Unevenly distributed effects of international migration: evidence from Bangladesh.

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Within the framework of Rubin's causal model, this paper estimates the effects of international migration on the welfare of Bangladeshi migrant households. Moving from the estimation of the average effect, the paper disaggregates the impact on the basis of households' quartile of expenditure and length of the migration period. The no-migration counterfactual scenario is then used to measure the effect on inequality and to build a transition matrix showing the relationship between migration/remittances and social mobility. The paper argues that those who benefit most from migration are the relatively better off households and that migration and remittances are both a source of inequality and a vehicle of social mobility. Finally, since most of the characteristics which seem to determine the probability of migration cannot be affected by governmental policies, it is also argued that the resources deployed for pro-migration policies cannot directly benefit the poorer sections of the population.

Keywords: International migration; Social mobility; Inequality; Counterfactual framework; Matching estimators; Bangladesh.

JEL classification: F22; D63; O12; O15; O53.

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1. Introduction

Since the beginning of the nineties, Bangladesh recorded significant progress in terms of all main social and economic indicators. The growth of real incomes, along with remarkable improvements in health and food security, induced some scholars to talk about a "Bangladesh surprise" (Asadullah et al., 2014). During this period, the country experienced a profound change and the emergence of international migration can be considered one of the distinguishing features of such transformation. Indeed, over the 2000-2010 period, Bangladesh was the country that registered the highest average number of net emigrants per year (UN, 2013). The surge in migrants' remittances mirrored the increase in the stock of international migrants. Officially recorded remittances outweighed official development assistance in the mid-nineties (Mohapatra et al., 2010) and in 2013 they were worth more than 10% of national GDP. In the recent history of Bangladesh, international migration and economic development appear deeply interconnected. Low domestic wages, overpopulation and environmental vulnerability worked jointly as push factors for outward migration, which has become an increasingly common "livelihood strategy" for households and individuals (Siddiqui, 2003). On the other hand, even though migration is a result of the limited economic opportunities available domestically, it can also be regarded as a key factor for recent social and economic development of the country (Bangladesh Bank, 2013; Siddique et al., 2012). Surprisingly, despite the general recognition of the potential contribution of migrants' remittances to the welfare of Bangladeshi households and despite the importance of Bangladesh itself as a "test case for development" (Faaland and Parkinson, 1976), the literature on migration and remittances has not yet produced a specific country-study. The contribution of this paper is twofold: on the one hand, it represents the first attempt to estimate the impact of migration and remittances in Bangladesh on the basis of a national representative survey; on the other, taking full advantage of the non-parametric nature of matching estimators, it studies the phenomenon from multiple perspectives. Specifically, the impact of migration is disaggregated by quartile of expenditure and households' counterfactual outcomes are used to build a transition matrix showing the effect of migration on migrant households' position in the expenditure distribution and to compute Bangladesh's Gini index in a no-migration counterfactual scenario. The paper finds that the relative magnitude of the positive effect is higher for the households belonging to lower expenditure quartiles and becomes negative (but not statistically significant) for the richest migrant households. Migration turns out to be successful in approximately half of the cases and it can be considered an important vehicle of social mobility. It also emerges that most of the international migrants come from relatively better-off households and that migration and remittances contributes to a modest increase in inequality. Finally, it comes out that the impact of migration tends to grow over time, supporting the idea that part of remittances are directly used for productive investment. Sensitivity checks prove that the results are robust to the introduction of different equivalence scales, even if the technical choices regarding households' economies of scale may considerably affect the magnitude of the impact. With regard to policy considerations, the analysis shows that most of the factors which influence the probability of migration seem to be beyond the scope of any policy intervention, meaning that the resources allocated in pro-migration policies cannot directly benefit the poorest households. The rest of the paper is organized as follows. Section 2 explores the literature, sections 3 and 4 describe data and methodology, section 5 illustrates the empirical strategy, section 6 discusses the results and some policy implications, section 7 concludes.

2. Literature review

The economic literature on migration and remittances is vast and the multidimensional nature of the subject favoured the emergence of several specific strands. The unit of analysis allows to make a first broad distinction between microeconomic and macroeconomic works. Macroeconomic studies relate the aggregate flows of migrants and remittances to other aggregate variables such as exchange rates (Lartey et al., 2012) and GDP growth rates (Kumar and Stauvermann, 2014), microeconomic works focus either on households or individuals. Secondly, some works focus on the countries of origin and others on the countries of destination. Thirdly, whereas some studies evaluate the relation between migration and socio-economic variables, others investigate the determinants of migration and remittances choices (Agarwal and Horowitz, 2002; Stark and Lucas, 1988) or explain who migrants are and in what they differ from stayers (Borjas, 1987). Finally, even though migration and remittances can be conceived as the two faces of a same coin, they are often treated separately: part of the literature focuses on migration, another part concentrates on remittances and some works emphasise the simultaneity of the two phenomena. As pointed out by Hanson (2010), because of such great abundance of perspectives, economic literature has still not been able to build a "Washington consensus" on migration and remittances. In particular, whereas literature on remittances tends to highlight their positive developmental impact, migration literature has paid more attention on the potential adverse effects of the phenomenon.

