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Impacts of transient and permanent environmental shocks on internal migration

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ABSTRACT

We examined whether floods and cyclones, the shocks that are transient in nature, affect interregional migration differently compared to riverbank erosion that causes loss of lands and thus generates permanent shocks. We tracked Household Income and Expenditure Survey 2000 participants in nine coastal districts of Bangladesh and collected further information in 2015. Our analyses suggest that both transient and permanent shocks induce households to migrate, but the effect is higher for the latter category. Using a difference-in-differences setting, we find that migrants' income and expenditure increase relative to their counterparts, indicating that facilitating migration may improve welfare in disaster-prone countries.

KEYWORDS

Natural disaster; permanent shock; transient shocks; internal migration

JEL CLASSIFICATION

I38; Q54; Q56; R23

I. Introduction

We analysed whether riverbank erosion that leads to loss of lands and thus imposes a permanent negative shock on households' economic status has a stronger influence on domestic migration decisions than the one induced by transient shocks like floods and cyclones. We also examined how the types of shocks affected migrant households' choice of destination and the association of migration with household income and expenditure.

The study of the differential impact of environmental shocks is useful in understanding the pattern of migration and whether migration can be used as an effective adaptation mechanism against natural disasters. Natural hazards caused global damage of US$1.5 trillion, affected around 2 billion people between 2003 and 2013 (FAO 2018) and increased international migration (Mahajan and Yang 2020). The issue is getting increasing importance as the frequency and intensity of natural disasters are on the rise with changing climate (Emanuel 2005; Stern 2008; Desmet et al. 2021) that may significantly affect the future well-being of households and communities around the world (Cattaneo and Peri 2016; Kahn et al. 2021; Noy, Nguyen, and Patel 2021). For example, natural disasters like cyclones and floods are projected to displace nearly 143 million people by 2050 if no adaptation strategies are implemented (Rigaud et al. 2018). Permanent flooding alone is projected to reduce global GDP by 0.19% and welfare by 0.24% by the year 2200, as people are expected to be forced to live in places with fewer amenities (Desmet et al. 2021).

We employed household-level information to assess individual migration decisions as they vary across locations, communities and past exposure to natural disasters (Cattaneo and Peri 2016; Peri and Sasahara 2019; Guiteras, Jina, and Mobarak 2015). We focused on Bangladesh, a developing nation, as natural disasters severely affect low-income people due to their dependence on natural resources and the lack of adaptive capacity and safety nets (O'Neill and Oppenheimer 2002). The disproportional impact of natural disasters on developing countries is evidenced by their estimated economic damage of US$550 billion to those economies between 2003 and 2013 (FAO 2018).[1,2]

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[1]Mejia et al. (2018) found that global temperatures had uneven macroeconomic effects, with adverse consequences concentrated in most low-income countries with a warmer climate. 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.

[2]Disasters may also affect life in many other ways, like lowering job prospects, reducing life satisfaction, lowering schooling and deteriorating mental health of the victims (Kellenberg and Mobarak 2011; Karbownik and Wray 2019).

Another reason for choosing Bangladesh for our study is that the country is ranked nine among those heavily suffering from natural disasters (Eckstein, Künzel, and Schäfer 2017). 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.

In Bangladesh, as well as in many other developing countries, households affected by shocks follow some common mitigation and coping strategies to maintain their livelihoods (Khandker 2012; Mozumder et al. 2009). For example, people may intensify the use of the commons to generate additional income in the face of the shocks (Islam and Nguyen 2018). A risk-averse individual may also find internal migration as an effective mitigation mechanism and choose to migrate to a place with a lower incidence of natural disasters (Cameron and McConnaha 2006; Grimm and Klasen 2015).

Studies examined the effects of natural disasters on internal migration and the choice of locations, including how migration decisions vary with types of shocks (e.g. Gröger and Zylberberg 2016; Berlemann and Steinhardt 2017; Bernzen, Jenkins, and Braun 2019; Hoffmann et al. 2020). Koubi et al. (2016) found long-term environmental events like droughts reduced migration while sudden-onset environmental events like floods raised the likelihood of migration. In contrast, Gray and Mueller (2012a) found drought increasing men's migration in rural Ethiopia. Interestingly, Mueller, Gray, and Kosec (2014) significant relief efforts after flooding reduced the intensity to migrate while, with relatively little relief support, heat stress increased the long-term migration of men in rural Pakistan.

Among the studies focusing on Bangladesh, Gray and Mueller (2012b) found flooding to have modest effects on the mobility of women and the poor. Chen and Mueller (2018) found no effect of flooding on migration in coastal Bangladesh but a positive effect of salinity on domestic migration. Bernzen, Jenkins, and Braun (2019) found that the exposure to severe river erosion significantly increased the short-term internal migration in the rural communities of coastal Bangladesh.

Previous empirical studies confirmed improvement in the well-being of the migrating households. For example, Beegle, De Weerdt, and Dercon (2011) found migration in Tanzania added 36% points to the consumption growth between 1991 and 2004. De Brauw, Mueller, and Woldehanna (2017) found migrants' welfare, including their food and non-food consumption, improved compared to their non-migrant counterparts. Such investigations are useful as the policy support for the disaster-affected people relies on smart adaptation strategies, reflected in their income and consumption growth.

Against this background, in 2015, we tracked participants of the Bangladesh Household Income and Expenditure Survey (HIES) 2000 in nine coastal districts of the country. Our investigation on those participants revealed that all types of natural disasters induced households to migrate, but the effect was stronger when the shock was permanent. We also found that temporary shocks were more likely to prompt migration to a nearby location than a distant location. Comparing income and expenditure of migrant- and non-migrant households in a difference-in-differences setting, we find that the migrant group is likely to be better off than their counterpart, implying that facilitating migration can improve welfare.

The remainder of this article is organized as follows. Section II 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 III briefly describes the survey and the data. Section IV presents the empirical strategy and the identifying assumptions. Results from our analysis are presented in Section V. Section VI concludes the paper.

II. Natural disasters and internal migration in coastal Bangladesh

The coastal zone of Bangladesh, which makes up approximately 30% of the total area of the country, is particularly vulnerable to natural disasters. The topographic and geo-physical location makes it prone to frequent floods, cyclones, and riverbank erosion (Poncelet et al. 2010; Alam et al. 2018). Depending on the nature and consequences of these natural disasters, we classify the environmental shocks into two major categories – transient and permanent.

Transient shocks

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

Located in the delta of the Ganges, Brahmaputra and Meghna river basin and a few metres above the sea level, Bangladesh regularly experiences flash, rainfall-induced and storm surge floods. Each year, the inundation of floods affects about 21% of the country (Mirza 2003). In the last 30 years, Bangladesh experienced severe floods during 1987–1988, 1998–1999, 2004–2005, 2007, 2010 and 2017. With 50% of the land less than eight metres 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 created significant hardship for the people in the catchment areas and resulted 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 every three years on average and destroy the homesteads and livelihoods of millions living there (Dasgupta et al. 2010). The country 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 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 cyclone victims move away because of resource scarcity, infrastructure damage, lack of social protection as well as the unavailability of income-generating alternatives in the affected areas (Poncelet et al. 2010).

Permanent shock

Permanent environmental shocks are those which provide a long-lasting exposure to a particular natural hazard. Depending on the characteristics, riverbank erosion can be considered the most common permanent shock in the coastal areas of Bangladesh.

