Natural Hazards and Internal Migration: The Role of Transient Versus Permanent Shocks*

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Abstract

We examined whether floods and cyclones, which can be considered as transient shocks, affect interregional migration differently compared to riverbank erosion that causes loss of lands and thus generates shocks that are permanent in nature. For our investigation, we tracked the 2000 Household Income and Expenditure Survey participants in nine coastal districts in Bangladesh and collected further information in 2015. We model migration on natural disasters and a range of household level variables. Our findings suggest that both transient and permanent shocks induce households to move to nearby cities but the effect is much higher for the latter category. Comparing income and expenditure of migrant- and non-migrant households in a matched difference-in-differences setting, we find that the former group is better-off relative to their counterparts, indicating that welfare can be improved by facilitating migration. Rising exposure to climate change induced natural disasters around the world imply that our findings will be increasingly relevant for designing policies to address vulnerability in disaster-prone countries with weak social safety nets.

Keywords: Climate change, Natural disaster, Coastal area, Permanent shock, Transient shocks, Internal migration

JEL Classification: I38, Q54, Q56, R23

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Highlights

1. We conducted a survey in 2015 by tracking the 2000 Household Income and Expenditure Survey participants in nine coastal districts in Bangladesh.
2. Both transient and permanent environmental shocks induce households to migrate to nearby cities but the effect is stronger for the latter category.
3. Migrant households are better-off relative to their counterparts, indicating that welfare can be improved by facilitating migration.
4. Our findings will be useful in designing policies to address vulnerability in disaster prone countries with weak social safety nets.

1. Introduction

This study analyses whether riverbank erosion that leads to loss of lands and thus imposes a permanent negative shock on households' economic status has higher influence on domestic migration decisions, compared to that of the transient shocks like floods and cyclones. We also examined how the types of shocks affect migrant households' choice of destination and the impact of migration on household income and expenditure.

Our study can be useful to policymakers and researchers by enhancing the understanding on whether migration can be used as an effective adaptation mechanism against natural disasters. Such analyses are particularly important as the frequency and intensity of natural hazards are on the rise (O'neill and Oppenheimer, 2002; Skoufias, 2003; Stern, 2008; IPCC, 2007; Desmet et al., 2018; Pugatch, 2019) that can significantly affect the well-being, economic and otherwise, of households and communities around the world (Cattaneo and Peri, 2016).[1] Natural hazards caused a global damage of US$1.5 trillion and affected around 2 billion people between 2003 and 2013 (FAO, 2018) and are projected to displace nearly 200 million people by 2050 (Myers, 2002). Permanent flooding alone is projected to reduce global real GDP by 0.19 per cent and welfare by 0.24 per cent, as people are expected to be forced to live places with less amenities (Desmet et al., 2018).[2]

Our analysis is conducted at the household level as the impact of disasters may vary across locations, communities and past exposure to natural disasters (Agrawal et al., 2012; Cattaneo and Peri, 2016; Peri and Sasahara, 2019; Guiteras et al., 2015). We have also focused on a developing country as natural disasters may severely affect people in those countries due to their dependence of natural resources and the lack of adaptation and safety nets (O'neill and Oppenheimer, 2002; Agrawal and Perrin, 2008).[3] This is evidenced by the fact that the economic damage between 2003 and 2013 due to natural disasters in developing countries was estimated to be US$550 billion (FAO, 2018).[4,5]

[1]Climate change tends to reduce agricultural output, affect cropping pattern, suppress productivity of workers exposed to heat, slow investment and may deteriorate health and other economic and non-economic outcomes (Moniruzzaman, 2015; Fischer, 2018; Heyes and Saberian, 2019). Filipski et al. (2019) find that after a disaster, households who did not bear economic losses, saved less and suffered from the "no tomorrow" tendency dominated over the precautionary motive for savings to use it during crisis.

[2]This is because economic damages caused by disasters can be long-lasting (Lynham et al., 2017; Caruso, 2017). Some studies find disaster affected people recover quickly with no long-run effects (e.g., Nguyen et al., 2018; Moniruzzaman, 2019; Fabian et al., 2019). Such difference in conclusions is not surprising as the econometric approaches of damage estimation suffer from the lack of comparability (Auffhammer, 2018).

[3]For instance, Barrios et al. (2006) found that climate change affects the pace of urbanization in sub-Saharan Africa but not in the other developing countries. Dasgupta (2018) find that, by the end of the 21st century, climate change may increase under-four child mortality by 20 per cent in some areas.

[4]Mejia et al. (2018) found that global temperatures had uneven macroeconomic effects, with adverse consequences concentrated in most low-income countries with warmer climates. Coronese et al. (2018) further indicated that available studies on the damages caused by natural disasters systematically underestimate the real losses in low-income countries.

[5]Disasters may affect life in other ways, like lowering job prospect, reducing life satisfaction, lowering schooling and deteriorating mental health of the victims (Kellenberg and Mobarak, 2011; Mottaleb et al., 2015; Takasaki, 2017; Karbownik and Wray, 2019).

Our study is particularly relevant as Bangladesh ranked 6th among countries that heavily suffers from adverse impacts of natural disasters (Kreft et al., 2016). The unique physical geography of coastal Bangladesh makes it highly vulnerable to the potential impacts of a rising sea-level (Brammer, 2014). As a result, more than 60 million people living in coastal areas of the country are severely impacted by climate change and related natural disasters.

Households affected by shocks follow a number of coping strategies to maintain their livelihood (Khandker, 2012).[6] A risk averse individual may prefer to migrate to a place where there is a lower risk of natural disaster (Brown et al., 2018). Thus, internal migration as an effective adaptation mechanism to natural hazards is generally accepted. Unfortunately, the internal migration issue is less covered in the literature, with past studies largely ignoring the role of environmental factors for migration (Mallick and Etzold, 2015). Only a few recent studies discussed migration as an alternative strategy to adapt with the adverse impacts of natural disasters (e.g., Black et al., 2011b; Poncelet et al., 2010; Chen and Mueller, 2018).

The empirical evidence identifying the nature and extent of internal migration as an adaptation strategy against environmental shocks are insufficient (Gemenne, 2011). Among the few exceptions, Chen and Mueller (2018) empirically assessed whether members of households in coastal Bangladesh have migrated due to flooding and salinity, either domestically or internationally. They found no effect of flooding but observed a strong positive effect of salinity on domestic migration while the effect was negative on international migration. Chen et al. (2017) found that the probability of migrating for at least one member in a household declines during flooding. Paul (2005) observed no migration in the aftermath of the 2004 tornado in Bangladesh as the availability of aid mitigated the effect of the shock. Besides, the nature of environmental shocks may affect migration differently but no studies examined how the nature of shocks affect migration and the choice of destination. Finally, while standard economic theories suggest that migrating households improve their well-being, only a few studies empirically confirmed this hypothesis (Beegle et al., 2011; De Brauw et al., 2017).

Against this background, we tracked the 2000 Household Income and Expenditure Survey participants in nine coastal districts in Bangladesh to collect further information in 2015. Our probit model results suggest that all type of natural disasters induce the surveyed households to migrate. In particular, natural hazards force people migrating to nearby cities but the effect is much stronger when the shock is permanent in nature. Comparing income and expenditure of migrant- and non-migrant households in a difference-in-differences model combined with matching, we find that the former group is better-off relative to their counterparts, implying that welfare can be improved by facilitating migration.

[6] Households that either held a large amount of collateralizable assets or face no (binding) borrowing constraints are able to maintain their consumption (Mozumder et al., 2009; Sawada and Shimizutani, 2008, 2011). People also intensify the use of the commons to generate additional income in the face of the shocks (Takasaki, 2011; Islam and Nguyen, 2018).

The remainder of this article is organized as follows. Section 2 discusses the determinants of domestic migration in coastal Bangladesh with a particular focus on the nature of shocks and their effects on migration decisions. Section 3 briefly describes the survey and the data. Section 4 presents the empirical strategy and the identifying assumptions. Results from our analysis are presented in Section 5. Section 6 concludes.

2. Natural disasters and internal migration in coastal Bangladesh

Migration can take different forms, internal or international, slow or rapid, forced or motivated and temporary or permanent (Portes, 2010). Each type of migration have a very complex set of determinants including economic, social, political, demographic or environmental factors. The environmental factor is particularly important as it has the capacity to affect all the other factors (Black et al., 2011a,b; Bunea, 2012). While economic pull factors dominated over social or demographic factors of internal migration in the past, with the rapidly changing climate, environmental push factors are becoming increasingly important to exert direct and indirect influences on internal migration decisions (Black et al., 2011a,b).[7]

The shocks faced by households in developing countries can be grouped into two general categories—covariate and idiosyncratic (Patnaik et al., 2016). Idiosyncratic shocks are related to the effect at the household or the individual level while covariate shocks affect a group of households, community, region or even the entire country. Thus, a household that experiences an idiosyncratic shock is more likely to rely on its neighbours for support, while households experiencing covariate shocks are less likely to do so as their neighbours are also exposed to the same shock. Based on these distinctions, environmental shocks are mostly covariate shocks in nature which makes their management more challenging (Patnaik et al., 2016).