According to Ratha (2006), workers' remittances constitute the most tangible link between migration and the development of receiving countries, producing micro and macro direct positive effects. Indeed, the empirical evidence produced by several country-case (Bertoli and Marchetta, 2014; Combes et al., 2014; Jimenez-Soto and Brown, 2012; Lokshin et al., 2010) and cross-country (Acosta et al., 2008; Gupta et al., 2008; Adams and Page, 2005) studies suggests that remittances play an effective role in reducing poverty. Besides the direct wealth effect on recipient households, Adams and Cuecuecha (2013, 2010) found that recipient households exhibit a higher marginal propensity to spend in investment goods and Giuliano and Luiz-Arranz (2009) demonstrated that remittances flows constitute an alternative source of investment financing, especially in countries characterized by a low level of financial development. Moreover, because of their substantial volume and moderate volatility, remittances constitute a safe source of foreign-exchange earnings, increasing recipient countries' creditworthiness and improving their capacity to cope with capital flights (WB, 2006). As anticipated, notwithstanding the mixed findings regarding inequality (Acosta et al., 2008; Brown and Soto, 2008; Barham and Boucher, 1998) and exchange rates (Lartey et al., 2012; Amuedo-Dorantes and Pozo, 2004), literature focussing on remittances seems to have reached a certain degree of consensus regarding their beneficial effects. On the contrary, since the literature on migration produced somewhat mixed results, scholars tend to be cautious in associating migration and development and have identified a number of migration's negative effects on sending countries' economic performances. Even though Mishra (2007), studying Mexican emigration over a thirty-years period, estimated a major redistributive effect from capital to labor remuneration at the cost of a small negative effect on GDP, “brain drain” literature pointed out how migration might actually cause a significant depletion of human capital (Wong and Yip, 1999; Beine et al., 2001). Taking advantage of a natural experiment, Gibson et al. (2011) found a negative effect of migration on several migrant households' indicators and other empirical studies produced similar results for what concerns children's education (McKenzie and Rapoport, 2011; Giannelli and Mangiavacchi, 2010) and on mental problems of left-behind household members (Graham et al., 2015).

For what concerns to the specific case of Bangladesh, Siddique et al. (2012) found a one-way positive causal relationship from remittances to GDP growth while Chowdhury (2011) demonstrated the existence of a similar relationship between remittances flows and financial deepening. Such results are somehow consistent with the conclusions of Stahl and Habib (1989), who argued that even though remittances are used by recipient households just for consumption expenditure, they nevertheless can indirectly trigger investment through their boosting effect on aggregate demand. As far the socio-economic implications of migration, Mendola (2008) found that household involved in international migration were more prone to invest in modern agricultural technology and Hadi (2001) argued that it can be interpreted as a determinant of behavioural change in the traditional rural communities of sending areas, prompting a relaxation of women's socially approved habits.

3. Data

This study employs the data collected during the 15th round of Bangladesh Household Income and Expenditure Survey (HIES), held between February 2010 and January 2011. HIES is a national representative survey conducted by the Bangladesh Bureau of Statistics in collaboration with the World Bank and, containing a wide and deep range of socio-economic information both at the individual and household level, is considered the most accurate and comprehensive source of data for what concerns the social and economic accounts of Bangladesh households. In particular, HIES 2010 collects data on 12,240 households, for a total of 55,580 individuals. The questionnaire includes sections on expenditure, income, consumption, education, employment, health, households' assets and – among others – migration. The module on migration gathers a relatively large set of information on 1,372 international and 728 domestic migrants who, before migrating, were part of the surveyed households. On the basis of this information, (international) migrant households are defined as those households satisfying at least one of the two following conditions: *(i)* the household has reported to currently have one (or more) member migrated abroad; *(ii)* one (or more) member of the household is reported to have been abroad for more than six consecutive months during the previous five years. Since the aim of the analysis is to evaluate the impact of migration on the welfare of migrant households, condition *(ii)* prevents to discard from the pool of migrant households those families whose welfare is likely to be still affected by the migration experience of their recent past. Following this definition, it results that 10.4% of Bangladeshi households can be considered as “migrant households”. It also turns out that, among households satisfying condition *(i)*, the average number of migrants is 1.18 and almost all of them (98.4%) are male. In general, the share of migrant households which received remittances in the previous twelve months is 82.0%, but it raises to 91.7% considering only the subgroup of migrant households which satisfy condition *(i)*. It should also be noted that, adopting households (rather than individuals) as unit of analysis, the present work implicitly adheres the framework on the new economics of labor migration (NELM). This framework, pioneered by Stark (Stark and Levhari, 1982; Stark and Lucas, 1988) in relation to rural-urban migration, models migration as the outcome of a dynamic contract between migrants and their families, implying that migration decisions are collectively taken at the household level.

Table 1. Households' descriptive statistics

	Overall	Non migrant	Migrant	Matched
Household size	4.65	4.51	5.89	5.96
Kids (aged 6-17)	1.29	1.28	1.40	1.39
Male adults (aged 18-45)	0.98	0.91	1.58	1.63
Male adults (aged 46-65)	0.34	0.33	0.42	0.42
Female adults (aged 18-45)	1.02	1.00	1.19	1.17
Female adults (aged 46-65)	0.30	0.29	0.44	0.46
Adults, old (aged 66+)	0.19	0.18	0.25	0.26
Years of education, adult males	4.36	4.37	4.28	4.66
Years of education, adult females	3.63	3.52	4.50	4.55
Urban (municipality)	26.80%	27.02%	24.94%	24.48%
Urban (metropolitan area)	9.15%	9.48%	6.35%	7.23%
Muslim	87.79%	86.94%	94.97%	95.22%
Landless	6.38%	6.85%	2.40%	2.35%
Semi-landless (<0.05 acres)	23.25%	24.60%	11.85%	11.83%
N	12,240	10,949	1,291	3,873

Source: Author's calculations, HIES 2010.

4. Methodology

4.1. Measuring welfare

This research considers the wellbeing of individuals in terms of their command over goods and services, conceived as the inputs of individual utility. Consumption (proxied by per capita expenditure) allows to convey it into a monodimensional money-metric measure which, compared to income, is less subject to measurement error and characterised by a lower volatility. It is worth noting that, because of consumption smoothing, expenditure should (at least partially) discount for the lumpy costs of financing migration. On a theoretical level, per capita consumption is formalised as

$$Y_i = e(p, u_i) / d(x_i)$$

where $e(.)$ is the household expenditure function, $d(.)$ the equivalence scale function, p a n-dimensional vector containing the prices of all the goods and services available in the market, x a k-dimensional vector of relevant household characteristics and u the (maximised) level of utility of the household. Total expenditure is defined by function e, which is nondecreasing, continuous, concave, homogeneous of degree 1 in p. The equivalence scale function d is meant to standardises household size on the basis household characteristics, allowing to compare the welfare of individuals belonging to households which differ in size and demographic composition. In practice, per capita consumption is estimated from the consumption section of the household survey. Since

HIES does not provide sufficient information to implement a rental equivalent approach, following Deaton and Zaidi (2002), the consumption flow of durable goods is estimated assuming an annual depreciation rate of 10%. For what concerns the equivalence scale functions, the most elementary one simply returns the number of household members whereas others, less trivial, use more of the information of x (i.e. the age of members). The scales adopted in the paper are described in OECD (2013).