Riverbank erosion is a major contributor to the destitution and marginalization of rural families in Bangladesh (Poncelet et al. 2010). Annually, it displaces about 60,000 individuals and erodes about 14,000 hectares of arable land (Mirza, Warrick, and Ericksen 2003). More problematic is that it mostly affects the poorest group of coastal communities (Ishtiaque and Nazem 2017). People living in the southwest coastal belt are particularly exposed to riverbank erosion and often find migration a viable mitigation strategy (Poncelet et al. 2010). Among the climate-induced migrants in Dhaka city, a significant proportion is from the coastal districts of Bangladesh (Adri and Simon 2018).

A comparison between the transient and the permanent shocks indicates that the victims of temporary shocks are still left with some resources, including their land, and can continue with a livelihood in their original location, although they may leave their homes temporarily. In contrast, permanent shocks either destroy most of the resources (e.g. loss of homestead and agricultural lands with riverbank erosion) or make them unusable (e.g. agricultural land affected by salinity), which reduces the production and employment opportunities of the affected households (Alam et al. 2018). As a result, households affected by permanent shocks are likely to have a higher propensity to leave their origin and migrate to another location permanently. Note that we consider transient and the permanent shocks as mutually exclusive as they did not largely overlap in our case; see Figure 1 for details.

III. Survey design and sampling procedure

The land 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. The coastal areas of Bangladesh cover 19 districts, most of which are frequently affected by environmental shocks like floods, cyclones and riverbank erosion (Dasgupta et al. 2014). In 2015, we conducted the Coastal Vulnerability and Livelihood Security (CVLS) survey to identify the link between transient and permanent environmental shocks and households' migration decisions, including the choice of destinations. The survey design targeted the areas affected by different types of natural disasters in recent years. Specifically, it organized face-to-face interviews for selected households in nine southwest districts in Khulna and Barisal divisions – Bagerhat, Barguna, Barisal, Bhola, Jhalokati, Khulna, Patuakhali, Pirojpur and Satkhira.

To better understand the dynamics of the internal migration scenario in Bangladesh, the CVLS survey tracked households in coastal areas, which were included in the Household Income and Expenditure Survey (HIES) that collected nationally representative information in 2000.[3] The total number of households for the selected districts in HIES-2000 was 1180, of which 1166 households had non-missing income and expenditure information. As common in longitudinal surveys, the CVLS survey suffered from attrition since the repeat survey was conducted with a gap of 15 years. CVLS survey was able to track nearly half of the HIES survey participants –455 households.[4] As expected, some households split up between 2000 and 2015. From HIES 2000 to CVLS 2015, a total of 93, 27 and 3 households split into 2, 3 and 4 families, respectively. As a result, we start with 578 households in our analysis sample.[5]

There are differences in some characteristics between the groups of HIES 2000 households that are included in the analysis and those who are not; see appendix, Table A1 for detail. However, there is no systematic variation between the two groups. For example, the analysis households have lower schooling that may affect their migration positively, compared to the other group. On the other hand, homeownership is higher for the analysis sample, which may affect migration in the opposite way. As a result, we expect that attrition will not affect the findings significantly. Similarly, there are differences in some characteristics between the HIES 2000 households suffering from disasters compared to their counterpart, but there is no systematic variation between the two groups; see appendix, Table A2 for detail.

The summary statistics of migrants against non-migrants indicate statistically significant differences for some variables (Table A3). Migrating households are less likely to be female-headed, non-Muslim, living in the owned houses and poorer. In a non-randomized experiment, such differences are likely, and we have controlled for them in the models. Importantly, the distributions of income, consumption, agricultural asset value and owned land were roughly similar for migrants and their counterparts.

The distribution of respondents among source and destination districts is shown in Table 1. It shows that about 36% of households in the survey migrated from one location to another.[6] Among them, around 30% moved to the nearest Khulna city, 25% migrated to the capital city Dhaka, and the rest 45% settled down in 21 other districts in Bangladesh. On the other hand, the origin of most of the migrants was Barishal (25% of all migration), followed by Khulna (16%), Bhola (12%), Jhalokhati and Satkhira (11% each) and other districts (25%). These internal migrants are mostly permanent or long-term migrants who did not indicate any intention of returning to their original location.

Information collected in the CVLS survey includes data on whether, in recent years, households suffered from any environmental shocks like floods, cyclones or riverbank erosion.[7] Households were also asked whether they received credit or relief support in the aftermath of natural disasters,

[3]The survey question specifically asked whether a household head migrated permanently to a new location. Previous studies found that often only single household members migrate (e.g. Gröger and Zylberberg 2016). Our empirical setting did not focus on the issue.

[4]The CVLS survey collected data from 2096 households, of which 1835 observations had relevant information. We dropped 1257 households as they were not included in HIES 2000 and thus could affect the representativeness of our sample. Figure 2 shows the locations of the analysis households in 2000 & 2015.

[5]Our findings are robust to the exclusion of the split households.

[6]This seems a bit high but consistent with some recent studies like Marshall and Rahman (2013).

[7]Objective measures of disasters are better than their subjective counterpart. For instance, Guiteras, Jina, and Mobarak (2015) find self-reported exposure to flooding to be weekly correlated to true exposure. While it is possible to employ objective measures of floods and cyclones, it is difficult to get an objective

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.

if any. We also collected information on household income by asking them about the earnings from different sources. Following a methodology that is consistent with HIES, the survey collected detailed information on household food and non-food expenditures. Food items include rice, food crops, wheat, lentils, edible oil, vegetables, poultry items, dairy items, salt, sugar, dry food and beverages. Non-food items in the survey data 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 that also include home productions.

Table 2 presents the summary statistics of key variables considered in our analysis. Panel (a) in the table reports the information collected through CVLS. Regarding the exposure to natural disasters, about 14% of the households experienced riverbank erosion, a permanent environmental shock, compared to transient environmental shocks like floods (5%) and cyclones (7%).[8] Information in panel (b), collected from HIES 2000, shows the baseline demographic and socioeconomic status of the households in our analysis sample.

IV. Empirical framework

We use the following model to examine the impact of different natural disasters on internal migration

$$Pr(M_i = 1|\boldsymbol{EHWZ}) = \alpha + \beta\boldsymbol{E_i} + \gamma\boldsymbol{H_i} + \theta\boldsymbol{W_i} + \psi\boldsymbol{Z_i} + \lambda_{\boldsymbol{d}} + \varepsilon_i \quad (1)$$

where, for each i, M takes the value of 1 if household migrates and 0 otherwise, $\boldsymbol{E}$, $\boldsymbol{H}$, $\boldsymbol{W}$ and $\boldsymbol{Z}$ are vectors of explanatory variables and ε is the error term.

The vector of explanatory variable $\boldsymbol{E}$ includes separate controls for exposure to disasters like floods, cyclones and riverbank erosion.[9] In some

measure of river erosion as it is concentrated in a narrow geographical location and often not tracked in a systematic way. As combining subjective and objective measures can be problematic, we relied on the former in our analyses. Please note that if the estimates are statistically significant, the issue is less of a concern for the validity of the results.

[8]The change in price levels (using CPI) between 2000 and 2015 was around 300% (BBS 2011, 2018).

[9]Our data includes information on exposure to salinity, drought and some other type of natural disasters. Since a very small group of households reported suffering from these disasters, we did not separately control for them in the reported analyses. Our conclusions remain unchanged when they are controlled for. Also, we do not have data on the number of occurrences of transient shocks that people have experienced, which restricts us from controlling for the factor in the model.

Table 2. Summary statistics of key variables.