The coastal zone of Bangladesh, which makes up approximately 30 per cent of the total area of the country, is particularly vulnerable to natural disasters. Its topographic and geo-physical location makes it prone to periodic floods, cyclones and riverbank erosion (Alam et al., 2018). The most common type of natural disasters in the coastal areas of Bangladesh are floods, cyclones and riverbank erosions (Poncelet et al., 2010). Depending on the nature and consequences of these natural disasters, we classify the covariate environmental shocks into two categories—transient and permanent.

2.1. Transient shocks

Transient environmental shocks can be defined as a temporary exposure to a particular natural hazard. Depending on the frequency, duration and intensity, floods and cyclones can be considered as common transient shocks in the coastal areas of Bangladesh.

Located at the delta of the Ganges, Brahmaputra and Meghna river basin and a few feet above the sea level, Bangladesh regularly experiences flash, rainfall-induced and storm surge floods. Each year, the

[7]Migration is usually explained by the push and pull factors in which the former refers to the desire for survival while the other one relates to the attraction of better living and economic conditions (Poncelet et al., 2010; Barrios et al., 2006).

inundation of floods affects about 21 per cent (or 31,000 km^2) of the country (Mirza, 2003). In the last 30 years, Bangladesh had experienced severe floods during 1987-1988, 1998-1999, 2004-2005, 2007, 2010 and 2017. With 50 per cent of the land less than eight meters above sea level and a coastline of 600 km, coastal flooding is an alarming problem for Bangladesh (WMO, 2017). Frequent flooding in the country reduced agricultural income and negatively affected other welfare outcomes in Bangladesh (Karim, 2018). Specifically, coastal flooding creates significant hardship for the people in the catchment areas and results in population displacements both in the short-and the long-term (Poncelet et al., 2010).

Cyclones, usually accompanied by high winds and storm-surges, hit coastal Bangladesh once in every three years on average (Dasgupta et al., 2010; Mallick and Etzold, 2015). Cyclones destroy the homesteads and livelihoods of millions of people in the coastal areas of Bangladesh. Bangladesh witnessed several cyclones in the last 50 years. Among them, Bhola in 1970, Gorky in 1991, Sidr in 2007, Nargis in 2008, Aila in 2009, and Komen in 2015 are some of the deadliest cyclones on record (Kabir et al., 2016). Cyclones alone claimed more than 100,000 lives and caused property damages of around US $3.5 billion in the last 25 years in Bangladesh (Dasgupta et al., 2010). Studies found that cyclones victims move away because of resource scarcity, infrastructure damage, lack of social protection as well as the unavailability of income-generating alternatives in affected areas (Poncelet et al., 2010; Mallick et al., 2017).

2.2. Permanent shock

The erosion of the coastline and riverbank and the subsequent loss of arable land is another significant concern for Bangladesh. While events such as flood and cyclone may cause the affected households to leave their homes temporarily, hazards like riverbank erosion that causes loss of land, is a shock that is permanent in nature. Households living close to riverbanks often experience the loss of homestead and agricultural land which reduces their production and employment opportunities, and subsequently threaten livelihood security (Alam et al., 2017, 2018). People living in the southwest coastal belt are particularly exposed to riverbank erosion and find migration a viable adaptation strategy (Poncelet et al., 2010; Brammer, 2014; Kabir et al., 2018).

Riverbank erosion is a major contributor to the process of destitution and marginalization of rural families in the country (Poncelet et al., 2010; Planning Commission, 2015, 2018). It has been estimated that about 60,000 individuals are displaced due to riverbank erosion and about 14,000 hectares of arable land are eroded annually (Mutton and Haque, 2004; Mirza et al., 2003). These recurrent natural disasters mostly affect the poorest group of coastal community residents (Ishtiaque and Nazem, 2017). Among the climate-induced migrants in Dhaka city, a significant proportion are from the coastal districts of Bangladesh, which are highly vulnerable to the natural hazards including riverbank erosion (Adri and Simon, 2018).

In the past, three major rivers in Bangladesh—Padma, Meghna, and Jamuna — eroded several thousands hectares of floodplain, damaged extensive road and rail networks and displaced millions (Das et al., 2014).

This process had a long-term impact on the livelihood of people, society and economy. However, due to the slow process and scattered incidents, it usually does not draw the attention of media and policy makers in the same way victims of floods and cyclones do. For instance, the victims of riverbank erosion receive less support from both the local and central government in the form of credit, relief or any other type of financial support to fight against this silent catastrophe. As a result, the victims of riverbank erosion leave their origin on their own and search for a place to survive socially and economically (Zaber et al., 2018).

3. Survey design and sampling procedure

The area of Bangladesh is divided into eight administrative divisions of which, Khulna, Barisal and Chittagong belong to the coastal zone. Each division is composed of several districts to make a total of 64 districts in the country and the coastal areas of Bangladesh cover 19 districts, most of which are frequently affected by environmental shocks like floods, cyclones and riverbank erosions (Dasgupta et al., 2014; Brammer, 2014). In 2015, we conducted a study—Coastal Vulnerability and Livelihood Security (CVLS) survey—to identify the link of transient and permanent environmental shocks with households' migration decisions and the choice of the destination. The survey design targeted the areas affected by different type of natural disasters in recent years. The CVLS survey organised face to face household interviews to collect data from nine southwest districts in Khulna and Barisal divisions –Bagerhat, Barguna, Barisal, Bhola, Jhalokati, Khulna, Patuakhali, Pirojpur and Satkhira.

To better understand the dynamics of internal migration scenario in Bangladesh, the CVLS survey tracked households in coastal areas who were included in the 2000 round of Household Income and Expenditure Survey (HIES), which collected nationally representative information in the country. The total number of households for the selected districts in HIES 2000 were 1,180 of which 1,166 households had non-missing income and expenditure information. As common in longitudinal surveys, our sample suffered from attrition since the repeat survey was conducted with a gap of 15 years. CVLS survey was able to track nearly half of them –455 households –whom we employed in our analysis.[8] As expected, some households split up between 2000 and 2015. By 2015, a total of 93 households from the baseline survey (HIES 2000) split into 2 families, 27 households split into 3 families and 3 households split into 4 families resulting in a total of 578 households in our analysis sample.[9] Figure 1 shows the location of analysis households in 2000 and 2015.

[Figure 1]

[8] Although, there are differences in some characteristics between the HIES 2000 households that are included in the analysis and those who are not, there is no systematic variations between the two groups (Table A.1). As a result, we expect our findings will not be affected by the attrition.

[9] CVLS survey collected data from 2,096 households of which 1,835 observations had relevant information. We dropped 1,257 households as they were not included in HIES 2000 and thus could affect the representativeness of our sample.

The distribution of respondents among source and destination districts is shown in Table 1. The table shows that about 36 per cent of households in the survey migrated from one location to another.[10] Among them, around 30 per cent moved to the nearest Khulna city, 25 per cent migrated to the capital city Dhaka and the rest 45 per cent settled down in 21 other districts in Bangladesh. On the other hand, the origin of most of the migrants were Barishal (25 per cent of all migration), followed by Khulna (16 per cent), Bhola (12 per cent), Jhalokhati and Satkhira (11 per cent each) and other districts (25 per cent). These internal migrants are mostly permanent or long-term migrants who, during the survey interview, did not indicate any intention of returning to their original location.

[Table 1]

Information collected in the CVLS survey include data on whether, in recent years, households suffered from any environmental shocks like floods, cyclones or riverbank erosions. Households were also asked whether they received credit or relief support in the aftermath of natural disasters, if any. We also collected information on household income by asking them about the earnings from different sources. The survey collected detailed household food and non-food expenditure information. Consumption of food items includes rice, food crops, wheat, lentils, edible oil, vegetables, poultry items, dairy items, salt, sugar, dry food and beverages. Non-food consumption items include fuel, house rent, transportation, education, toiletries, clothing, utensils and medical items. We computed expenditure for each household by combining all food and non-food expenditures.