4.2 Counterfactual framework and treatment effect

The impact of migration and remittances on household welfare can be evaluated by comparing the measures of the reference indicators actually observed with those which would have been witnessed in a no-migration counterfactual scenario. The key assumption behind all the analyses conducted in a counterfactual framework is that every analytical unit belonging to the population of interest has a potential outcome under each treatment state (Morgan and Winship, 2007). Adopting this framework, the impact of the exposure to a treatment (with respect to the exposure to an alternative set of causes) on a given analytical unit is the difference between the outcomes associated to the two treatment states. Since it is possible to observe (at most) only one outcome for each unit, causal inference can be conceived as a problem of missing data (Imbens and Rubin, 2015; Holland, 1986). In the case of a binary treatment, the observational rule for the outcome of the variable of interest Y can be formalised as:

$$\mathrm{Y}_i^{\mathrm{obs}} = \mathrm{D}_i\,\mathrm{Y}_i^{(1)} + (1-\mathrm{D}_i)\,\mathrm{Y}_i^{(0)}$$

where $\mathrm{Y}_i^{(0)}$ and $\mathrm{Y}_i^{(1)}$ indicate the two potential outcomes of the variable of interest of the i-th observation and D_i is a binary variable indicating the exposure to one of the two alternative sets of causes, treatment (D_i=1) and control (D_i=0). In the present analysis, the variable of interest is the logarithm of per capita expenditure (computed on a household-level basis) and the treatment is defined as currently having, or having had in the previous five years, at least one member emigrated abroad. It follows that treated and migrant households coincide. As the observational rule imposes, for every individual it is possible to observe either $\mathrm{Y}_i^{(0)}$ or $\mathrm{Y}_i^{(1)}$, depending on whether the i-th household has been exposed to the treatment and the individual treatment effect is defined as:

$$\tau_i = \mathrm{Y}_i^{(1)} - \mathrm{Y}_i^{(0)} \quad .$$

Since the research aims to evaluate the impact of migration on each migrant household, the fundamental quantity of interest is

$$\tau_i^{\text{treat}} = (Y_i^{(1)} - Y_i^{(0)} \mid D_i = 1)$$

and it is obtained by estimating the unobserved potential outcomes ($Y_i^{(0)}$) of migrant households (the estimator for individual effects is described in section *5.12*). The expected value of τ_i^{treat} is the average treatment effect on the treated (ATET) that, defined as

$$\text{ATET} = E\,(\, Y_i^{(1)} - Y_i^{(0)} \mid D_i = 1\,)\ ,$$

represents the average impact of migration and remittances on the welfare of the migrant households members expressed in percentage change of their expenditure. In order to estimate the effect of migration on households belonging to different quartiles of expenditure or characterized by a different length of exposure to the treatment, the expected value of the treatment effect is conditioned not only by the exposure to the treatment, but also on the set of condition Θ_i . The estimator is thus defined as

$$\text{ATET}_{|\Theta} = E\,(\, Y_i^{(1)} - Y_i^{(0)} \mid D_i = 1, \Theta_i\,)$$

where Θ contains the set of additional conditions, e.g. the quartile of expenditure of the household in the counterfactual scenario.

4.3 Methodological issues

As pointed out by migration literature, the estimation of the impact of migration and remittances on the welfare of those left behind raises a series of methodological issues. Following the classification provided by Adams (2012), these issues can be summarised as those arising because of *(a)* the simultaneity of the decisions regarding migration with other choices (labor supply, education, fertility, etc.) that also influence the outcome of the variable of interest, *(b)* the self-selection of migrants, who systematically differ from the stayers, *(c)* the reverse causality nexus between poverty and migration/remittances and *(d)* the presence of relevant omitted/unobservable variables. On a theoretical level, a randomised experiment would allow to overcome all these difficulties and to estimate an unbiased average treatment effect (ATE = $E\,(Y_i^{(1)} - Y_i^{(0)})$), but the nature of migration phenomenon makes this solution infeasible. Natural experiments, allowing to fully overcome the problem of self-selection and to estimate an unbiased ATET, can be considered as the first-best feasible methodological solution. Unfortunately they are rare and the few, as in the case of the New Zealand's visa lotteries, have been heavily exploited (Gibson et al., 2013, 2011, 2010; Stillman et al., 2009). Moreover, even though these studies adhere to the best methodological practice, they often do not allow to focus on very representative case-studies. In the absence of available natural experiments, regression-based approaches result to be the most common methodological solution and the variable of interest is expressed as a linear function of a set of exogenous explanatory variables. Regression-based approaches relate causality with the notion of *ceteris paribus* (Wooldridge, 2010) and, usually, the treatment effect is the estimated coefficient of a treatment indicator. In order to address the above-mentioned methodological issues, it is usually implemented the Heckman's correction procedure (Heckman, 1979) or, alternatively, scholars resort to instrumental variables (IV) estimator. In practice, since the relevance of the instruments can only be tested from a statistical point of view and their exogeneity can not be tested at all, finding appropriate instrumental variables turns out to be everything but easy (Jalan and Ravallion, 2003). On the other hand, as pointed out by Puhani (2000), the results obtained using a Heckman's two-stage model may be misleading if normality assumption is violated.

4.4. Matching methods

In social sciences, matching methods gained momentum after the works of Dehejia and Wahba (1999, 2002) and found application in a number of migration studies (Bertoli and Marchetta, 2014; Möllers and Meyer, 2014; Jimenez-Soto and Brown, 2012; Ham et al., 2011). Whereas these works rely on propensity scores, the present study perform matching on *linearised* propensity scores (see section *5.11*), which produce better matches and a more precise identification of the overlapping region. The main theoretical difference between regression-based and matching methods lies in the notion of causality implicitly arising from a different interpretation of the covariates. Indeed, according to Imbens and Rubin (2015), regression models only rely on observed outcomes and fail in drawing an explicit distinction between potentially causal treatments and intrinsic attributes of the units under examination. They also argue that the ATET of the two approaches coincide only in the special case of a linear regression without additional covariates in the context of a completely randomised experiment. On a practical level, matching methods present three main advantages. Firstly, because of their non-parametric nature, the estimates of the counterfactual outcomes do not directly rely on the specification of any particular functional model. Secondly, the estimated treatment effect is not constant but different for every unit. Thirdly, the balance of the covariates ensures that matched observations really resemble the treated ones.