Variable definition	Mean	SD
Panel (a): Information collected through CVLS survey (at 2015)		
Experienced flood in last 10 yrs	0.05	0.23
Experienced cyclone in last 10 yrs	0.07	0.25
Experienced river erosion in last 10 yrs	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	7324
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)	3510	15,430
Monthly household income in BDT (in 2000)	3560	3587
Monthly household consumption in BDT (in 2000)	6125	4064
N	578	

Notes: 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 household income and expenditure in 2015 are reported in current prices. The inflation rate between 2000 and 2015 (i.e. before and after migration data collection time periods) was 300% as calculated using CPI (with changing base) reported in BBS (BBS 2011, 2018).

separate models, $\boldsymbol{E}$ represents exposure to shocks categorized as transient (floods or cyclones) and permanent (riverbank erosion). $\boldsymbol{H}$ is the vector of baseline household characteristics that include household size and household head's sex, age, age^2, marital status, literacy and religion. $\boldsymbol{W}$ captures the effect of household wealth by including variables like the size of landholding, agricultural asset value, home ownership type, the availability of electricity connection in the residence and household income. The vector $\boldsymbol{Z}$ includes separate dummies for receiving credit and/or relief – alternative coping instruments against natural hazards.

Finally, we control for the division fixed effects (FEs), λ_d, to net out the effect of time-invariant variables (such as the transportation and job opportunity in a division) that may lead to an endogeneity problem. For example, our FEs will account for if households along the riverbank, who are more likely to experience riverbank erosion, are also better connected to major cities and may have a higher tendency to migrate.[10]

We use probit regression to estimate Equation (1). The use of a binary response model ensures the estimated probabilities lie between zero and one and allows independent variables to have non-constant partial effects. We have also employed alternative models like logit and linear probability model for robustness check, but only report probit model results considering the space constraints.

We also examine the determinants of destination choices. In particular, we examine how factors like transient and permanent shocks affect the choices of destinations with different characteristics. The research is motivated by the fact that the 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). We use the following model to determine the choice of alternative destinations

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

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 independent variables that are similar to our previous model, including the division fixed effects. To address the case that there are multiple destinations for migration, we use the multinomial probit model to estimate Equation (2).[11]

Next, we investigate how migration affects household income and expenditure. Unfortunately, the non-random selection of households in our survey data will not allow identifying purely causal impact. To address this issue, we have taken a number of measures to make our estimate of (partial) correlation as close as possible to the true impact of migration. Still, our identified average treatment effect

[10]Unfortunately, our analysis sample is not large enough to control for the district fixed effects.
[11]The multinomial probit model for migration choices is motivated by the framework of the random utility model, discussed in Davies, Greenwood, and Li (2001).

(ATE) of migration, as we discussed below, should be taken with caution, more appropriately as a hint to the true ATE.

The ATE of migration can be inferred through the difference in the outcome variable between the households who migrated and those who did not. However, the results are more meaningful when a similar set of households are selected using the propensity score matching (PSM) (Emran, Robano, and Smith 2014). 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 conditions, the difference-in-differences (DD) method can overcome the problem. The availability of longitudinal data for 2000 and 2015 for both groups of households – who migrated and who did not – allowed us to employ a fixed effect DD model as follows

$$Y_{it} = \beta_1 + \beta_2 Post_t + \beta_3 M_i \times Post_t + \lambda_i + \varepsilon_i \quad (3)$$

where, for each household i and time t, Y represents (the log of) income, M is a dummy for migration (reference group is no migration), and *Post* is a dummy for the year 2015 (reference year is 2000) while λ in the model controls for household fixed effects.[12] In the model, the constant β_1 indicates the average income of the reference group before migration, while β_2 gives the overtime changes in the dependent variable for the same group. The coefficient of interest, β_3, indicates the overtime differential increase in migrants' income, compared to the reference group.

We employed a similar model for investigating the impact on household expenditure in which the set of explanatory variables additionally included household income – the most important determinant of expenditure (Hasan 2016a, 2016b, 2019).

DD model may suffer from certain problems like the selection on idiosyncratic temporary shocks known as 'Ashenfelter's dip' (Blundell and Dias 2009). Thus combining DD with PSM (matching DD) is believed to be more useful in overcoming the underlying assumptions of both methods (Blundell and Dias 2009; Emran, Robano, and Smith 2014). The identifying assumption in the DD estimation is the parallel trend. In other words, the difference in income between the two groups would have remained the same without migration (and similar to the model with household expenditures). We cannot test our identifying assumption directly. In such case (or when the common trend assumption is not valid), DD with matching that is additionally conditioned on the outcome variable is useful (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).

V. Estimation results and discussion

Types of shocks and migration

We start with identifying the links between different types of environmental shocks and internal migration by employing Equation (1) and probit regressions. The marginal effects, which are estimated at the mean values of all other covariates, are reported in Table 3.[13] 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% throughout this analysis, at which the results indicate a significant effect of flood and riverbank erosion on migration but not for cyclone (a transient shock). Also, the effect is the highest for riverbank erosion (the permanent shock).

When we include additional control variables in the model, estimated effects remain similar (Column 2 of Table 3). Religion, credit, and relief affect migration significantly. Muslim households may have a higher propensity to migrate due to their access to extensive

[12]Equation (3) is, in fact, a conventional difference-in-differences model with household fixed effects and so it drops the migration variable from the model.
[13]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.

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 10 yrs	0.525 **	0.531 ***	0.506 ***			
	(0.220)	(0.199)	(0.192)			
Experienced cyclone in last 10 yrs	0.361	0.371	0.355			
	(0.274)	(0.284)	(0.275)			
Experienced river erosion in last 10 yrs	0.839 ***	0.872 ***	0.831 ***			
	(0.169)	(0.183)	(0.178)			
Experienced transient shock				0.530 **	0.542 **	0.517 **
				(0.223)	(0.227)	(0.222)
Experienced permanent shock				0.858 ***	0.903 ***	0.864 ***
				(0.176)	(0.193)	(0.188)
Household size		−0.024	−0.028		−0.024	−0.027
		(0.018)	(0.019)		(0.020)	(0.020)
Household head is female		−0.210 *	−0.180*		−0.163	−0.137
		(0.127)	(0.108)		(0.121)	(0.106)
Age of the household head (years)		−0.002	−0.003		−0.003	−0.003
		(0.003)	(0.003)		(0.003)	(0.003)
Household head is married		−0.019	−0.003		−0.000	0.014
		(0.105)	(0.098)		(0.105)	(0.099)
Household head is muslim		0.119 **	0.074		0.106 **	0.065
		(0.051)	(0.053)		(0.049)	(0.050)
Literacy of household head		−0.003	−0.006		−0.019	−0.020
		(0.059)	(0.059)		(0.056)	(0.056)
Electricity connection at home		−0.055	−0.061		−0.037	−0.043
		(0.110)	(0.112)		(0.124)	(0.125)
Owned land (in decimals)		−0.001	−0.004		0.001	−0.001
		(0.008)	(0.009)		(0.008)	(0.008)
Lives in owned house		0.031	0.004		0.055	0.030
		(0.034)	(0.037)		(0.036)	(0.033)
Received credit after disaster		0.109 *	0.125 **		0.108 *	0.122 **
		(0.058)	(0.056)		(0.057)	(0.055)
Received relief after disaster		−0.143 **	−0.203 *		−0.137 **	−0.193 *
		(0.063)	(0.104)		(0.064)	(0.100)
Ln(agricultural asset value in BDT)		0.008	0.008		0.009	0.009
		(0.011)	(0.011)		(0.011)	(0.012)
Ln(Monthly household income in 2000)		−0.034	−0.023		−0.036	−0.026
		(0.021)	(0.020)		(0.023)	(0.022)
Constant	0.366 ***	0.400 ***	0.403 ***	0.365 ***	0.399 ***	0.402 ***
	(0.043)	(0.042)	(0.038)	(0.043)	(0.042)	(0.038)
Division fixed effects	No	No	Yes	No	No	Yes
Pseudo R^2	0.26	0.30	0.31	0.28	0.32	0.32
AIC	566.11	563.15	562.57	553.03	551.27	552.22
BIC	583.55	641.62	654.12	566.11	625.38	639.41
N	578	578	578	578	578	578