Table 2 presents the summary statistics of important variables considered in our analysis. Panel (a) in the table reports the information collected through CVLS. Regarding the exposure to natural disasters, as collected in CVLS survey, about 14 per cent of the households experienced riverbank erosion, a permanent environmental shock, compared to transient environmental shocks like floods (5 per cent) and cyclones (7 per cent). The household income and expenditure are reported in current prices which, when adjusted for inflation between 2000 and 2015, appear to be close with the HIES 2000 figures in Panel (b).[11] All information in panel (b) is collected from HIES 2000, indicating the demographic and socio-economic status of households in our analysis sample.

[Table 2]

[10] This seems a bit high but consistent with some recent studies. For example, Marshall and Rahman (2013) find that the population growth rate between 2000-2010 in coastal areas was nearly half of the national average. Unfortunately, we could not find any reliable source providing the rate of outmigration in the surveyed districts and thus used unweighted analysis throughout this study.

[11] The inflation rate between 2000 and 2015 was around 300 per cent as calculated using CPI (with changing base) reported in Bangladesh Bureau of Statistics (2011, 2018).

4. Empirical framework

We examine the impact of different type of natural disasters on internal migration by using the following model

$$Pr(M_i = 1|EHWZ) = \alpha + \beta E_i + \gamma H_i + \theta W_i + \psi Z_i + \lambda_d + \varepsilon_i \quad (1)$$

where, for each i, M takes the value of 1 if household migrates and 0 otherwise, E, H, W and Z are vectors of explanatory variables and ε is the error term. The vector of explanatory variable E includes separate controls for exposure to disasters like floods, cyclones and riverbank erosions.[12] In some separate models E represents exposure to shocks categorized as transient (floods or cyclones) and permanent (riverbank erosions). H is the vector of household characteristics that include household size and sex, age, age squared, marital status, literacy and religion of household head. The wealth components are represented by the vector W that includes amount of land owned by the household, agricultural asset value and a dummies indicating house ownership and electricity connection in their residence. The vector Z includes separate dummies for receiving credit or relief by the household that can be considered as alternative coping instruments against natural hazards. Finally, we control for the division fixed effects λ_d in our model to net out the effect of time-invariant variables (such as the transportation and job opportunity in a division) that can be correlated with the explanatory variables and thus can potentially lead to the problem of endogeneity.

We use probit regression to estimate equation (1). This is due to the fact that the binary response model ensures the estimated probabilities to lie within zero and one and allow independent variables to have non-constant partial effects. While we also employed alternative estimation techniques like logit and linear probability model (LPM), we only report results from the probit models considering the space constraints.

We also examine the determinants of destination choices. In particular, we examine how factors like transient and permanent shocks affect choices of destinations with different characteristics. This is motivated by the fact that personal preference of the migrant and the availability of amenities can influence households to move to a specific type of destination (Von Reichert and Rudzitis, 1992; Mishra, 2016). In determining the choice of alternative destinations, we use the following model[13]

$$Pr(M_i = 1, 2, 3|EHWZ) = \alpha + \beta E_i + \gamma H_i + \theta W_i + \psi Z_i + \lambda_d + \varepsilon_i \quad (2)$$

where, M now is a categorical variable taking a value of zero for no migration, 1 for migration to Dhaka city, 2 for migration to Khulna city and 3 for migration to other locations. In that model we use a set of

[12] Our data includes information on exposure to salinity, drought and some other type of natural disasters. Since a very small group of households suffer from these disasters, we did not separately control for them. Our conclusions remain unchanged when they are included in the model.

[13] The multinomial probit model for migration choices is motivated by the framework of the random utility model discussed in Davies et al. (2001).

independent variables that are similar to our previous model including the division fixed effects. Because of the advantage of binary choice models over the linear probability model mentioned earlier, we use the multinomial probit model to estimate equation (2).

Next, we empirically analyze the impact of migration on household income and expenditure. The average treatment effect (ATE) of migration on any outcome variable can be inferred through the use of propensity score matching (PSM).[14] We estimate the ATE of migration by using the baseline independent variables as the predictor of migration. Unfortunately matching suffers from the uncertainty of selecting the right set of variables to predict selection. Furthermore, the same counterfactual may not exist in the sample in practice (Blundell and Dias, 2009). Under certain condition, the difference-in-differences (DD) method can overcome the problem. The availability of longitudinal data for 2000 and 2015 for both group of households—who migrate and who do not—allow us to employ a fixed effect DD model as follows

$$Y_i = \alpha + \beta_1 M_i + \beta_2 Post_i + \beta_3 M_i \times Post + \lambda_h + \varepsilon_i \tag{3}$$

where, for each i, Y represents income, M is a dummy for migration (reference group is no migration) and $Post$ is a dummy for 2015 values (reference year is 2000) while λ_h in the model controls for household fixed effects. We employed a similar model for investigating the impact on household expenditure in which we additionally included household income as an explanatory variable as income is the most important determinant of expenditure (Hasan, 2016).

DD model also suffers from certain problems like the selection on idiosyncratic temporary shocks known as "Ashenfelter's dip" (Blundell and Dias, 2009). Thus combining DD with matching (matching DD) is believed to be useful to partially overcome the underlying assumptions of both methods (Blundell and Dias, 2009; Emran et al., 2014). The identifying assumption in the DD estimation is the parallel trend. In other words, in our case, the difference in income between the two groups would have remained the same without the migration of the migrating households (and similar for the model with household expenditures). We cannot test our identifying assumption directly. In such case (or when common trend assumption is not valid), DD with matching is useful when the matching is additionally conditioned on the outcome variable (Chabé-Ferret, 2015, 2017). As a result, in our preferred specification, we use matching DD in which matching is conditional on a set of predictors as well as the outcome variable–household income (or expenditure in separate models).

[14] A discussion on the use of PSM can be found in Blundell and Dias (2009).

5. Estimation results and discussion

5.1. Types of shocks and migration

We start with identifying the links between different types of environmental shocks and internal migration employing equation (1) and probit regressions. The marginal effects, that are estimated at the mean values of all other covariates, are reported in Table 3.[15] Column 1 presents results that are estimated using separate controls for natural disasters—flood, cyclone and riverbank erosion—but excludes other control variables as well as the division fixed effects. We employed a significance level of 5 per cent throughout this analysis, at which, the results indicate a significant effect of all types of natural disasters on migration that is lowest for cyclone (a transient shock) and highest for riverbank erosion (the permanent shock).

[Table 3]

When we include additional control variables to the model, estimated effects change marginally (Column 2 of Table 3). Among the significant variables, household size negatively affects migration. Household size may have an ambiguous effect on internal migration decision. In one way, larger households might be able to diversify their income by sending one of their members to a different location (Li et al., 2014). Such households can better adapt through diversifying jobs and incomes and thus being less likely to migrate. In contrast, the larger the family size, the more difficult it would be to migrate due to the associated cost of migration. The significantly negative effect of household size in our study indicates that the latter hypothesis can be more relevant for Bangladesh.

Receiving credit has a negative effect on internal migration. This can be due to the fact that, while the availability of credit in the aftermath of a disaster may allow people to mitigate some of the negative effects, it can induce more migration as people need to repay the loan, which can be quite substantial when money is borrowed at high interest rates. On the other hand, we observe lower migration of the people who receive relief as it allows them to spend money on mitigating the negative effect of natural hazards and permit them to stay at their place of origin. This is similar to the findings of Paul (2005) who observed that better relief management in the aftermath of the tornado in north-central Bangladesh resulted no migration.

The Column 3 of Table 3 presents the estimated results of the model that additionally controls for the fixed effects at the division level. The previous results largely remain unchanged while the impact of natural disasters become slightly smaller. The estimated effect of flood is positive and is similar to some previous findings. For example, Gray and Mueller (2012) observed modest effect of flooding on internal mobility in Bangladesh. On the other hand, cyclone has a much lower effect on internal migration, probably because of its' temporariness in nature. In this model, riverbank erosion, which washes away assets and homesteads of

[15] Since the individual regression coefficients of probit models are difficult to interpret, we reported marginal effects. Full regression outputs, including all other robustness check results are available from the authors upon request.

exposed households, increases domestic migration significantly. The results reveal that riverbank erosion is the key driver of internal mobility since the victims of this hazard become destitute who eventually migrate as also observed in Das et al. (2014).

Next, we compare the effect of transient and permanent shocks. Columns 4-6 of Table 3 repeats the previous analysis conducted in columns 1-3 but the group shocks in the model now replaces separate controls for flood, cyclone and riverbank erosion. Again, the results are largely similar. In the final model with all controls and division fixed effects, presented at column 6, people affected by transient shocks are 52 per cent more likely to migrate. On the other hand, permanent shocks induce people to migrate more by 87 per cent compared to people who do not suffer from any natural hazard. The difference between the effect of transient and permanent shock is also statistically significant at any conventional level of significance.