Conditional independence is the fundamental assumption behind matching and requires that, after controlling for an appropriate set of exogenous covariates X, potential outcomes are orthogonal to treatment assignment (households' migration status). Formally:

$$(Y_i^{(0)}, Y_i^{(1)}) \perp\!\!\!\perp D_i \mid X_i$$

Conditional independence is a necessary but not sufficient condition to implement matching methods in observational studies, which additionally require the observable nature of the set of covariates X (selection on observables assumption). Under selection on observables, it is possible to estimate the treatment effect matching treated units with untreated ones which exhibit the same value of X. Since X_i is a k-dimensional vector, the probability of finding a match between treated and untreated units exponentially decrease with the increasing of k (and falls to zero in presence of continuous covariates). This difficulty, known as "curse of dimensionality", has been addressed by Rosenbaum and Rubin (1983), who defined a function $f : \mathbf{R}^j \rightarrow \{ \mathbf{R} \cap (0, 1) \}$ such that

$$f(X_i) = Prob[D_i = 1 \mid X_i]$$

and demonstrated that

$$(Y_i^{(0)}, Y_i^{(1)}) \perp\!\!\!\perp D_i \mid f(X_i)$$

where $f(X_i)$ acts as a balancing score and, when represents the unit-level probability of selection into the treatment, it is called propensity score. Propensity scores can be estimated with a probability model and allow to match households on the basis of a monodimensional measure, overcoming the dimensionality problem. Each migrant household is matched with one or more households which share the same characteristics except for the exposure to the treatment and the outcomes of matched untreated households are used to estimate the unobservable potential outcomes of migrant ones. The validity of the (weak) overlapping condition, given by

$$Prob[D_i = 1 \mid f(X_i)] < 1 \qquad \forall\, i,$$

ensures that it is possible to estimate the ATET for the entire subsample of treated units.

It is worth stressing that, if selection on observables holds (which is equivalent to say that issue (*d*) is not a cause of concern), matching methods provide a solution for issues (*a*) and (*b*). Indeed, they allow to correct for the self-selection of migrant households and the estimates take into account the effect that remittances and changes in household's composition may have on the opportunity costs faced by household members (which can affect, *inter alia*, individual labor supply). Even though selection on observables cannot be tested, this concerns is mitigated by the fact that HIES 2010 presents a large sample size, a favourable treated-untreated ratio and, covering a wide range of topics, allows to estimate the balancing scores on an uncommonly large set of information.

4.4 Caveats

Firstly, it should be noted that considering only two potential outcomes for each unit implicitly introduces the stable unit treatment assumption (SUTVA). In economic terms, it means that the estimates only account for partial equilibrium effects and do not consider the effects that migration and remittances may produce, for example, on aggregate demand, exchange rate, wages and unemployment. Consequently, the estimates can be considered robust for the marginal migrant household but the counterfactual scenario should rather be considered as a nuanced benchmark.

Secondly, the survey does not provide information regarding the endogenous recomposition which some migrant households could experience. For instance, this phenomenon may take place when the head of a household composed by three people (head/husband, wife and a child) emigrates and the two left-behind members, looking for a more efficient household dimension, find convenient to join the wife's brother family. When this newly-formed household is surveyed, it is recorded as a migrant household and the migrant is registered as the brother-in-law of the head. Even in presence of longitudinal data or of specific questions regarding the dynamics of household recomposition, this situation would be challenging to handle. Indeed, the bifurcation introduced by the causal exposure does not regard the outcomes of the households but the population of households itself. On a theoretical level, finding a definition of the treatment would be extremely difficult and, on a practical level, it would require an excessive amount of information. To misquote Eraclitus, it is not possible to step twice in the same river, but sometimes it could be convenient to assume so.

5. Empirical strategy

This section illustrates the empirical strategy follwed in the study, explaining the main steps made to obtain the final results, from the inclusion of the covariates to the choice of the estimator and the check of overlapping and balance conditions.

5.1. Choice of the probability model and general rules for the inclusion of covariates

Estimation of propensity scores requires the choice of a probability model and the selection of the identifying variables. A binary treatment calls for a binary response model and literature recommends the use of either a probit or a logit model (Caliendo and Kopeinig, 2008). The paper opted for a probit model. The probability of selection into the treatment is thus given by

$$\widehat{Prob}[D_i=1 \mid X_i] = \hat{f}(X_i) = \Phi(X_i{}'\beta)$$

where Φ(.) is the c.d.f. of a standard normal distribution. The choice of the set of covariates X that identifies the probability model is a crucial step because, in theory, they are the observable conditioning variables which ensure the independence between potential outcomes and selection into the treatment. In practice, being conditional independence an abstract concept, the covariates of observational studies should not be conceived as the real conditioning variables but rather as proxies capturing the maximum amount of households' relevant conditioning information. For this reason, and because of the lack of direct interpretation of probit coefficients, as long as it improves the quality of the estimates, there is no need to avoid the inclusion of interaction terms or nonlinear transformations of the covariates (Imbens and Rubin, 2015). On the other hand, flexibility does not mean theoretical inconsistency and the inclusion of every covariate needs to be theoretically justified on the basis of the criteria of relevance and exogeneity. Included predictors should be relevant in the sense that they simultaneously influence both the probability of the selection into the treatment and the outcome of the variable of interest. On the other hand, exogeneity is meant as the absence of any causal relationship moving from the exposure to the treatment to the predictors of the probability model. Since the concept of causality is intrinsically related to time (Holland, 1986), covariates whose value is already determined before the exposure to the treatment can generally be considered as exogenous. It is worth noting that the final set of covariates used in this study considerably differs from those adopted in other works which adopted similar methods: these differences arise both because of theoretical considerations and of the structure of the dataset, which makes available an uncommon amount of information. Finally, it has to be specified that the sets of covariates on which propensity scores have been estimated do take into account the effect of migration on household composition. In other words, before running the probability mode, "missing" migrants members have been reintroduced in their original households.