Notes: 1. Standard errors, clustered at the district level, are reported in the parentheses.
2. The marginal effects are estimated at the mean values of all other covariates.
**p* < 0.10, ***p* < 0.05, ****p* < 0.01.

religious and social networks that supports their migration. Receiving credit has a positive effect on internal migration, which is in line with Chen and Mueller (2018) who find that a minimum amount of income or wealth is required for migration.[14] On the other hand, we observe that people who receive relief support are less likely to migrate as it allows them to spend money on mitigating the adverse effect of natural hazards and stay put. The impact of relief is consistent with Paul (2005) who observed that better relief management in the aftermath of tornadoes in north-central Bangladesh resulted in no migration.

The differences between credit and relief can explain their differential impacts. Receiving credit is a sort of monetary support that may allow people to finance migration. However, the conditionality associated with credit may also force the recipients to migrate and earn more to pay the interest on their loans. In contrast, relief is usually uncondi-

[14]Credit can be determined simultaneously with migration, making it endogenous in our model. Dropping it from the control variable as a robustness check does not affect our results qualitatively.

tional in-kind support, like providing food and non-food durable items that assists people in surviving in the original location in the aftermath of natural disasters.[15]

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 impacts of natural disasters become slightly smaller. The estimated effect of flooding is positive and is similar to some previous studies like Gray and Mueller (2012b) who found a modest effect of flooding on internal migration in Bangladesh. On the other hand, cyclone has an insignificant and much lower effect on internal migration, probably because of the transient nature of the shock. In this model, riverbank erosion, which washes away homesteads, agricultural land and assets of exposed households, increases domestic migration significantly. The results, which are similar to the findings of Das et al. (2014), reveal that riverbank erosion is one of the key drivers of internal migration since the victims of this hazard become destitute and eventually migrate.

Next, we compare the effect of the shocks by dividing them into two categories – transient and permanent. Columns 4–6 of Table 3 repeat the previous analysis conducted in Columns 1–3 but group flood and cyclone together to represent them as a transient shock, leaving riverbank erosion as the permanent shock. Again, the results are largely similar. In the final model with all controls and division fixed effects, presented in Column 6, people affected by transient shocks are 52% more likely to migrate. On the other hand, permanent shocks induce people to migrate 87% more 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, in Columns 4–6, the group shocks replace separate controls for flood, cyclone and riverbank erosion. While the results are largely similar, the model used for generating the results in Columns 4–6 are superior, as indicated by the lower values of the Akaike information criterion (AIC) and Bayesian information criterion (BIC). As a result, for the remaining analyses, we use grouped shocks as our preferred model variables.

Our results are robust to a number of modifications in the model. For example, we get similar results when we use a linear probability model (Table A4) or use logistic regression for our analysis. We also arrive at similar conclusions when we repeat the analysis on a propensity score matched set of households to address the concern of selectivity of the analysis sample resulting from attrition. In all cases, our model fit appears reasonable as given by (McFadden's) Pseudo R^2 (or adjusted R^2 in the case of the linear probability model). Thus, the previous set of analyses successfully demonstrates that transient and permanent shocks affect domestic migration at a different scale, with relatively higher effects for permanent shocks.

Destination choice

At this stage, we start looking at how different types 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, again estimated at the mean values of all other covariates. The determinants of migrating to Dhaka are presented in 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 neighbouring Khulna than its' effect on migrating to the distant capital city Dhaka. The higher effect for Khulna can be due to its proximity to the origin, which motivates people to plan to return to their origin after recovery. On the other hand, when we consider

[15]Surprisingly, the regional public spending for disaster risk reduction in Bangladesh does not seem to be determined by risk and exposure but only weakly by vulnerability (Karim and Noy 2015).

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	3.652 **	4.720 **	0.573 *
	(1.388)	(1.484)	(0.258)
Experienced permanent shock	5.403 ***	5.533 ***	0.585 **
	(0.998)	(1.136)	(0.191)
Household size	−0.004	−0.194 *	−0.088
	(0.104)	(0.091)	(0.068)
Household head is female	-14.198 ***	-3.521 ***	0.194
	(1.087)	(0.689)	(0.345)
Age of the household head (years)	0.007	0.165	0.076 **
	(0.083)	(0.107)	(0.031)
Literacy of household head	−0.572	−0.479	−0.076
	(0.416)	(0.629)	(0.236)
Electricity connection at home	0.408	1.024	−0.332
	(0.406)	(0.629)	(0.534)
Household head is married	−0.399	−1.461 *	0.624
	(0.420)	(0.626)	(0.354)
Lives in owned house	0.894 *	1.596 **	−0.202
	(0.411)	(0.551)	(0.139)
Owned land (in decimals)	−0.073 *	−0.051	0.006
	(0.037)	(0.045)	(0.034)
Ln(agricultural asset value in BDT)	0.058	0.079	0.022
	(0.047)	(0.041)	(0.048)
Received credit after disaster	-0.971 **	0.261	0.535 *
	(0.345)	(0.277)	(0.230)
Received relief after disaster	-1.957 **	−2.157 *	-0.427 **
	(0.646)	(0.927)	(0.171)
Ln(Monthly household income in 2000)	-0.373 **	−0.117	0.004
	(0.127)	(0.161)	(0.056)
Constant	0.651	−4.003	-2.565 **
	(2.812)	(2.823)	(0.711)
Division fixed effects	Yes	Yes	Yes
N		578	

Notes: 1. Standard errors, clustered at the district level, are reported in the parentheses.
2. Reference category is households who do not migrate.
3. The marginal effects are estimated at the mean values of all other covariates.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

migration to other locations, we find a positive impact for both types of shocks which are much lower (Column 3). The coefficient estimate for the transient shock is also not statistically significant at the 5% level. Thus, in all cases, we again observe higher effects of the permanent shock relative to that of the transient shock.

The effects 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 different destinations. For instance, household size has a negative effect on moving to Khulna city (significant at the 10% level) or other locations but no effect on moving to the distant metropolitan city Dhaka. The observed pattern can be because Dhaka is usually considered as the last choice of destination 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 metropolitan cities, the case is much stronger for Dhaka. As women in the country are less likely to be in wage work or salaried jobs due to conservative social values (Ahmed and Sen 2018) or lack of social capital (Bakshi, Mallick, and Ulubaşoğlu 2019), the female-headed households are less likely to take the opportunity of higher income in the metropolitan city Dhaka. Workplace discrimination against women in Bangladesh can also be a potential reason (Ahmed and Maitra 2010). Interestingly, female-head did not matter for moving to other locations as migration is likely to be supported by their friends and relatives. Among other variables, people living in their own houses are more likely to migrate to Khulna. We believe that home-ownership may induce people to relocate temporarily to the nearby city with the plan to come back later when they recover from the shock.