One important point of consideration here is to figure out the best approach to model environmental shocks. Columns 1-3 of Table 3 include all types of environmental shocks as separate independent variables whereas Columns 4-6 group flood and cyclone together to represent them as a transient shock, leaving riverbank erosion as the permanent shock. While model results are largely similar, the model in column 6 can be considered superior as indicated by the lower values of the Akaike information criterion (AIC) and Bayesian information criterion (BIC) compared to the values of the corresponding models. As a result, we continue to use grouped shocks in the latter part of our study.

Our results are robust to a number of modifications in the model. For example, we get a similar results when we use a linear probability model (see appendix Table A.2). We also arrive at a similar conclusion when we use logistic regression for our analysis. In all cases, our model fit appears reasonable as given by the Pseudo R^2 (or adjusted R^2 in case of LPM). As a result, the previous analysis successfully demonstrates that transient and permanent shocks affect domestic migration in a different scale with relatively higher effects of the permanent shocks.

5.2. Destination choice

At this stage, we start looking at how different type of shocks affect the choice of destination for migration. We employ equation (2) and estimate it using multinomial probit regression. Table 4 presents the marginal effects estimated from the multinomial probit model, again calculated at the mean values of all other covariates. The determinants of migrating to Dhaka are presented at column 1. The results indicate that both transient and permanent shocks are important in explaining migration to Dhaka city but the impact of the permanent shock is much higher. Similarly, both transient and permanent shocks significantly affect migration to Khulna city (column 2). However, as expected, the effect of the transient shock is much higher for the neighboring Khulna than its' effect on migrating to the distant capital city Dhaka. This can be due to the proximity of Khulna that motivate people to plan to return to their origin as soon as they recover. On the other hand, when we consider migration to other locations, we find a positive impact for both types of shocks which are much lower and not statistically significant at the conventional level of significance (column 3). Again, in all cases, the higher effect of the permanent shock relative to the transient shock are statistically significant.

[Table 4]

The effect of other variables in Table 4 are largely similar to those in Table 3. However, there are some interesting differences in the effect of the explanatory factors on migrating to a specific type of destination. For instance, household size has a negative effect on migrating to Khulna city (that is only significant at the 10 per cent level of significance) or other locations but no effect on migrating to the distant metropolitan city Dhaka. This can be due to the fact that Dhaka can be considered as the last choice for migration and so the family size does not matter when there is no other option left (Adri and Simon, 2018). On the other hand, while female headed households are less likely to migrate to any of the metropolitan cities, Dhaka or Khulna, the case is much stronger for the former. It is expected, as the female headed households are less likely to take the opportunity of higher income in the metropolitan city Dhaka as women are less likely to be in wage work or salaried jobs due to the conservativeness (Ahmed and Sen, 2018) or the lack of social capital (Bakshi et al., 2019). The discrimination against women in Bangladesh in workplaces can also be a potential reason (Ahmed and Maitra, 2010, 2015). Interestingly, female head did not matter for moving to other locations as, in the context of Bangladesh, the migration is likely to be supported by their relatives. Electricity connection, expected to capture the impact of households' socio-economic status (SES), is positively associated with migrating to Khulna but not to other locations. It can be the case that households with higher SES migrate temporarily to the nearby city with the plan to come back later when they recover from the shock. People living in their own house also behave in a similar way to having electricity connection, probably for the same reason.

The most interesting case is receiving credit and relief which are considered as important substitute coping instruments to natural disaster. Receiving credit negatively affects migrating to Dhaka city but positively affects migrating to other locations. Receiving credit can be tied with the condition of not migrating to a distant place but may encourage migration to nearby locations as it may allow them to be engaged with some income generating activities using local networks. Relief has a negative impact on migration but the impact is not statistically significant for migrating to other locations. As we discussed earlier, this can be due to the fact that relief allows households to overcome the shock and to continue to stay in their origin as they can manage their livelihood in the affected area.

We arrive at similar conclusions when we employ independent probit regressions (see appendix Table A.3) or the multinomial logit regression or a linear probability model to explain the choice of migration destinations. Thus, our analysis indicates that both temporary and permanent shocks have significant and positive impact on the migration choice to metropolitan cities but not to other locations. However, in all cases, transient shocks have a lower effect on migration than the shock that is permanent in nature. When a shock does a permanent damage to people's economic conditions and livelihoods so that they do not have any intention to come back, they tend to migrate to a place with more opportunities like the megacity Dhaka. On the other hand, when there is any scope or people have the capacity to manage the shock, households prefer to stick at their location of origin or temporarily move to nearby cities.

5.3. Impact on income and expenditure

Our next objective is to look at the impact of migration on household income and expenditure. In our investigation, we start with the propensity score matching (PSM) technique to find out the effect of migration. In doing so, to predict migration, we employed the baseline characteristics of all the independent variables of our previous models and estimated propensity score (PS) for each of the household. Then, to estimate the average treatment effect (ATE) of migration, we used the estimated PSs to select similar households and compared the income/expenditure of those who migrated against those who did not (Table 5). We used PSs for common support in two ways. First, by dropping treatment observations whose PS is higher than the maximum or less than the minimum PS of the controls (approach 1). Second, by dropping 10 per cent of the treatment observations at which the PS density of the control observations is the lowest (approach 2).[16] The results with the first approach are presented in columns 1 and 3 in the table while the even numbered columns report results with the second approach. The results indicate that migration significantly raises household income around 14 per cent but the effect become smaller and statistically insignificant when we follow the second approach of imposing common support. However, for household expenditure, the ATE remains significant in both approach, showing that migration increases household expenditure by around 18-21 per cent.

[Table 5]

Next, we employed the difference-in-differences (DD) model in equation (3) to avoid the shortcomings of the PSM technique. Estimated results of the DD model are presented at Table 6. Column 1 results show that, over time, income of both groups increased significantly. The DD estimate indicates that, the increase was nearly 48 per cent higher for the people who migrated compared to those who did not. This is equivalent to an annual growth of 2.5 per cent for fifteen years. It is important to recognize that the effect can be due to the various macroeconomic and local factors occurred between 2000-2015 that are not controlled for in our models. However, our results indicate that migration has been important for such income growth.

[Table 6]

[16] To calculate the ATEs, we used the default set up in the Stata program psmatch2 that employs the single nearest neighbor (without caliper) to calculate the matched outcome. Nonetheless, results with the changed method of matching indicate that our results are largely immune to such changes.

Next, to add the strength of matching in our DD approach, we repeat the previous analysis with dropping treatment observations following approach 1 (Table 6, column 2).[17] The results remain largely similar with this selection. Since we cannot test our identifying assumption directly, in our final model, we combine DD with matching in which the migration is also conditioned on the outcome variable. Even with the new modeling approach, the estimates remain largely unchanged (Table 6, column 3). In this preferred specification, migrant households income increase nearly 52 per cent more (2.8 per cent annually) than the households who remain in their place of origin.

We observe a similar picture when we repeat our previous analysis with household expenditure (Table 6, columns 4-6). However, in all cases, the change in migrant expenditure is much lower compared to that of income. In the preferred specification, we follow approach 1 and predict migration on the previous set of variables as well as the outcome. In that model, household expenditure is 15 per cent higher for migrants than their counterpart (column 6). All the models of income and expenditure in Table 6 have reasonable goodness of fit.

Another way to combine the DD model with matching is to compare the (weighted) differenced outcome of matched treatment and control.[18] Our estimated results with matching on the previous set of independent variable and using the inverse probability weights indicate that the income and expenditure of migrating households increase disproportionately compared to their counterpart. However, the increase is not statistically significant for income at the conventional level of significance (see appendix, Table A.4). We emphasize less on this model results due to the problem with interpretation, as the dependent variable is the logarithm of change in the dependent variable.

The previous results are robust to changes in model specification. For example, allowing differential impact for those suffered transient shock and those suffered permanent shock also provides a similar conclusion. Thus, the previous analysis indicates that households disproportionately benefit from migration compared to those who did not migrate. Such findings are consistent with previous studies like Beegle et al. (2011) and De Brauw et al. (2017) who find large increase in consumption after migration. This is expected as people optimally choose to migrate to maximize their future utility and both income and expenditure can be considered as good proxies for household welfare.

We have extended our analysis to examine whether migration locations have differential effects on household income and expenditure. For that, we estimate DD models with three treatment groups—migrating to Dhaka city, migrating to Khulna city and migrating to other locations—against the same reference group (no migration). Results in Column 1 and 3 of Table 7 are generated using a simple DD model while the even numbered column results are derived following our preferred approach in the previous table. The results indicate that, the group migrated to Dhaka benefited in terms of their income but not in terms of

[17] This pre-screened DD approach is employed in important studies like Crump et al. (2009); Gibson and McKenzie (2014).
[18] For an example with that approach, see Emran et al. (2014).

expenditure. The impact is not statistically significant for the group migrating Khulna. On the other hand, those who migrated to other locations did not benefit in terms of income but expenditure.