5.2. Sample weights

As observed by Zanutto (2006), the use of sample weights should be avoided in the estimation of probability model. Indeed, matching methods are strictly based on individual characteristics and, consequently, all the information needed for the estimation of each score is entirely contained in the correspondent unit. On the other hand, following DuGoff et al. (2014), sample weights have been included among the predictors of propensity scores. This choice is justified by the fact that sample weights, for their very nature, contain relevant information on the observation. Finally, the weights has been used to generalise sample results to the entire population.

5.3. Demographic characteristics

Adopting a NELM theoretical framework, the demographic structure of the household is of a major importance and should be adequately captured by *X* and the set of covariates describing household demographic structure included in this study is wider and more detailed than the ones adopted by similar works. Still, since migration affects post-treatment fertility choices, all the covariates reflecting the demographic characteristics have been carefully computed in order to avoid this source of endogeneity. Consequently, neither household dimension nor age dependency ratio, used respectively by Jimenez-Soto ans Brown (2012) and Bertoli and Marchetta (2014), have been included. By contrast, the predictors included in the model are the number of working age male and female adult members (divided in two age groups, 18-45 and 46-65), the number of elderly members and the number of kids between six and seventeen years old (under the hypothesis they are old enough to be exogenous to migration).

5.4. Information on household head

The individual characteristics of household head are likely to be relevant in explaining both the economic performance and the migration decision of the household and in some works they have been included among the covariates (Möllers and Meyer, 2014; Jimenez-Soto and Brown, 2012; Calero, 2009). Yet, as pointed out by Cox-Edwards and Oreggia (2009), in absence of adequate pre-treatment information, household headship should be considered endogenous to migration and thus excluded from predictors. Endogeneity of headship clearly emerges from Bangladesh data: the percentage of female headed household is 13.9%, but it raises to 44.7% among migrant households and falls to 10.3% in the non-migrant subsample. Such a remarkable difference can be explained by the fact that, when the husbands emigrate, headship is inherited by wives.

5.5. Education

Economic theory recognizes a fundamental importance to human capital formation and the educational attainment of household members is likely to be a key predictor for both household consumption and migration propensity. In the case of Bangladesh, since the returns on education and the average level of education differ between males and females, this information has been disaggregated according to a sex-wise criterion. The level of education is thus captured by two variables indicating the average years of education of female and male adult members, while the educational attainment of younger members is excluded in order to avoid usual concerns about endogeneity. HIES data on individual educational achievements have been converted into years of schooling following the information on Bangladesh education system provided by UNESCO (2011).

5.6. Households' environment

Besides the variables which capture information on households' demographic structure and human capital endowment, literature has stressed the importance of households' local environment. These information are captured by a set of regional dummies, by a dummy for households living in urban areas and by another dummy for households living in one of the four metropolitan areas.

5.7. Religion

Since nine out of ten households are Muslim, since Islam is a pillar of national identity and since, except for the "secularist" parenthesis of the rule of Mujibur Rahman, the country has historically pursued policies inspired by a moderate islamism (Lewis, 2011), it is possible to conceive the existence of a correlation between the average economic performance of the families and their religious beliefs. On the other hand, since Muslim oil countries have traditionally been the destination countries, household religion might also affect probability of migration. For these reasons – and because its exogeneity – the religious belief of households has been included among predictors.

5.8. Entrepreneurship

Entrepreneurial attitude of household members could be relevant in determining the economic performance of the household they belong as well as the probability of migration. It can also be considered as a proxy for other relevant unobservable characteristic. HIES 2010 has a section on non-agricultural enterprise activities which contains information about the type of business the household is involved in and when the activity started. This information allows to create dummies for household's involvement in formal and informal non-agricultural business. In order to avoid endogeneity issues, dummies activate only if the household started a business before the migration of a member.

5.9. Other predictors

As discussed before, according to DuGoff et al. (2014), sample weights should be included among the predictors. Other variables, as the access to public electricity network, might be used as predictors, even though their exogeneity is less clear. The same goes for land ownership: on the one hand, it surely affects both the well-being of household and the migration decision but, on the other hand, it could be endogenous to migration (land could have been sold for financing migration or, viceversa, could have been purchased with the remittances). Anyway, Bangladesh's land market is characterized by a low volume of transactions (Mendola, 2008) and the dummies inserted into the set of covariates only account for the two extremes of land ownership: landlessness/semi-landlessness and, alternatively, the ownership of a large farm.

Table 2. Specifications of the probability model

Specifications		A	B	C	D	E	F	G
Demographic structure	Male adults (18-45)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Male adults (46-65)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Female adults (18-45)	0.193	0.014	0.015	0.013	0.015	0.101	0.003
	Female adults (46-65)	0.000	0.000	0.000	0.000	0.000	0.420	0.002
	Old adults (65+)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Kids (6-17)	0.000	0.000	0.001	0.016	0.006	0.004	0.004
Education	Male adults average education		0.000	0.000	0.000	0.000	0.000	0.000
	Female adults average education		0.000	0.000	0.000	0.000	0.000	0.000
Geographical variables	Regional dummies (χ^2)			0.000	0.000	0.000	0.000	0.000
	Urban area			0.000	0.000	0.025	0.018	0.020
	Metropolitan area			0.000	0.000	0.000	0.000	0.000
Land ownership	Landless				0.000	0.000	0.000	0.000
	Semi-landless (<.0.05 acres)				0.000	0.000	0.000	0.000
	Landlord (>4 acres)				0.469	0.750	0.588	
Other variables	Religious belief (Muslim)					0.000	0.000	0.000
	Entrepreneurship (formal)					0.000	0.000	0.000
	Entrepreneurship (informal)					0.000	0.000	0.000
	Access to electricity network					0.000	0.000	0.000
	Sample weights					0.000	0.000	0.000
Interactions / Nonlinear transformations	Squared male adults (18-65)						0.000	0.000
	Squared female adults (18-65)						0.253	
	Male adults*Male education						0.000	0.000
	Female adults*Female education						0.283	
	Squared male education						0.861	
	Squared female education						0.001	0.000
	McFadden's pseudo-R^2	0.1109	0.1509	0.2103	0.2191	0.2747	0.2935	0.2932
	Log-likelihood	-3667	-3502	-3257	-3221	-2991	-2914	-2915

Note: the table reports coefficients' p-values. Source: Author's calculations.