The most interesting case is receiving credit and relief, which are considered important substitute coping instruments for natural disasters. 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. As previously discussed, relief negatively impacts migration, but the impact is not statistically significant for migrating to Khulna or other locations.

We arrive at similar conclusions when we employ independent probit regressions (Table A5) or multinomial logit regressions or linear probability models to explain the choice of migration destinations. Findings are similar when we repeat the analysis on a set of households that are more alike (through propensity score matching) to address the concern of selection in our analysis sample due to attrition. Thus, our analysis indicates that both temporary and permanent shocks have a significant and positive impact on migration. However, in all cases, transient shocks have lower effects on migration than the effects of permanent shocks.

Impact on income and expenditure

Our next objective is to look at the impact of migration on household income and expenditure. We start with the propensity score matching (PSM) technique to find out the effect of migration. We employed the baseline characteristics of all the independent variables of our previous models and estimated propensity score (PS) for each household to predict migration. 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% 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 Table 5, while Columns 2 and 4 report results with the second approach. The results indicate that migration raises household income by around 13%, but the effect becomes slightly smaller (11%) and statistically insignificant when we follow the second approach of imposing common support. On the other hand, the effect of migration on household expenditure (17–19%) remains highly significant in both approaches. The higher significance of expenditure is expected as it is usually measured more precisely than income in household surveys.

Next, we employed the difference-in-differences (DD) model in Equation (3) to avoid the shortcomings of the PSM technique discussed earlier. Estimated results of the DD model are presented in Table 6. Column 1 results show that, over time, the income of both groups increased significantly.[17] The DD estimate indicates that the increase was nearly 48% higher for the migrant population. This is equivalent to annual growth of 2.5% for fifteen years. It is essential to recognize that various macroeconomic and local factors that occurred between 2000–2015 and are not controlled for in our models can be responsible for some of the effects. However, our results indicate that migration is likely to be important for such income growth.

To add the strength of matching in our DD approach, we now repeat the previous analysis with dropping treatment observations following approach 1 (Column 2), as employed in Gibson and McKenzie (2014). It is reassuring to find that the results remain largely similar to the approach. 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. The estimates remain largely unchanged even with the new modelling approach (Column 3). In

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

[17]The positive and significant estimates of the coefficient *Post* indicate that incomes and expenditures of stayers also increased. However, our empirical strategy and available data cannot identify whether it is due to migration or the overall improvements in the macroeconomic factors of the economy.

this preferred specification, migrant households' income increase nearly 52% more (2.8% 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 (Columns 4–6). However, in all cases, the change in migrant expenditure is much lower than income. In the preferred specification, we follow approach 2 and predict migration on the previous set of variables and the outcome. In that model, household expenditure is 15% higher for migrants than for their counterparts (Column 6). It is worthwhile to mention that all the models of income and expenditure in the table have reasonable goodness of fit, indicating the validity of our models.

The propensity score matched treatment effects are more closely aligned to the average treatment effect for the treated (ATT). Next, we employed the difference-in-differences approach with matching (the DDM estimator) to more closely estimate the average treatment effect (ATE), in which we are more interested. To address the possible bias of not being treated, following Emran, Robano, and Smith (2014), we used the inverse probability weighted (IPW) matching estimator developed by Hirano and Imbens (2001). The IPW matching weights the observations in the treatment group by the probability of being treated (i.e. $\frac{1}{PS}$) and weights the observations in the control group by the probability of not being treated (i.e. $1 - \frac{1}{PS}$). The dependent variable in the model is the log of changes in income (consumption), and so the DDM estimator indicates their growth rate.

Table 5. Impacts of migration on household income and expenditure: PSM estimate.

	Ln (household income)		Ln (household expenditure)	
	(1)	(2)	(3)	(4)
ATE	0.125 **	0.109	0.172 **	0.192 ***
	(0.063)	(0.077)	(0.068)	(0.071)
N	558	523	558	523

Notes: 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% of the treatment observations at which the pscore density of the control observations is the lowest.
2. Bootstrapped standard errors are reported in the parentheses.
* $p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

The results with matching, combined with the application of inverse probability weights, indicate that the income and expenditure of migrating households increase disproportionately compared to their counterparts. However, the increases are not statistically significant at the conventional level of significance (see appendix, Table A6). One potential reason for this can be the missing values of the dependent variables since some of our observations had negative overtime changes in (real) income and consumption. These missing values make the DDM estimates less useful to infer the ATE of migration on income and consumption, and we emphasized these results less.

The previous set of results is robust to changes in model specifications. For example, allowing differential impact for those who suffered from transient shocks and those who suffered from permanent shocks also provides a similar conclusion. However, the results are only significant for household income (Table A7). Overall, the analysis of income and consumption indicates that households are more likely to benefit from migration than their counterpart. Such findings are consistent with some previous studies conducted in other continents that find a large increase in consumption after migration (Beegle, De Weerdt, and Dercon 2011; De Brauw, Mueller, and Woldehanna 2017). The beneficial effect of migration on households' economic condition is expected as people optimally choose to migrate to maximize their future utility, and both income and expenditure can be considered good proxies for household welfare.

We extended our analysis to examine whether our results are robust to incorporating differential impacts of migration locations on household income and expenditure (Table 7). We estimate DD models with three treatment groups – migrating to Dhaka, migrating to Khulna and migrating to other locations – against the same reference group (no migration). Results in Column 1 and 3 of the table are generated using a simple DD model, while Column 2 and 4 results are derived following our preferred approach. The results indicate that the group that migrated to Dhaka benefited in terms of their income but not expenditure, although the real benefit may not be very high due to the higher cost of living there. The impact is not statistically significant for the group

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	1.226 ***	1.245 ***	1.220 ***	0.832 ***	0.860 ***	0.835 ***
	(0.063)	(0.065)	(0.064)	(0.039)	(0.039)	(0.040)
Migrated × post	0.393 ***	0.375 ***	0.417 ***	0.148 **	0.117 *	0.141 **
	(0.105)	(0.107)	(0.106)	(0.065)	(0.065)	(0.066)
Constant	7.821 ***	7.799 ***	7.819 ***	8.552 ***	8.539 ***	8.554 ***
	(0.036)	(0.037)	(0.036)	(0.022)	(0.022)	(0.022)
Adjusted R^2	0.13	0.13	0.13	0.16	0.20	0.16
N	1,156	1,116	1,136	1,156	1,116	1,136

Notes: 1. Standard errors, clustered at the household level, 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.

migrating to Khulna. On the other hand, those who migrated to other locations did not benefit in terms of income but expenditure.

Table 7 results are intuitive as employment and earning opportunities are much higher in the metropolitan city Dhaka. However, people living there can be forced to spend on non-consumption expenditures 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 opposite to the case when people migrate 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 a positive effect on expenditure.

To sum up, Table 7 results indicate that migration location is important for household welfare. Compared to people who do not migrate, households disproportionately benefit by migrating to Dhaka or other locations, depending on the choice of income or expenditure as the indicator of welfare. However, while migration into urban areas increase income and expenditure, its net impact may still not be positive if the destinations are more expensive than their hometowns.

