubin, D. (1983), 'The Central Role of the Propensity Score in Observation Studies for Causal Effects', *Biometrika*, **70**, 41–55.
Rosenbaum, P. and Rubin, D. (1985), 'Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score', *The American Statistician*, **39**, 33–8.
Smith, D. and Todd, P. (2005), 'Does Matching Overcome Lalonde's Critique of Nonexperimental Estimators?', *Journal of Econometrics*, **125**, 305–53.
UNDP (2006), *Pacific Human Development Report 2006*. United Nations Development Programme, UNDP, Suva, Fiji.
Winship, C. and Morgan, S. (1999), 'The Estimation of Causal Effects from Observational Data', *Annual Review of Sociology*, **25**, 659–706.
Wooldridge, J. (2010), *Econometric Analysis of Cross Section and Panel Data*, 2nd edn. MIT Press, London.
World Bank (2006), *Home and Away: Expanding Job Opportunities for Pacific Islanders through Labor Mobility*. The World Bank, Washington, D.C.
Yang, D. and Martinez, C. (2006), 'Remittances and Poverty in Migrants' Home Areas: Evidence from the Philippines', in Ozden, C. and Schiff, M. (eds), *International Migration, Remittances and the Brain Drain*. The World Bank/Palgrave Macmillan, Washington, D.C.; 81–122.

Appendix I

TABLE A1
Variable Names and Descriptions

Variable	Variable description
Log HH Income	Log of household's total income including subsistence income in US$
Log Household Size	Number of household members, including migrants in the case of migrant households
Dependency Ratio	Proportion of household members below 14 and over 60 years of age. Includes migrants in the case of migrant households.
Female Head	Dummy for household with female head
HH Head Age	Age of household head
Urban	Dummy for household in urban areas (omitted category household in rural areas)
Outer-Island	Dummy for household in outer-island (omitted category household in rural areas)
Tertiary Educated	Number of household members with tertiary education
Female Head and Tertiary Educated	Interaction dummy female household head and dummy presence of household member with tertiary education
Agricultural Land	Dummy household owns agricultural land in 2003 (omitted category does not own agricultural land in 2003)
Outer-Island and Agricultural Land	Interaction dummy agricultural land, dummy outer-island
Community Migration History	Average length of stay of the first person who migrated from each household in the community (PSU)
Community Average Remittances	Average amount of remittances received by households in the community (PSU)

TABLE A2
Descriptive Statistics: Means and Standard Deviations (Standard Deviations in Parentheses)

	All Households (n = 500)	Migrant (n = 291)	Non-Migrant (n = 209)
Log Household Income (US$)	7.713 (2.982)	7.555 (3.610)	7.934 (1.754)
Log Household Size	1.787 (0.571)	1.975 (0.454)	1.525 (0.614)
Dependency Ratio	0.318 (0.227)	0.261 (0.178)	0.397 (0.2622)
Female Head	0.220 —	0.261 —	0.163
HH Head Age	51.894 (14.898)	55.010 (14.685)	47.555 (14.119)
Urban	0.500 —	0.539 —	0.445 —
Outer-Island	0.250 —	0.210 —	0.306 —
Tertiary Educated	0.478 (1.068)	0.643 (1.250)	0.249 (0.683)
Female Head and Tertiary Educated	0.074 —	0.096 —	0.043 —
Agricultural Land	0.514 —	0.526 —	0.498 —
Outer-Island and Agricultural Land	0.164 —	0.148 —	0.187 —
Community Migration History	6.958 (3.475)	7.957 (3.192)	5.567 (3.380)
Community Average Remittances (US$)	2730 (1239)	2833 (1072)	2585 (1430)

TABLE A3
Migration Probit Model Results: Community-level Controls (Dependent Variable: Migrant Household = 1)