5.10. *Specification of the probability model*

The choice of the final specification of the probability model has been made following a stepwise approach. Specifically, in the light of previous paragraphs' considerations, in each of the first six steps it has been included an additional group of covariates. Table 2 reports coefficients' p-values, the McFadden's pseudo-R^2 and the log-likelihood of each specification (coefficient have no causal interpretation and has been omitted). As expected, it emerges that almost all the variables discussed in the previous paragraphs turn out to be significant in predicting the probability of selection into the treatment, and every groups of variables significantly improves the statistical fit of the model. The final choice has been on specification (G) and it is the one that will be used thereafter. On the basis of the assumptions of the model and following Imbens and Rubin (2015), (G) mimics the unit-level assignment probability function which, theoretically speaking, depends itself by the assignment mechanism that rules the migration in Bangladesh.

5.11. Choice of the matching variable

The choice of the matching variable is a crucial step and can substantially affect final results. Whereas most of the studies (Bertoli and Marchetta, 2014; Möllers and Meyer, 2014; Jimenez-Soto and Brown, 2012; Mendola, 2007) match on the estimated propensity scores $\hat{f}(X_i)$, in this analysis matching is performed on the logit of the scores, defined as

$$\hat{\ell}(X_i) = \log\left(\frac{\hat{f}(X_i)}{1-\hat{f}(X_i)}\right)$$

and conceivable as a linearised propensity score (*lps*). The main advantage of matching on this monotonic transformation of propensity scores is due to the fact that it makes comparable the distances between observations irrespectively of their position in the distribution, making the matching procedure more precise. Moreover, on a practical level, it simplifies the identification of the region of common support and ensures the theoretical consistency of the imposition of a caliper (see below).

5.12. Matching estimator

The analysis makes use of a nearest neighbour matching (NNM) algorithm with replacement and imposing a caliper. With NNM, the counterfactual outcome of each treated unit is estimated taking the average of the closest M untreated observations (in the present analysis, M = 3). Formally, building on Abadie et al. (2004), $I_M(i)$ is defined as the set of the indices for the matches of the i-th unit that are at least as close as the M-th match (distance d_M) and, in any case, not more distant than d_{caliper}

$$I_M(i) = \{l=1,\ldots,N \mid D_l=0,\ \text{abs}[\hat{\ell}(X_i)-\hat{\ell}(X_l)] \leqslant \min[d_M(i),\ d_{caliper}]\}$$

and the estimator for $Y_i^{(0)}$ results

$$\widehat{Y_i^{(0)}} = \frac{1}{\# I_M(i)} \sum_{l \in I_M(i)} Y_l$$

where $\# I_M(i)$ is the number of the matches of the i-th unit. As pointed out by Smith and Todd (2005), the increase of M reduces the variance of the estimator (it uses more information) at the expenses of the bias (incremented, since the average quality of the matches will be lower). For what concerns replacement, as in the case of Dehejia and Wahba (2002), it results necessary because, for high values of the logit, there is a relative abundance of treated observations.

5.13. Common support

The estimation of all the counterfactual outcomes requires that every treated unit is matched with at least one unit exposed to the control treatment. This condition is satisfied when the region of common support, the overlapping region between the p.d.f. of the logit for treated and untreated units, coincide with the region in which the p.d.f. of the logit of treated units assumes positive values. The imposition on a caliper, a maximum distance between two logit in order to be considered “close enough” for matching, offers a straightforward solution to the common support problem. According to Austin (2011), when at least one of the predictors is not binary, the optimal caliper width should range between 0.2 and 0.55 the standard deviation of the estimated logit. Choosing specification (G) and imposing a caliper of 0.5 times the standard deviation of *lps*, the caliper width (d_{caliper}) turns out to be 1.159, large enough to match all the treated units.