In the past, three major rivers in Bangladesh – Padma, Meghna, and Jamuna – eroded several thousand hectares of the floodplain, damaged extensive road and rail networks and displaced millions of people (Das et al. 2014). This process had a long-term impact on the livelihood of people, society and the economy. However, due to the slow onset process and scattered incidents, the victims of river erosion did not receive much media attention compared to those received by the victims of floods and cyclones. Low media coverage induces lower mitigation projects, leading to higher migration (Beine, Noy, and Parsons 2019; Magontier 2020; Vorlaufer and Vollan 2020).[18] The victims of riverbank erosion thus receive less public support in the form of credit, relief or other means to fight against this silent catastrophe and a vast majority of them leave their origin to move to a place to survive socially and economically (Zaber, Nardi, and Chen 2018).

Our findings, in line with the recommendation in Melde, Laczko, and Gemenne (2017), imply that the government can play a role in facilitating the migration process to improve the welfare of the victims of natural disasters. To effectively do so, the government should focus more on permanent shocks as the victims of such shocks have a higher propensity to migrate. The importance of facilitating migration is further emphasized by the fact that migration is also beneficial for those who stay behind (Bryan, Chowdhury, and Mobarak 2014; Shayegh and Casey 2017; Shayegh 2017). Internal migration may thus boost aggregate productivity. For example, Bryan and Morten (2019) estimated that the aggregate productivity gain from reducing all barriers to internal labour migration was around 22% in Indonesia.

Strengthening adaptive and mitigation capacity, which may include facilitating internal migration,

[18]Private market may also react less to a slow onset process. For example, the disclosure of the future risk of sea-level rise to the properties of Kapiti Coast in New Zealand did not affect their prices (Filippova et al. 2020).

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

	Ln(household income)		Ln(household expenditure)	
	(1)	(2)	(3)	(4)
Post	1.226 ***	1.220 ***	0.832 ***	0.835 ***
	(0.063)	(0.063)	(0.039)	(0.040)
Migrated to Dhaka	0.926 ***	0.932 ***	−0.061	−0.063
× post	(0.178)	(0.179)	(0.111)	(0.112)
Migrated to Khulna	0.286 *	0.293 *	0.176 *	0.174 *
× post	(0.164)	(0.165)	(0.103)	(0.103)
Migrated to other	0.168	0.210	0.246 ***	0.236 ***
location × post	(0.140)	(0.141)	(0.087)	(0.088)
Constant	7.821 ***	7.819 ***	8.552 ***	8.554 ***
	(0.035)	(0.036)	(0.022)	(0.022)
Adjusted R^2	0.14	0.15	0.17	0.17
N	1,156	1,136	1,156	1,136

Note: See footnotes in Table 6.

also requires developing rural institutions (Botzen, Deschenes, and Sanders 2019). Involving the local community and women in the decision process can particularly enhance the adaptive capacity of affected households (Grillos 2018). Complementary policy supports, such as financial incentives for facilitating migration, providing low-income housing and creating employment opportunities, are needed to help the cities that are struggling to provide basic services to their residents (Dustmann and Okatenko 2014; Kirchberger 2017; Depetris-Chauvin and Santos 2018). While the adaptation policies should be pro-poor, efficient strategies to promote internal migration should also consider the complementarity among markets, governments, and communities (Sawada and Takasaki 2017).

It should be noted that the migration process, even when it is internal, may generate some uncomfortable situations that would require some cautionary steps. For example, Kleemans and Magruder (2017) find that an increasing share of migrants decreases income and reduces employment of the host community. Studies find that people's concerns about immigrants negatively affecting their earning capacities and employment opportunities may develop an anti-immigration sentiment in local communities (Scheve and Slaughter 2001; Mayda 2006). Public policies should address such concerns to make migration a viable strategy against natural disasters.

Although based on a single country analysis, our findings may be valid for many other disaster-prone countries with weak social safety nets. The findings, and consequently the policy implications, can even be relevant for some developed countries that are experiencing environmental shock-induced migration. Our study is particularly important as rising exposure to climate change will increase the frequency and intensity of natural disasters around the world.

VI. 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 differential impact of transient and permanent environmental shocks on migration decisions and the choice of destinations. We also examined how household income and expenditure changed after migration. Controlling for a diverse set of socioeconomic and demographic factors, we found that both transient and permanent environmental shocks force households to migrate, specifically to large cities. However, the influence of the permanent shock (riverbank erosion) on migration is much stronger than that of transient shocks (floods or cyclones). Our investigation indicates that the income and expenditures of migrating households increase more than their non-migrant counterparts.

Our analysis suggests that internal migration can be considered an important adaptive capacity against natural shocks. Migration can be a win-win strategy for adaptation, as it benefits migrants and those who stay behind by reducing the pressure on resources at the origin. Thus, facilitating migration by governments can be useful in addressing the rising vulnerabilities of natural disasters. However, the emphasis should be given to the victims of permanent shocks as they are more likely to be adversely affected and thus forced to migrate.

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Appendix A Tables and figures

Table A1. Comparison of summary statistics.

	HIES 2000 households		
	Included in CVLS survey	Not included in CVLS survey	*p*-value of the difference
	(1)	(2)	(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)	
2100ptYears 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

Notes: 1. Standard deviations are reported in the parentheses.
2. The number of households in the CVLS survey included 93 split households that are dropped from the analysis.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A2. Comparison of summary statistics.

	Analysis sample households		
	Affected by disaster	Not affected by disaster	*p*-value of the difference
	(1)	(2)	(3)
Household size	5.83	5.41	0.06
	(2.13)	(2.08)	
Household head is female	0.02	0.06	0.12
	(0.15)	(0.24)	
Age of the household head (years)	47.95	44.26	0.01
	(13.15)	(12.26)	
Household head is married	0.91	0.90	0.72
	(0.29)	(0.30)	
Household head is muslim	0.96	0.82	0.00
	(0.20)	(0.39)	
Years of schooling of household head	4.21	3.15	0.02
	(4.48)	(4.31)	
Maximum school year (among members)	7.08	5.64	0.00
	(4.29)	(4.39)	
Literacy of household head	0.58	0.48	0.05
	(0.50)	(0.50)	
Household has a personal phone	0.00	0.01	0.39
	(0.00)	(0.08)	
Electricity connection at home	0.27	0.20	0.13
	(0.44)	(0.40)	
Owned land (in decimals)	0.58	0.78	0.28
	(1.25)	(1.91)	
Lives in owned house	0.80	0.92	0.00
	(0.40)	(0.28)	
Agricultural asset value in BDT	785	3,095	0.07
	(2,217)	(13,859)	
Monthly household income in BDT	2,866	3,493	0.06
	(3225)	(3169)	
Monthly household consumption in BDT	6489	5734	0.07
	(3852)	(3925)	
N	124	331	455

Notes: 1. Standard deviations are reported in the parentheses.
2. The number of households in the CVLS survey included 93 split households that are dropped from the analysis.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table A3. Comparison of summary statistics.