	Without Community Controls		With Community Controls	
Variable Name	Coefficient	z-stat	Coefficient	z-stat
Log Household Size	1.27**	2.21	1.28***	8.41
Log Household Size^2	0.02	0.10	—	
Dependency Ratio	−2.99***	−8.48	−2.84***	−7.77
Female Head	0.32*	1.69	0.16	0.79
HH Head Age	−0.08**	−2.33	−0.07*	−1.92
HH Head Age^2	0.00***	2.96	0.00***	2.70
Urban	−0.07	−0.04	−0.22	−1.23
Outer-Island	−0.03	−0.11	−0.31	−1.36
Tertiary Educated	0.14**	1.94	0.13*	1.76
Female Head and Tertiary Educated	0.08	0.32	—	
Agricultural Land	0.08	0.47	−0.02	0.07
Outer-Island and Agricultural Land	−0.27	−0.84	−0.09	−0.59
Community Migration History	—	2.21	0.14***	8.41
Community Average Remittances	—	0.10	4.31E−06	
Constant	0.17		−1.03	−7.77
LR chi^2 (12)	210.15		247.70	
Prob > chi^2	0.00		0.00	
Pseudo R^2	0.31		0.36	
Observations	500		500	

Notes: Standard errors clustered at the community (PSU) level. ***Statistically significant at 1% level, **statistically significant at 5% level, *statistically significant at 10% level.

Appendix II: Testing for Migrant Household Self-Selection

A probit regression model is used to estimate the probability (P) of a household *not* having a migrant (M) abroad:

$$P(M_1 = 1) = \Phi(\beta_0 + \beta_1 Z + \beta_2 K + \varepsilon). \quad \text{(A1)}$$

Regarding the characteristics of the household and individual migrants (Z) in Equation (A1), two issues should be noted. First, for households with migrants, the characteristics of individual household members include those who are currently living abroad. For example household size includes both migrant and non-migrant household members. Second, variables such as household wealth, which could be endogenous,[21] are excluded from the estimated model. However, although migration costs (K) in Equation (A1) were not directly observable, a variable measuring the history of migration in the community (*Community Migration History*) is used as a proxy.[22] Early migrants contribute to the reduction of migration costs by providing both cash and in-kind assistance to other community members willing to migrate. The newcomers draw on existing networks of migrants to find jobs and accommodation. Therefore, the longer the history of migration in a community as measured by the mean length of absence of each household's oldest migrant, the lower the migration costs and the higher the expected propensity to migrate of the household (Massey, 1990; Massey *et al.*, 1994). This variable (*K, or, Community Migration History*) identifies the probit equation, as there is no reason to believe migration costs would have any effect on household income. The parameter estimates of the probit model are then used to construct the self-selection variable λ, (the Inverse Mill's Ratio) for non-migrant households. Table A4 shows the probit results of the migration Equation (A1).[23] It should be recalled that the dependent variable is the probability of the household *not* having a migrant.

TABLE A4

Results of Migration Probit Model (Dependent Variable: Non-Migrant Household = 1)

Variable Name	Coefficient	z-stat
Log Household Size	−1.45**	−2.16
Log Household Size^2	0.04	0.21
Dependency Ratio	2.87***	6.42
Female Head	−0.17	−0.69
HH Head Age	0.07	1.18
HH Head Age^2	−0.00*	−1.63
Urban	0.21	0.99
Outer-Island	−0.01	−0.03
Tertiary Educated	−0.13	−1.23
Female Head and Tertiary Educated	0.04	0.15
Agricultural Land	−0.02	−0.06
Outer-Island and Agricultural Land	0.51	1.04
Community Migration History	−0.14***	−4.01
Constant	1.26	0.73
LR chi2(13)	187.69	
Prob > chi2	0.00	
Pseudo R^2	0.37	
Observations	500	

Notes: Robust z-statistics. Standard errors clustered at community level. ***Statistically significant at 1% level, **statistically significant at 5% level, *statistically significant at 10% level.

[21] We only observe the household wealth after migration and remittances have direct and indirect effects on household wealth.

[22] As census data on the migration history of the surveyed communities were not available, a community-level variable was therefore constructed from the household data. For each household in the community, the length of stay abroad of the first member who migrated was identified. The community-level mean of the first migrant's length of stay was computed for all households in the community, excluding the household observation in each instance. For sensitivity testing, an alternative 'migration network/history' instrument was constructed using the average number of migrants in the community. See next footnote.

[23] Similar results were also obtained when the average number of migrants in the community was used as the identifying variable in the probit migration equation. Results available from authors on request.