[Table 7]

The results in Table 7 are intuitive as the opportunity of working and earning is much higher in the metropolitan city Dhaka and people migrated there are expected to have higher income. However, people living there can be forced to spend on non-consumption expenditure that may not be captured in the survey as reflected in the null effect on expenditure. They may also need to save money to compensate for the damage done by the disaster. Interestingly, the scenario is completely opposite to the case when people migrates to other locations. While the scope of earnings is not that high in those locations, formal and informal support from friends and family may explain a null effect on income but positive effect on expenditure.

To sum up, Table 7 indicates that migration location was important for household welfare. Compared to people who did not migrate, households disproportionately benefited by migrating to Dhaka or other locations depending on the relevancy of income and expenditure as indicators of household welfare. The results largely remain unchanged if we interact the type of shocks with the migration destinations, although understandably the permanent shock appears to be more significant than the other type in most cases (see appendix, Table A.5).

Our analysis primarily suggest that the government should play a role in facilitating the migration process to improve the welfare of the victims of natural disasters. This is in line with the results of Bryan et al. (2014), who randomly assigned an $8.50 incentive to households in rural Bangladesh to temporarily migrate to cities during the lean season. They found that such a small incentive induces 22 per cent of households to send a seasonal migrant and their expenditure at the origin increases significantly. Adaptation by internal migration is effective as the incremental cost of adapting to climate change is small compared with a counterfactual outcome with no adaptation measures (Dasgupta et al., 2010). The importance of facilitating migration is further emphasized by the fact that migration is beneficial to both who move out and who stay behind (Shayegh and Casey, 2017).

It is worth noting that strengthening the adaptive capacity, which may include facilitating internal migration, also requires developing rural institutions (Agrawal et al., 2012). Involvement of local community, specifically including women in the decision process, can also be effective in enhancing the adaptive capacity of affected households (Takasaki, 2014; Grillos, 2018). Complementary policy support such as financial incentive for facilitating migration, providing low-income housing and creating employment opportunities need to be set up to help settle the rising influx of migrants into the cities that are struggling to provide basic services to its' residents (Dustmann and Okatenko, 2014; Kirchberger, 2017; Depetris-Chauvin and Santos, 2018). However, in formulating public policies to promote migration, it is important to be aware that a pro-poor adaptation policy should consider the complementarity among markets, governments, and communities (Sawada and Takasaki, 2017).

6. Conclusion

We explored the nexus of environmental shocks caused by natural disasters and internal migration in the southwest parts of Bangladesh. In particular, we investigated the impact of transient and permanent environmental shocks on migration decision and the choice of destinations. We also investigated how household income and expenditure changed after migration. Controlling for a diverse set of socio-economic and demographic factors, we found that both transient and permanent environmental shocks force households to migrate, specifically to nearby cities. However, the influence of the permanent shock (riverbank erosions) on migration is much stronger than that of transient shocks (floods or cyclones). Our analysis on income and expenditure indicates that migration can be an effective adaptation mechanism against environmental shocks as households' income and expenditure increase following migration, compared to those who do not migrate.

Our analysis suggests that internal migration can be considered as an important adaptive capacity. Thus the government can assist the migration process to address the rising vulnerabilities of natural disasters. Migration is a win-win strategy for adaptation, as it benefits both who migrates as well as those who stay behind, by reducing the pressure on resources at the origin.

Tables and Figures

Table 1: **Distribution of survey respondents across origin and destination district**

	Migrated from									
Migrated to	Bagerhat	Barguna	Barisal	Bhola	Jhalokati	Khulna	Patuakhali	Pirojpur	Satkhira	All
Bagerhat	6	0	0	0	0	6	0	0	0	12
Bandarban	0	0	0	0	0	0	3	0	0	3
Barguna	0	1	0	0	0	1	0	0	0	2
Barisal	0	0	0	0	0	3	2	0	0	5
Bhola	0	0	0	1	0	1	1	0	0	3
Brahmanbaria	0	0	0	1	0	0	0	0	1	2
Chandpur	0	0	0	0	0	1	0	0	3	4
Chittagong	1	4	0	16	0	2	1	0	1	25
Dhaka	1	3	18	3	13	4	1	8	1	52
Faridpur	0	1	0	0	0	2	0	0	1	4
Feni	0	0	0	0	0	0	0	0	1	1
Gazipur	1	0	0	0	0	0	0	0	0	1
Gopalganj	2	0	0	0	0	2	0	0	2	6
Jessore	2	0	0	0	0	6	0	0	0	8
Khulna	1	0	33	4	10	3	1	9	2	63
Madaripur	1	0	0	0	0	0	0	0	1	2
Munshiganj	1	0	0	0	0	0	0	0	0	1
Mymensingh	0	0	0	0	0	0	0	0	1	1
Narayanganj	0	0	0	0	0	0	2	0	0	2
Natore	0	0	0	0	0	1	0	0	0	1
Patuakhali	0	0	0	0	0	0	0	0	1	1
Shariatpur	0	0	0	0	0	0	0	0	1	1
Satkhira	1	0	0	0	0	1	0	0	6	8
Migration	17	9	51	25	23	33	11	17	22	208
No Migration	55	59	0	65	0	69	50	0	72	370
Total	72	68	51	90	23	102	61	17	94	578

Note: 1. A total of 125 people who reported to migrate from Khulna to Khulna moved from rural areas of the district to the city.

Table 2: **Summary statistics of important variables**

Variable definition	Mean	SD
Panel (a): Information collected through CVLS survey (at 2015)		
Experienced flood in last 10yrs	0.05	0.23
Experienced cyclone in last 10yrs	0.07	0.25
Experienced river erosion in last 10yrs	0.14	0.34
Experienced transient shock	0.11	0.32
Experienced permanent shock	0.14	0.34
Received credit after disaster	0.51	0.50
Received relief after disaster	0.32	0.47
Monthly household income in BDT (in 2015)	12,029	7,324
Monthly household consumption in BDT (in 2015)	16,623	25,912
Panel (b): Information collected from HIES (at 2000)		
Household size	5.80	2.32
Household head is female	0.05	0.23
Age of the household head (years)	45.77	12.66
Household head is married	0.90	0.30
Household head is muslim	0.86	0.35
Literacy of household head	0.51	0.50
Electricity connection at home	0.21	0.41
Owned land (in decimals)	0.79	1.87
Lives in owned house	0.89	0.32
Agricultural asset value in BDT (in 2000)	3,510	15,430
Monthly household income in BDT (in 2000)	3,560	3,587
Monthly household consumption in BDT (in 2000)	6,125	4,064
N	578	

Note: 1. At 31 March 2015 (in the beginning of the survey period), the exchange rate was $US 1 = BDT 78.40 (domestic currency) (Bangladesh Bank, 2018).
2. The inflation rate between 2000 and 2015 (i.e., before and after migration data collection time periods) was 300 per cent as calculated using CPI (with changing base) reported in Bangladesh Bureau of Statistics (2011, 2018).

TABLE 3: **Effect on Internal migration: Marginal effects from probit models**

	All shocks			Grouped shocks		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced flood in last 10yrs	0.525***	0.539***	0.509***			
	(0.143)	(0.137)	(0.135)			
Experienced cyclone in last 10yrs	0.361***	0.380***	0.359***			
	(0.116)	(0.120)	(0.117)			
Experienced river erosion in last 10yrs	0.839***	0.878***	0.832***			
	(0.115)	(0.124)	(0.129)			
Experienced transient shock				0.530***	0.548***	0.519***
				(0.087)	(0.092)	(0.094)
Experienced permanent shock				0.858***	0.908***	0.865***
				(0.113)	(0.126)	(0.131)
Household size		-0.025**	-0.029**		-0.025**	-0.028**
		(0.012)	(0.013)		(0.012)	(0.012)
Household head is female		-0.192	-0.168		-0.142	-0.122
		(0.194)	(0.188)		(0.176)	(0.173)
Age of the household head (years)		-0.002	-0.003		-0.003	-0.003
		(0.002)	(0.002)		(0.002)	(0.002)
Household head is married		-0.009	0.004		0.012	0.023
		(0.108)	(0.107)		(0.105)	(0.105)
Household head is muslim		0.125*	0.075		0.111	0.066
		(0.073)	(0.075)		(0.073)	(0.075)
Literacy of household head		-0.005	-0.008		-0.020	-0.021
		(0.055)	(0.055)		(0.054)	(0.055)
Electricity connection at home		-0.051	-0.059		-0.033	-0.040
		(0.066)	(0.067)		(0.066)	(0.067)
Owned land (in decimals)		-0.006	-0.007		-0.004	-0.005
		(0.016)	(0.016)		(0.016)	(0.015)
Lives in owned house		0.031	0.003		0.055	0.028
		(0.089)	(0.090)		(0.092)	(0.091)
Received credit after disaster		0.105**	0.124**		0.104**	0.121**
		(0.049)	(0.048)		(0.049)	(0.049)
Received relief after disaster		-0.148***	-0.210***		-0.144**	-0.201***
		(0.056)	(0.068)		(0.057)	(0.068)
Ln(agricultural asset value in BDT)		0.008	0.008		0.010	0.009
		(0.007)	(0.007)		(0.007)	(0.007)
Constant	0.366***	0.399***	0.403***	0.365***	0.397***	0.401***
	(0.024)	(0.032)	(0.033)	(0.024)	(0.033)	(0.033)
Division fixed effects	No	No	Yes	No	No	Yes
Psedu R^2	0.26	0.30	0.31	0.28	0.31	0.32
AIC	566.11	562.80	561.27	553.03	550.97	551.04
BIC	583.55	636.92	648.46	566.11	620.72	633.88
N	578	578	578	578	578	578