	Analysis sample households		
	Migrated (1)	Not migrated (2)	*p*-value of the difference (3)
Household size	5.53	5.52	0.93
	(1.98)	(2.17)	
Household head is female	0.03	0.06	0.19
	(0.18)	(0.24)	
Age of the household head (years)	45.67	45.01	0.58
	(12.17)	(12.89)	
Household head is married	0.91	0.90	0.69
	(0.29)	(0.30)	
Household head is muslim	0.92	0.82	0.00
	(0.28)	(0.39)	
Years of schooling of household head	3.85	3.18	0.11
	(4.22)	(4.46)	
Maximum school year (among members)	6.43	5.78	0.13
	(4.13)	(4.57)	
Literacy of household head	0.52	0.49	0.56
	(0.50)	(0.50)	
Household has a personal phone	0.00	0.01	0.26
	(0.00)	(0.08)	
Electricity connection at home	0.24	0.21	0.45
	(0.43)	(0.40)	
Owned land (in decimals)	0.50	0.87	0.03
	(1.18)	(2.04)	
Lives in owned house	0.84	0.91	0.01
	(0.37)	(0.28)	
Agricultural asset value in BDT	1943	2801	0.45
	(11,395)	(12,248)	
Monthly household income in BDT	2796	3660	0.00
	(1868)	(3774)	
Monthly household consumption in BDT	5797	6031	0.53
	(3274)	(4281)	
N	178	277	455

Notes: 1. Standard deviations are reported in the parentheses.
2. The number of households in the CVLS survey included 93 split households that are dropped from the analysis.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4. Effect on internal migration: marginal effects from OLS estimates.

	All shocks			Grouped shocks		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced flood in last 10 yrs	0.416 ***	0.397 ***	0.400 ***			
	(0.066)	(0.052)	(0.041)			
Experienced cyclone in last 10 yrs	0.343 ***	0.322 ***	0.337 ***			
	(0.101)	(0.105)	(0.087)			
Experienced river erosion in last 10 yrs	0.569 ***	0.541 ***	0.495 ***			
	(0.050)	(0.058)	(0.048)			
Experienced transient shock				0.462 ***	0.441 ***	0.446 ***
				(0.062)	(0.064)	(0.043)
Experienced permanent shock				0.586 ***	0.564 ***	0.522 ***
				(0.049)	(0.057)	(0.044)
Household size		−0.016	−0.019 *		−0.016	−0.018 *
		(0.011)	(0.010)		(0.011)	(0.010)
Household head is female		−0.104	−0.098		−0.081	−0.075
		(0.096)	(0.084)		(0.090)	(0.078)
Age of the household head (years)		−0.002	−0.002		−0.002	−0.002
		(0.002)	(0.002)		(0.002)	(0.001)
Household head is married		0.021	−0.011		0.029	−0.002
		(0.069)	(0.066)		(0.068)	(0.065)
Household head is muslim		0.096 *	0.053		0.085	0.043
		(0.054)	(0.039)		(0.055)	(0.039)
Literacy of household head		−0.007	−0.001		−0.017	−0.010
		(0.027)	(0.026)		(0.026)	(0.024)
Electricity connection at home		−0.044	−0.034		−0.036	−0.026
		(0.065)	(0.069)		(0.070)	(0.074)
Owned land (in decimals)		−0.004	−0.006		−0.003	−0.005
		(0.006)	(0.006)		(0.006)	(0.006)

(*Continued*)

Table A4. (Continued).

	All shocks			Grouped shocks		
	(1)	(2)	(3)	(4)	(5)	(6)
Lives in owned house		0.004	−0.010		0.016	0.002
		(0.057)	(0.052)		(0.060)	(0.055)
Ln(agricultural asset value in BDT)		0.006	0.006		0.006	0.007
		(0.007)	(0.006)		(0.007)	(0.007)
Received credit after disaster		0.097 *	0.114 **		0.096 *	0.113 **
		(0.049)	(0.042)		(0.047)	(0.041)
Received relief after disaster		−0.115	−0.167 *		−0.108	−0.162 *
		(0.085)	(0.083)		(0.084)	(0.082)
Ln(Monthly household income in 2000)		−0.025 *	−0.017		−0.022	−0.015
		(0.013)	(0.012)		(0.013)	(0.012)
Constant	0.529 ***	0.556 ***	0.562 ***	0.529 ***	0.555 ***	0.561 ***
	(0.044)	(0.042)	(0.042)	(0.042)	(0.042)	(0.041)
Division fixed effects	No	No	Yes	No	No	Yes
R^2	0.28	0.33	0.38	0.30	0.34	0.39
AIC	884.54	861.79	802.23	861.07	840.78	781.98
BIC	898.54	941.13	895.57	870.40	915.45	870.65
N	786	786	786	786	786	786

1. Standard errors, clustered at the district level, are reported in the parentheses.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5. Choice of destination for internal migrants: Marginal effects from independent probit models.

	Migrated to		
	Dhaka (1)	Khulna (2)	Other locations (3)
Experienced transient shock	3.711 ***	3.801 ***	0.293
	(1.036)	(0.509)	(0.262)
Experienced permanent shock	5.594 ***	4.508 ***	−0.105
	(0.848)	(0.469)	(0.287)
Household size	0.106 **	−0.032	−0.065
	(0.040)	(0.091)	(0.040)
Age of the household head (years)	−0.009	0.065	0.056 **
	(0.078)	(0.047)	(0.025)
Household head is married	0.172	-1.411 ***	0.543 *
	(0.549)	(0.241)	(0.290)
Literacy of household head	−0.087	−0.505 *	−0.069
	(0.426)	(0.230)	(0.105)
Electricity connection at home	0.621	1.254 ***	−0.324
	(0.339)	(0.139)	(0.264)
Owned land (in decimals)	−0.112 *	−0.053	0.015
	(0.053)	(0.036)	(0.028)
Lives in owned house	1.338 ***	1.510 ***	−0.159
	(0.238)	(0.194)	(0.196)
Ln(agricultural asset value in BDT)	0.063 **	0.090 ***	0.012
	(0.022)	(0.024)	(0.028)
Received credit after disaster	-1.500 ***	-0.353 **	0.453 **
	(0.197)	(0.128)	(0.171)
Received relief after disaster	-1.711 ***	-1.275 **	−0.316
	(0.445)	(0.515)	(0.241)
	()	()	()
Constant	−1.569	−2.041	−1.459 *
	(1.462)	(1.224)	(0.734)
Division fixed effects	No	No	No
Pseudo R^2	0.88	0.81	0.07
N	450	496	556

1. Standard errors, clustered at the district level, are reported in the parentheses.
2. Reference category is households who do not migrate.
3. The marginal effects are estimated at the mean values of all other covariates.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A6. Impacts of migration on household income and expenditure: DDM estimate.

	Ln(household income) (1)	Ln(household expenditure) (2)
ATE	0.121	0.310
	(0.117)	(0.221)
N	336	217

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

Table A7. Impacts on household income and expenditure by types of shocks experienced: OLS estimates.

	Ln(household income)		Ln(household expenditure)	
	(1)	(2)	(3)	(4)
Post	1.264 ***	1.264 ***	0.877 ***	0.877 ***
	(0.057)	(0.057)	(0.036)	(0.036)
Post × transient shock	0.460 ***	0.460 ***	0.053	0.053
	(0.160)	(0.160)	(0.100)	(0.100)
Post × permanent shock	0.376 **	0.376 **	0.019	0.019
	(0.147)	(0.147)	(0.092)	(0.092)
Constant	7.821 ***	7.821 ***	8.552 ***	8.552 ***
	(0.036)	(0.036)	(0.022)	(0.022)
District fixed effects	No	Yes	No	Yes
Adjusted R^2	0.12	0.12	0.15	0.15
N	1,156	1,156	1,156	1,156

See footnotes in Table 6.