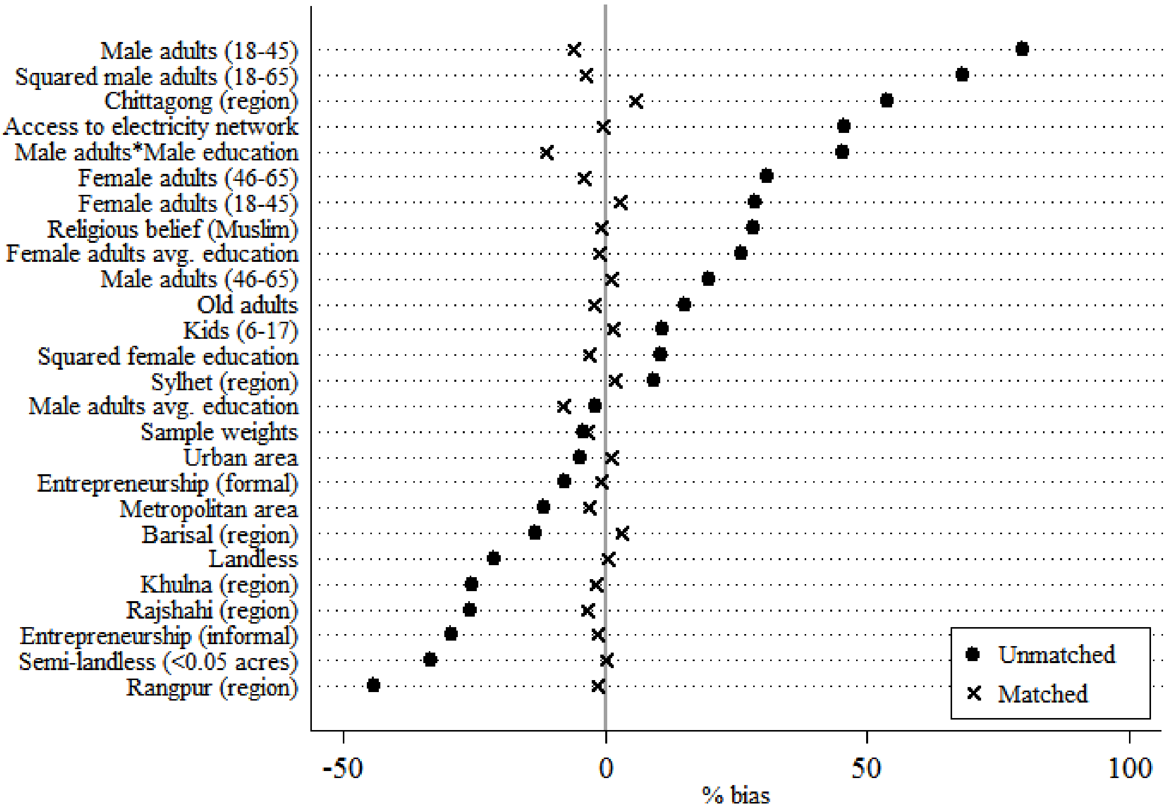
5.14. Balance

From a certain perspective, matching can be seen as a method of strategic subsampling (Morgan and Winship, 2007) based on the observables relevant covariates contained in X and aimed to pick up, among untreated units, a counterfactual group which shares the same characteristics of the treated one. In the present case, balance is achieved if the condition

$$D_i \perp\!\!\!\perp X_i \mid \hat{\ell}(X_i)$$

is verified. When the estimand is the treatment effect on the treated, the subsampling is among the untreated observations. Hence, the quality of the estimates crucially depends on the balance of the conditioning covariates among the treated and matched control groups. Getting a look at the distribution of the *lps* before and after the matching can provide a first insight of balance achievement [Appendix, fig. A1]. Secondly, following Sianesi (2004), the regression of the probability model has been repeated excluding the unmatched observations and none of the predictors turns out to be significant and the McFadden's pseudo-R^2 is virtually zero, confirming balance. Thirdly, balance is confirmed checking Rubin's standardised bias (Rosenbaum and Rubin, 1985), a weighted difference of the mean of the covariates between treatment and matched control groups.

Figure 1. Standardised bias of the covariates



Source: Author's calculations

6. Results and policy considerations

What is the impact of migration and remittances on the welfare of the household members left behind? The clearest and less disputable result emerging from the analysis is that, on average, migration and remittances have a positive and significant impact on the welfare of migrants' household members. At the first sight, this finding could even seem self-evident: if migration was detrimental to welfare, why should rational people – after the early waves – continue to emigrate? Anyway, since HIES 2010 does not contain any information on migrants' well-being, this deduction is not correct. On the other hand, the finding is consistent with the fundamental assumption of the NELM approach, the idea that migration can be conceived as part of a household strategy. Indeed, whereas a negative or not significant effect would have suggested that migration is an individual decision, a situation which clearly benefits those left-behind is in line with the idea that the decisions regarding migration are taken at the household level.

Table 3. Average Treatment Effect

Equivalence scale	Sample ATET	Population ATET
No equivalence scale	30.89%*** (0.022)	28.82%
OECD (Oxford) scale	30.69%*** (0.021)	28.62%
OECD (modified) scale	28.67%*** (0.021)	26.68%
Squared root scale	18.96%*** (0.021)	17.48%

Notes: * indicates significance at the 10% level, ** at the 5% and *** at the 1% level; SE in parentheses; SE of Sample ATET are computed following Abadie and Imbens (2006); Equivalence scales described in OECD (2013). Soruce: Author's calculations.

Even if the impact of migration on migrant households' welfare appears unambiguously positive, the precise quantification its magnitude results sensitive to the assumptions regarding households' economies of scale. Specifically, if the effect is measured in relative terms, equivalence scales always reduce the magnitude of positive impacts and, viceversa, magnify the negative ones. On the contrary, when the effect is measured in absolute terms, they can affect the results in both directions. If the impact is negative, its negative effect is always amplified. If the impact is positive, equivalence scales reduce its magnitude up to a certain point. After this point, which depends positively on the equivalence elasticity of the scale and negatively on net impact of migration and remittances on total household expenditure, the estimated impact results bigger than the impact that would have been estimated without introducing the scale.

Table 4. Quartile ATET

Quartile	Number of units	Sample Quartile ATET	Population Quartile ATET
I	55	64.88%*** (0.094)	65.10%
II	323	55.24%*** (0.045)	52.23%
III	546	32.80%*** (0.034)	29.47%
IV	367	-6.76% (0.050)	-8.05%

Notes: * indicates significance at the 10% level, ** at the 5% and *** at the 1% level; SE in parentheses; SE of Sample ATET are computed following Abadie and Imbens (2006); Modified OECD scale (OECD, 2013). Source: Author's calculations.

Quartile ATET shows that the impact of migration is higher for relatively poorer households, while for richest households it is negative but not statistically significant. It can be interpreted both on the basis of the lower base level of expenditure of poorer households and on the basis of the different opportunity costs faced by migrants characterised by different backgrounds.

Since the net impact of remittances is given by the difference between the amount remitted and the income of migrants if they had not migrated, if the expected income (at home) of poorer migrants is lower than the ones of richer migrants, the impact for poorer households results – *ceteris paribus* – higher. Secondly, it is also possible to imagine that poor migrants have stronger incentives to remit than those migrants whose families are less in need.

Table 5. ATET over time

Years since migration	Number of units	Sample ATET over time	Population ATET over time
Less than 2	210	14.21%*** (0.060)	15.15%
2	228	16.06%*** (0.037)	17.09%
3	170	21.42%*** (0.046)	20.37%
4	105	30.36%*** (0.116)	23.60%
5	88	33.48%*** (0.128)	25.90%
6 or more	355	44.08%*** (0.048)	41.45%
Returned (currently, no migrants in the HH)	135	35.35%*** (0.049)	34.90%

Notes: * indicates significance at the 10% level, ** at the 5% and *** at the 1% level; SE in parentheses; SE of Sample ATET are computed following Abadie and Imbens (2006). Source: Author's calculations.