Note: 1. Robust standard errors are reported in the parentheses.
* p <0.10, ** p <0.05, *** p <0.01.

TABLE 4: **Choice of destination for internal migrants: Marginal effects from multinomial probit model**

	Migrated to		
	Dhaka (1)	Khulna (2)	Other locations (3)
Experienced transient shock	3.605***	4.692***	0.569
	(0.659)	(0.693)	(0.394)
Experienced permanent shock	5.289***	5.510***	0.578
	(0.668)	(0.749)	(0.672)
Household size	0.004	-0.179*	-0.087*
	(0.092)	(0.090)	(0.043)
Household head is female	-13.528***	-3.477**	0.193
	(1.038)	(1.416)	(0.509)
Age of the household head (years)	-0.006	0.155	0.076
	(0.089)	(0.123)	(0.057)
Literacy of household head	-0.601	-0.522	-0.078
	(0.408)	(0.455)	(0.216)
Electricity connection at home	0.477	1.096**	-0.336
	(0.539)	(0.523)	(0.276)
Household head is married	-0.354	-1.446*	0.625
	(0.616)	(0.725)	(0.420)
Lives in owned house	0.963	1.591**	-0.201
	(0.640)	(0.646)	(0.321)
Owned land (in decimals)	-0.140	-0.067	0.007
	(0.094)	(0.080)	(0.064)
Ln(agricultural asset value in BDT)	0.056	0.085*	0.021
	(0.044)	(0.049)	(0.030)
Received credit after disaster	-0.946**	0.285	0.536***
	(0.402)	(0.393)	(0.192)
Received relief after disaster	-1.886***	-2.179***	-0.430
	(0.528)	(0.580)	(0.264)
Constant	-1.838	-4.733*	-2.533*
	(2.064)	(2.798)	(1.319)
Division fixed effects	Yes	Yes	Yes
N		578	

Note: 1. Robust standard errors are reported in the parentheses.
2. Reference category is households who do not migrate.
* p <0.10, ** p <0.05, *** p <0.01.

TABLE 5: **Impacts of migration on household income and expenditure: PSM estimate**

	Ln(household income)		Ln(household expenditure)	
	(1)	(2)	(3)	(4)
ATE	0.132*	0.117	0.168***	0.188***
	(0.073)	(0.081)	(0.063)	(0.066)
N	578	578	578	578

Note: 1. This odd numbered columns present result with the imposition of a common support by dropping treatment observations whose pscore is higher than the maximum or less than the minimum pscore of the controls while the even numbered columns impose common support by dropping 10 per cent of the treatment observations at which the pscore density of the control observations is the lowest.
2. Standard errors are reported in the parentheses.
* p <0.10, ** p <0.05, *** p <0.01.

Table 6: **Impacts of migration on household income and expenditure: OLS estimates**

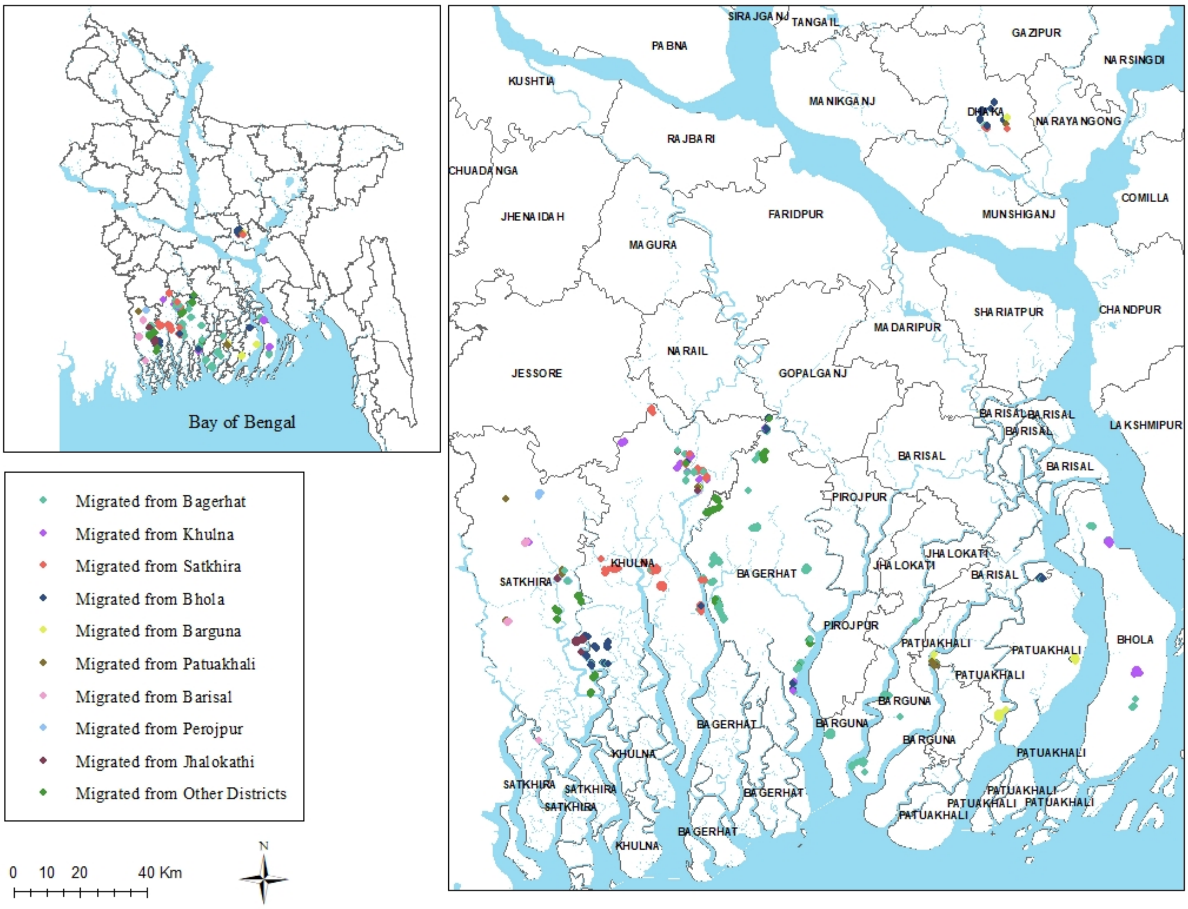
	Ln(household income)			Ln(household expenditure)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post migration	1.226***	1.245***	1.220***	0.832***	0.860***	0.835***
	(0.061)	(0.062)	(0.062)	(0.039)	(0.038)	(0.039)
Migrated ×	0.393***	0.375***	0.417***	0.148**	0.117*	0.141**
post migration	(0.109)	(0.111)	(0.109)	(0.066)	(0.066)	(0.067)
Constant	7.821***	7.799***	7.819***	8.552***	8.539***	8.554***
	(0.025)	(0.026)	(0.026)	(0.016)	(0.016)	(0.016)
Adjusted R^2	0.56	0.57	0.56	0.58	0.60	0.58
N	1,156	1,116	1,136	1,156	1,116	1,136

Note: 1. Standard errors are reported in the parentheses.
2. Reported number of observations is twice of the actual sample due to reshaping the data for difference-in-difference estimation.
* p <0.10, ** p <0.05, *** p <0.01.