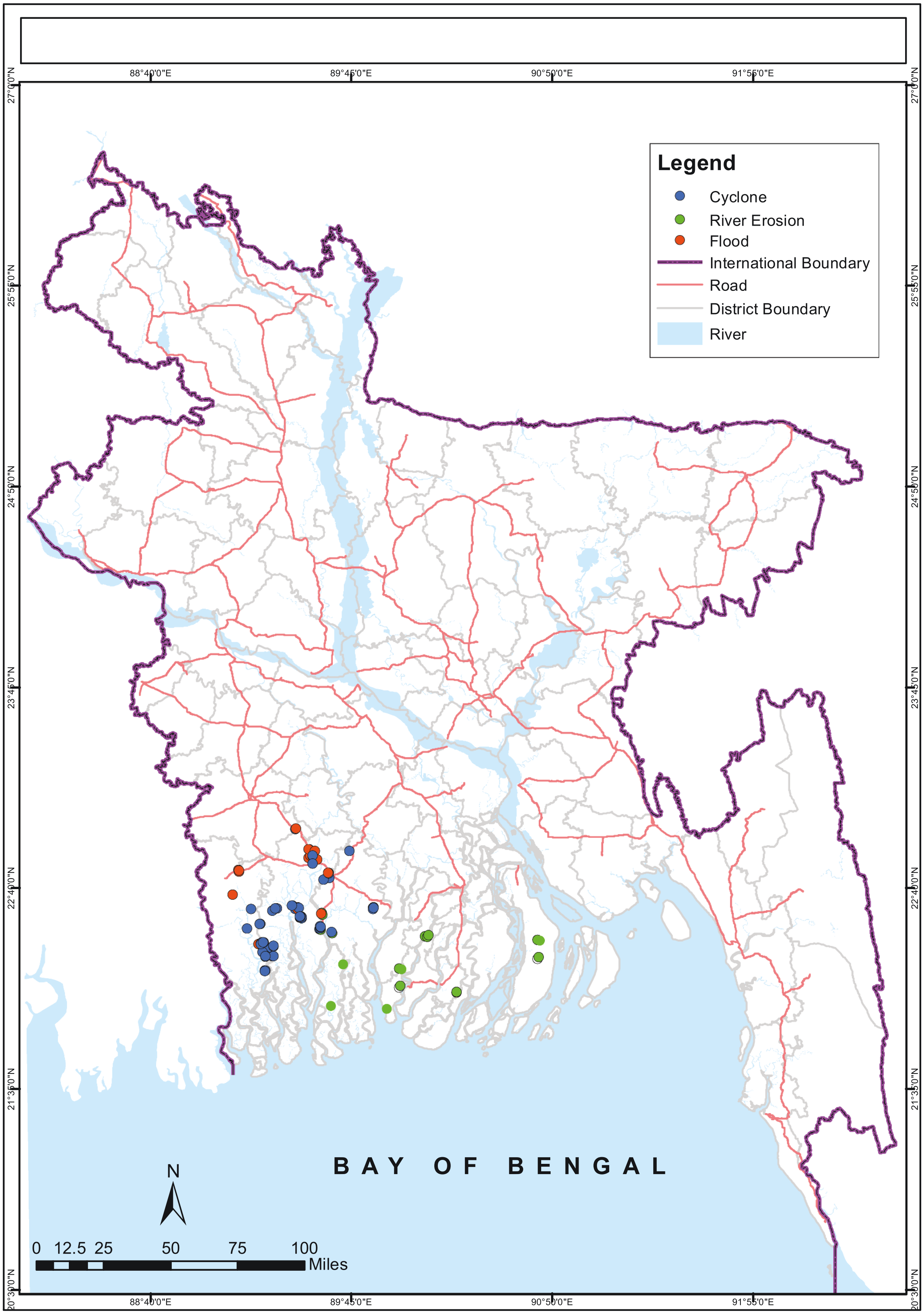

Figure 1. Areas affected by transient and permanent shocks in Bangladesh. Polygon indicates current location of migrants while its' colour represents their district of origin.

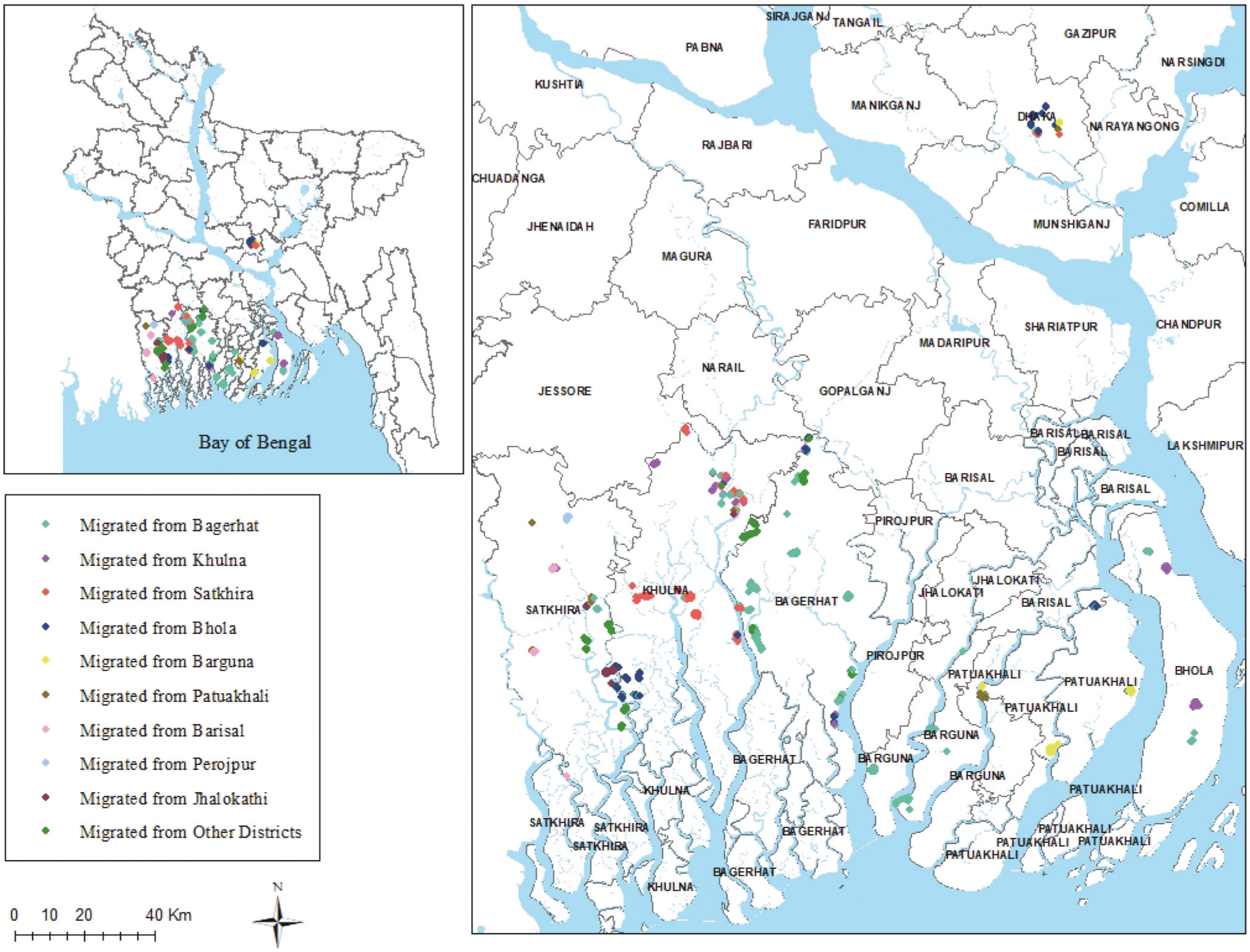

Figure 2. Origin and destination of migrant households.