By disaggregating the results with respect to time, it emerges that the treatment effect tends to increase along with the length of the treatment period. This finding is consistent with the idea that recipient households use at least part of the remittances for investment purpose and, consequently, that remittances play a *direct* role in development. Indeed, if remittances were entirely spent for consumption, the standard of living of recipient households should not grow over time. Even though there is a series of alternative explanations that contends this interpretation (increasing remit capacity, self-selection of successful migration experiences, consumption smoothing), their joint explanatory power is able to account for only a part of the effect.

Table 6A. Variation of migrant households' ranking in the expenditure distribution: transition matrix from counterfactual (no migration) to observed scenario

Counterfactual scenario quintile (no migration)	Observed scenario quintile (migration)				
	I	II	III	IV	V
I	0.5%	0.5%	0.4%	0.3%	0.7%
II	0.9%	1.7%	4.0%	4.6%	6.9%
III	0.7%	3.6%	4.5%	9.7%	11.9%
IV	1.0%	2.9%	6.7%	9.9%	13.7%
V	0.3%	2.2%	2.5%	3.7%	6.1%

Notes: Modified OECD scale (OECD, 2013); sample weights included. Source: Author's calculations.

Percentage on diagonal: 22.7%
Percentage that moved up by at least one quintile (migration success): 52.6%
Percentage that moved down by at least one quintile (migration failure): 24.7%

Table 6B. Distributions of migrant households

Expenditure quintiles	Quintile to which migrant HH belong (marginal distributions of transition matrix)		Relative frequency of migrant HH	
	Observed	Counterfactual	Observed	Counterfactual
I	3.2%	2.6%	1.6%	1.4%
II	10.6%	16.5%	5.5%	8.5%
III	18.1%	27.2%	9.3%	14.1%
IV	28.1%	37.7%	14.5%	19.5%
V	40.2%	15.9%	20.8%	8.3%

Notes: Modified OECD scale (OECD, 2013); sample weights included. Source: Author's calculations.

The estimation of counterfactual outcomes also allows to investigate the impact of migration on social mobility and inequality. The first one has been originally captured building a transition matrix linking migrant households' observed outcomes to their estimated counterfactuals. The matrix shows that migration is a risky strategy but, when successful, it guarantees a great improvement of the well-being of households' members. On average, it results that about half of migrant households have been successful in climbing the social ladder, “migrating” to a higher expenditure quintile. On

the other hand, in one out of four cases migration seems to have worsened the economic condition of the households. Finally, looking at the marginal distributions, it emerges that international migration is a phenomenon which does not directly regards the most disadvantages sections of Bangladesh's population. Quite the opposite, about four out of five international migrants come from relatively better-off households while less than three percent of them originates from household belonging to the poorest quintile. Having an emigrated member is common among relatively wealthy families, but it's quite rare among the households belonging to the first quintile.
As far inequality, migration results to increase expenditure inequality by 1.58 Gini points. This finding is consistent with Brown and Jimenez (2008) and Barham and Boucher (1998), even if in this case the difference is smaller and the 95% confidence intervals of the two estimates overlap.

Table 7. Gini indexes comparison: observed vs. counterfactual

Scenario	Gini index	Lower bound (95%)	Upper bound (95%)
Observed (migration)	33.15	31.22	35.01
Counterfactual (no migration)	31.57	29.63	33.52

Notes: Modified OECD scale (OECD, 2013); sample weights included. Source: Author's calculations.

Moving from a positive analysis to some brief normative considerations, the results may seem to call for development policies aimed at making the migration strategy available also to poor households. On the contrary, the results of this study cannot be taken as evidence in support of such policy conclusions. Firstly, nearly all of the households belonging to the lowest expenditure quintile fall outside of the overlapping region and, consequently, the analysis has not much to say of the effect of migration on their welfare. Secondly, as clearly emerges from *Figure 1*, almost none of the relevant households' characteristics (e.g. all the variables related to the demographic structure) can be directly influenced by governmental policies. Since Bangladesh has implemented policies aimed at incentivizing outward migration and export of national manpower (e.g. establishing the Ministry of Expatriates' Welfare and Overseas Employment and the Probashi Kallyan Bank, a financial institution aimed to deliver subsidized financial services to migrants), besides the legitimate concerns regarding the effectiveness of these institutions in achieving their official objectives, the analysis suggests that – from a partial equilibrium perspective – the resources deployed in these policies mostly benefit relatively better-off households.

7. Conclusions

This research explores from different perspectives the impact of international migration on the welfare of Bangadeshi migrant households. The analysis indicates that, on average, migration produces a significant and substantial positive impact on the welfare of migrants' family members, a result which has proved to be robust to different assumptions regarding households' economies of scale. Quartile ATET shows that the welfare effect is stronger for the households belonging to the first quartile, while it is not statistically significant for the households belonging to the fourth. Looking at the expenditure distribution, it emerges that households engaged in migration are concentrated in the third and fourth quintiles, whereas less than three percent originate from the first. This finding suggests that the direct benefits of migration and remittances are unbalanced in favour of relatively wealthy households, even though the poorest sections of the population may benefit from some general equilibrium effect (not estimated). In general, international migration appears to be a household strategy characterised by high expected return and significant risk: it is a major cause of social mobility, but is precluded to the poorest households. By adopting social mobility as a yardstick for the success of migration, it turns out that in about half of the cases migrant households are able to climb the social ladder but, on the other hand, one out of four migration experiences ends up with the households falling in a lower expenditure quintile. Migration and remittances produce also a negative effect of inequality, but it appears relatively modest. As regards policy implications, the analysis shows that since most of the characteristics that determine migration choices cannot be influenced by policymakers, it is likely that any policy aimed to make migration easier, if effective, would directly benefit relatively better-off households.

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Appendix

Figure A1. P.d.f. of linearised propensity score