Table 7: **Impacts of migration location on household income and expenditure: OLS estimates**

	Ln(household income)		Ln(household expenditure)	
	(1)	(2)	(3)	(4)
Post migration	1.226***	1.220***	0.832***	0.835***
	(0.061)	(0.062)	(0.039)	(0.039)
Migrated to Dhaka	0.926***	0.932***	-0.061	-0.063
× post migration	(0.217)	(0.218)	(0.110)	(0.110)
Migrated to Khulna	0.286	0.293	0.176*	0.174*
× post migration	(0.195)	(0.195)	(0.094)	(0.094)
Migrated to other	0.168	0.210*	0.246***	0.236**
location × post migration	(0.113)	(0.112)	(0.093)	(0.095)
Constant	7.821***	7.819***	8.552***	8.554***
	(0.025)	(0.025)	(0.016)	(0.016)
Adjusted R^2	0.57	0.57	0.58	0.58
N	1,156	1,136	1,156	1,136

Note: See footnotes in Table 6.



Note: 1. Polygon indicates current location of migrants while its' colour represents their district of origin.

FIGURE 1: **Origin and destination of migrant households**

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Appendix A: Tables

Table A.1: **Comparison of summary statistics**

	HIES 2000 households		
	Included in CVLS survey (1)	Not included in CVLS survey (2)	p-value of the difference (3)
Household size	5.52	5.03	0.00
	(2.10)	(2.05)	
Household head is female	0.05	0.09	0.02
	(0.22)	(0.28)	
Age of the household head (years)	45.27	46.28	0.19
	(12.60)	(12.90)	
Household head is married	0.90	0.88	0.25
	(0.30)	(0.32)	
Household head is muslim	0.85	0.88	0.14
	(0.35)	(0.32)	
Years of schooling of household head	3.44	5.39	0.00
	(4.38)	(5.04)	
Maximum school year (among members)	6.04	7.57	0.00
	(4.41)	(4.64)	
Literacy of household head	0.51	0.62	0.00
	(0.50)	(0.49)	
Household has a personal phone	0.00	0.03	0.00
	(0.07)	(0.18)	
Electricity connection at home	0.22	0.48	0.00
	(0.41)	(0.50)	
Owned land (in decimals)	0.72	0.56	0.09
	(1.76)	(1.58)	
Lives in owned house	0.88	0.72	0.00
	(0.32)	(0.45)	
Agricultural asset value in BDT	2,465	1,725	0.35
	(11,916)	(13,792)	
Monthly household income in BDT	3,322	4,036	0.03
	(3,193)	(6,353)	
Monthly household consumption in BDT	5,940	7,740	0.00
	(3,915)	(7,467)	
N	455	711	1,166

Note: 1. Standard Deviations are reported in the parentheses.
* p <0.10, ** p <0.05, *** p <0.01.

Table A.2: **Effect on internal migration: Marginal effects from OLS estimates**

	All shocks			Grouped shocks		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced flood in last 10yrs	0.455***	0.442***	0.357***			
	(0.066)	(0.063)	(0.052)			
Experienced cyclone in last 10yrs	0.335***	0.323***	0.266***			
	(0.066)	(0.066)	(0.054)			
Experienced river erosion in last 10yrs	0.674***	0.649***	0.477***			
	(0.028)	(0.032)	(0.034)			
Experienced transient shock				0.489***	0.473***	0.384***
				(0.044)	(0.043)	(0.039)
Experienced permanent shock				0.689***	0.669***	0.501***
				(0.027)	(0.031)	(0.033)
Household size		-0.014***	-0.014***		-0.013***	-0.013***
		(0.005)	(0.005)		(0.005)	(0.004)
Household head is female		-0.108	-0.092		-0.083	-0.072
		(0.080)	(0.066)		(0.074)	(0.062)
Age of the household head (years)		-0.001	-0.001		-0.001	-0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Household head is married		0.004	-0.014		0.013	-0.006
		(0.046)	(0.041)		(0.044)	(0.040)
Household head is muslim		0.083**	0.048		0.074**	0.041
		(0.034)	(0.030)		(0.034)	(0.029)
Literacy of household head		-0.006	-0.001		-0.017	-0.009
		(0.027)	(0.024)		(0.026)	(0.023)
Electricity connection at home		-0.029	-0.017		-0.019	-0.010
		(0.031)	(0.028)		(0.030)	(0.027)
Owned land (in decimals)		-0.006	-0.005		-0.004	-0.004
		(0.007)	(0.006)		(0.007)	(0.006)
Lives in owned house		0.016	0.008		0.032	0.020
		(0.041)	(0.036)		(0.042)	(0.036)
Ln(agricultural asset value in BDT)		0.005	0.004		0.005	0.004
		(0.003)	(0.003)		(0.003)	(0.003)
Received credit after disaster		0.072***	0.075***		0.070***	0.073***
		(0.023)	(0.020)		(0.023)	(0.020)
Received relief after disaster		-0.104***	-0.111***		-0.098***	-0.108***
		(0.029)	(0.025)		(0.029)	(0.025)
Constant	0.360***	0.382***	0.381***	0.360***	0.380***	0.380***
	(0.012)	(0.014)	(0.013)	(0.011)	(0.014)	(0.013)
Division fixed effects	No	No	Yes	No	No	Yes
R^2	0.32	0.35	0.50	0.34	0.37	0.51
AIC	1140.55	1110.04	820.88	1102.78	1075.55	794.83
BIC	1155.71	1190.88	921.93	1112.88	1151.34	890.83
N	1,156	1,156	1,156	1,156	1,156	1,156

Note: 1. Robust standard errors are reported in the parentheses.
* p <0.10, ** p <0.05, *** p <0.01.

Table A.3: **Choice of destination for internal migrants: Marginal effects from independent probit models**

	Migrated to		
	Dhaka (1)	Khulna (2)	Other locations (3)
Experienced transient shock	3.442***	3.545***	0.264
	(0.587)	(0.350)	(0.238)
Experienced permanent shock	5.392***	4.265***	-0.098
	(0.679)	(0.437)	(0.516)
Household size	0.106*	-0.046	-0.061**
	(0.057)	(0.053)	(0.022)
Age of the household head (years)	-0.049	0.049	0.056*
	(0.069)	(0.054)	(0.030)
Household head is married	0.195	-1.316***	0.469*
	(0.438)	(0.345)	(0.223)
Literacy of household head	-0.093	-0.552*	-0.056
	(0.283)	(0.292)	(0.112)
Electricity connection at home	0.596*	1.274***	-0.287*
	(0.279)	(0.199)	(0.145)
Owned land (in decimals)	-0.184**	-0.067	0.011
	(0.076)	(0.047)	(0.032)
Lives in owned house	1.509***	1.589***	-0.135
	(0.335)	(0.317)	(0.172)
Ln(agricultural asset value in BDT)	0.070*	0.088***	0.011
	(0.033)	(0.026)	(0.015)
Received credit after disaster	-1.613***	-0.355*	0.424***
	(0.247)	(0.177)	(0.099)
Received relief after disaster	-1.855***	-1.306***	-0.288**
	(0.464)	(0.351)	(0.112)
Constant	-3.409**	-3.461***	-1.873**
	(1.507)	(1.098)	(0.692)
Division fixed effects	No	No	No
Psedu R^2	0.85	0.77	0.06
N	796	866	926

Note: 1. Robust standard errors are reported in the parentheses.
2. Reference category is households who do not migrate.
* p <0.10, ** p <0.05, *** p <0.01.

Table A.4: **Impacts of migration on household income and expenditure: DDM estimate**

	Ln(household income) (1)	Ln(household expenditure) (2)
ATE		
Migrated to	0.121	0.310**
a different location	(0.083)	(0.156)
N	672	434

Note: 1. Standard errors are reported in the parentheses.
* p <0.10, ** p <0.05, *** p <0.01.

Table A.5: **Impacts of destination type on household income and expenditure by types of shocks experienced: OLS estimates**

	Ln(household income)		Ln(household expenditure)	
	(1)	(2)	(3)	(4)
Post × transient shock	1.101***	1.101***	0.769***	0.769***
	(0.242)	(0.242)	(0.173)	(0.173)
Post × permanent shock	1.263***	1.263***	0.006	0.006
	(0.319)	(0.319)	(0.316)	(0.316)
Post × transient shock	1.148**	1.148**	-0.039	-0.039
× migrated Dhaka	(0.525)	(0.525)	(0.265)	(0.265)
Post × permanent shock	0.854**	0.854**	0.781**	0.781**
× migrated Dhaka	(0.392)	(0.392)	(0.338)	(0.338)
Post × transient shock	0.794*	0.794*	0.136	0.136
× migrated Khulna	(0.445)	(0.445)	(0.214)	(0.214)
Post × permanent shock	-0.224	-0.224	0.946***	0.946***
× migrated Khulna	(0.354)	(0.354)	(0.335)	(0.335)
Post × transient shock	-0.495	-0.495	0.410	0.410
× migrated other districts	(0.407)	(0.407)	(0.304)	(0.304)
Post × permanent shock	0.337	0.337	0.835***	0.835***
× migrated other districts	(0.349)	(0.349)	(0.313)	(0.313)
Constant	8.305***	8.305***	8.891***	8.891***
	(0.014)	(0.014)	(0.007)	(0.007)
District fixed effects	No	Yes	No	Yes
Adjusted R^2	0.21	0.21	0.14	0.14
N	1,156	1,156	1,156	1,156

Note: See footnotes in Table 6.

Appendix B: For the referees (not intended for publication)

TABLE B.1: **Effect on Internal migration: Marginal effects from logit models**

	All shocks			Grouped shocks		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced flood in last 10yrs	0.634***	0.648***	0.355***			
	(0.098)	(0.108)	(0.098)			
Experienced cyclone in last 10yrs	0.459***	0.490***	0.277***			
	(0.078)	(0.092)	(0.081)			
Experienced river erosion in last 10yrs	0.981***	1.042***	0.557***			
	(0.104)	(0.119)	(0.143)			
Experienced transient shock				0.584***	0.622***	0.363***
				(0.061)	(0.071)	(0.079)
Experienced permanent shock				0.983***	1.056***	0.581***
				(0.102)	(0.116)	(0.135)
Household size		-0.023**	-0.020***		-0.023***	-0.021***
		(0.009)	(0.008)		(0.009)	(0.008)
Household head is female		-0.106	-0.120		-0.095	-0.103
		(0.135)	(0.097)		(0.134)	(0.092)
Household head is married		0.035	-0.026		0.037	-0.019
		(0.079)	(0.058)		(0.081)	(0.058)
Household head is muslim		0.121**	0.052		0.113*	0.046
		(0.060)	(0.044)		(0.059)	(0.044)
Literacy of household head		-0.012	-0.000		-0.026	-0.007
		(0.043)	(0.030)		(0.043)	(0.031)
Electricity connection at home		-0.048	-0.034		-0.038	-0.028
		(0.050)	(0.037)		(0.051)	(0.038)
Owned land (in decimals)		-0.006	-0.003		-0.005	-0.003
		(0.013)	(0.008)		(0.012)	(0.008)
Lives in owned house		0.035	-0.009		0.046	-0.001
		(0.070)	(0.049)		(0.072)	(0.051)
Ln(agricultural asset value in BDT)		0.009	0.005		0.010*	0.006
		(0.006)	(0.004)		(0.006)	(0.004)
Received credit after disaster		0.124***	0.099***		0.124***	0.100***
		(0.039)	(0.034)		(0.040)	(0.034)
Received relief after disaster		-0.158***	-0.156***		-0.158***	-0.158***
		(0.046)	(0.049)		(0.046)	(0.047)
Constant	0.379***	0.415***	0.176***	0.375***	0.412***	0.178***
	(0.020)	(0.027)	(0.047)	(0.020)	(0.027)	(0.043)
Division fixed effects	No	No	Yes	No	No	Yes
Psedu R^2	0.27	0.31	0.46	0.28	0.32	0.47
AIC	1104.08	1075.69	774.36	1088.33	1059.27	762.30
BIC	1124.30	1161.59	889.09	1103.49	1140.11	872.04
N	1,156	1,156	1,084	1,156	1,156	1,084

Note: 1. Robust standard errors are reported in the parentheses.
* p <0.10, ** p <0.05, *** p <0.01.

Table B.2: **Choice of destination for internal migrants: Marginal effects from multinomial logit model**

	Migrated to		
	Dhaka (1)	Khulna (2)	Other locations (3)
Experienced transient shock	5.470***	6.880***	0.566
	(0.950)	(1.184)	(0.554)
Experienced permanent shock	7.914***	8.404***	-0.059
	(1.181)	(1.499)	(1.196)
Household size	0.165	-0.043	-0.109*
	(0.125)	(0.128)	(0.057)
Age of the household head (years)	-0.019	0.195	0.122
	(0.119)	(0.128)	(0.082)
Household head is married	-0.372	-1.861**	0.628
	(0.830)	(0.862)	(0.463)
Literacy of household head	-0.518	-0.569	-0.096
	(0.533)	(0.577)	(0.274)
Electricity connection at home	0.510	1.251	-0.470
	(0.761)	(0.764)	(0.364)
Owned land (in decimals)	-0.153	-0.032	0.010
	(0.142)	(0.113)	(0.085)
Lives in owned house	1.028	1.812**	-0.239
	(0.746)	(0.767)	(0.412)
Ln(agricultural asset value in BDT)	0.123	0.169**	0.016
	(0.074)	(0.081)	(0.037)
Received credit after disaster	-1.531***	0.017	0.745***
	(0.485)	(0.489)	(0.252)
Received relief after disaster	-2.053***	-2.177**	-0.496*
	(0.752)	(0.861)	(0.284)
Constant	-5.326*	-9.513***	-3.590*
	(2.825)	(3.242)	(1.895)
Division fixed effects	No	No	No
Psedu R^2		0.42	
N		578	

Note: 1. Robust standard errors are reported in the parentheses.
2. Reference category is households who do not migrate.
* p <0.10, ** p <0.05, *** p <0.01.

Table B.3: **Choice of destination for internal migrants: OLS estimate**

	Migrated to		
	Dhaka	Khulna	Other locations
	(1)	(2)	(3)
Experienced transient shock	0.322***	0.523***	0.037
	(0.067)	(0.052)	(0.062)
Experienced permanent shock	0.641***	0.736***	0.016
	(0.062)	(0.046)	(0.115)
Household size	0.001	-0.005	-0.013**
	(0.003)	(0.004)	(0.005)
Household head is female	-0.055	-0.128**	-0.006
	(0.048)	(0.061)	(0.053)
Household head is married	-0.008	-0.095**	0.059
	(0.026)	(0.037)	(0.040)
Household head is muslim	0.017*	0.051***	0.029
	(0.009)	(0.014)	(0.028)
Literacy of household head	-0.006	-0.025	0.011
	(0.012)	(0.015)	(0.027)
Electricity connection at home	0.006	0.073***	-0.059*
	(0.014)	(0.017)	(0.034)
Lives in owned house	0.031	0.062*	-0.051
	(0.023)	(0.032)	(0.046)
Received credit after disaster	-0.043***	-0.004	0.095***
	(0.010)	(0.011)	(0.023)
Received relief after disaster	-0.058***	-0.041**	-0.085***
	(0.013)	(0.015)	(0.027)
Owned land (in decimals)	-0.003	-0.003	0.000
	(0.002)	(0.003)	(0.007)
Ln(agricultural asset value in BDT)	0.002	0.004*	0.001
	(0.001)	(0.002)	(0.003)
Age of the household head (years)	-0.000	0.002	0.012**
	(0.002)	(0.003)	(0.005)
Constant	-0.002	-0.024	-0.197
	(0.055)	(0.067)	(0.133)
Division fixed effects	Yes	Yes	Yes
R^2	0.81	0.73	0.28
N	844	866	926

Note: 1. Robust standard errors are reported in the parentheses.
2. Reference category is households who do not migrate.
* p <0.10, ** p <0.05, *** p <0.01.

Table B.4: **Impacts of migration on household income and expenditure by types of shocks experienced: OLS estimates**

	Ln(household income)			Ln(household expenditure)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × transient	1.435^{***}	1.435^{***}	1.305^{***}	1.017^{***}	1.017^{***}	0.940^{***}
shock	(0.280)	(0.280)	(0.273)	(0.174)	(0.174)	(0.171)
Post × permanent	1.813^{***}	1.813^{***}	1.813^{***}	0.390^{***}	0.390^{***}	0.390^{***}
shock	(0.454)	(0.454)	(0.454)	(0.150)	(0.150)	(0.150)
Post × transient	0.426	0.419	0.612	-0.137	-0.123	-0.073
shock × migrated	(0.390)	(0.394)	(0.385)	(0.201)	(0.202)	(0.200)
Post × permanent	-0.133	-0.134	-0.133	0.539^{***}	0.532^{***}	0.539^{***}
shock × migrated	(0.477)	(0.478)	(0.477)	(0.172)	(0.173)	(0.172)
Constant	8.302^{***}	8.286^{***}	8.304^{***}	8.888^{***}	8.883^{***}	8.892^{***}
	(0.015)	(0.015)	(0.015)	(0.007)	(0.007)	(0.007)
Adjusted R^2	0.20	0.20	0.21	0.14	0.14	0.14
N	1,156	1,120	1,144	1,156	1,120	1,144

Note: See footnotes in Table 6.