Natural hazards and internal migration: The role of transient versus permanent shocks*

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Abstract

We analyse internal migration triggered by natural disasters in Bangladesh. We conducted a survey in nine coastal districts and two major cities in Bangladesh to investigate 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. Our findings suggest that transient shocks induce households to move to nearby cities while permanent shocks push people to big cities with more opportunities. Comparing income and expenditure of migrants and non-migrant households, we find that the former group is better-off relative to their counterpart, 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, particularly for 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.

*We acknowledge support from the National Science Foundation (Award #1204762, #1832693). We are grateful to Shyamal Chowdhury for his valuable inputs in survey design and at various stages in pursuing this research. We also thank the respondents who spent their valuable time to participate in the 'Coastal Vulnerability and Livelihood Security (CVLS)' survey and the staff members at the Evaluation & Consulting Services (ECONS) who implemented the survey with utmost diligence. We thank Tobias Pfutze, Mihaela Pintea, Mahadev Bhat, Abu Shonchoy, Shahe Imran and seminar participants at the Florida International University, Boston University, Southern Economic Association (SEA), Canadian Economic Association (CEA), Western Economic Association International (WEAI), and Eastern Economic Association (EEA) conferences for helpful comments.

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1. Introduction

The predictions about the dangers of climate change are increasingly being realised today as, among others consequences, frequency and intensity of natural hazards are on the rise all over the world (O'neill and Oppenheimer, 2002; Skoufias, 2003; Stern, 2008; IPCC, 2007; Desmet et al., 2018).[1] Disasters triggered by extreme weather events and climatic shocks in the form of cyclones, floods, storm surges, riverbank erosion, tornadoes and earthquakes—among others—significantly affect the well-being, economic and otherwise, of households and communities (Cattaneo and Peri, 2016). FAO (2018) estimated that, between 2003 and 2013, natural hazards caused a global damage of US$1.5 trillion and affected 2 billion people. It is projected that by 2050, nearly 200 million people will be displaced due to environmental disruptions (Myers, 2002). Studies focusing on GDP and welfare indicated that permanent flooding may reduce global real GDP and welfare by an average of 0.19% and 0.24%, respectively, as people will be forced to live places with less attractive amenities (Desmet et al., 2018). What is more daunting is that the economic damage caused by disasters can be long-lasting (Lynham et al., 2017; Caruso, 2017).

The intensity and impacts of climate change and natural hazards vary over locations and groups (Agrawal and Perrin, 2008; Agrawal et al., 2012; Cattaneo and Peri, 2016). For instance, Barrios et al. (2006) found that climatic change, proxied by rainfall, changes 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 percent in some areas. However, natural hazards may severely affect the people of the developing countries due to their dependence of natural resources and the lack of adaptation and safety net instruments to fight against negative environmental shocks (O'neill and Oppenheimer, 2002; Agrawal and Perrin, 2008).[2] This is evidenced by the fact that the economic damage between 2003 and 2013 due to environmental hazards in developing countries is estimated to be US$550 billion (FAO, 2018). Mejia et al. (2018) find that global temperatures have uneven macroeconomic effects, with adverse consequences concentrated in most low-income countries as they have hot climates.[3] Coronese et al. (2018) has further indicated that available studies on the estimates of damage caused by natural

[1] Climate change reduces agricultural output, suppresses productivity of workers exposed to heat, slows investment, and deteriorate health which lowers per capita output, in both the short and medium term. It may also have far reaching effects. For example, Para-PeñaS and Reilly (2018) find that the concurrent year of the winter waves in Colombia caused by El-Nino reduced theft rates during 2007-2012.

[2] Negative effect of climate change on natural resource dependent communities also apply in the developed country setting; see Fischer (2018) for an example on the US.

[3] Disasters may affect life in other ways, like reducing life satisfaction, lower schooling and deteriorate mental health of the victims (Kellenberg and Mobarak, 2011; Mottaleb et al., 2015; Takasaki, 2017).

disaster, by employing mean regression techniques on yearly summed data, usually focus on trend and thus systematically underestimate the real losses in low-income countries.

Bangladesh ranked 6th among countries that heavily suffers from natural disasters (Kreft et al., 2016). More than 60 million people living in coastal areas of the country are highly vulnerable to climate change and other environmental hazards. This is particularly because the unique physical geography of coastal Bangladesh make it even more vulnerable to the potential impacts of a rising sea-level (Brammer, 2014).

The most common type of natural disasters in the coastal areas of Bangladesh are cyclones, floods and riverbank erosions Poncelet et al. (2010). Tropical cyclones are very frequent in the coastal areas of Bangladesh. For instance, in recent years, the southern coast of Bangladesh was hit by three consecutive cyclones: Sidr in 2007, Nargis in 2008, and Aila in 2009 (Kabir et al., 2016; Mallick, 2014). Cyclones alone claimed more than 100,000 lives and caused property damages of around US $3.5 billion in the country in last 25 years (Dasgupta et al., 2010).

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 inundation of floods affects about 21% (or 31,000 square kilometres) of the country (Mirza, 2003). Using a measure of self-reported flood, in combination with historical data, Karim (2018) indicated that frequent flooding in the country has reduced agricultural income and negatively affected other welfare outcomes in Bangladesh.

The erosion of the coastline and riverbank and the subsequent loss of arable land is another significant concern for Bangladesh. It is one of the principal contributors to the process of destitution and marginalization of rural families in the country (Poncelet et al., 2010; Planning Commission, 2015, 2017). 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).

Households affected by shocks, either natural or man-made, follow a number of strategies to maintain their consumption (Khandker, 2012). For example, after the Kobe Earthquake in 1995, households that either held a large amount of collateralizable assets or faced no (binding) borrowing constraints were able to maintain their consumption (Mozumder et al., 2009; Sawada and Shimizutani, 2008, 2011). In the face of shocks, people also intensify the use the commons, either for their own or for their kins, to generate additional income (Takasaki, 2011; Islam and Nguyen, 2018).

A risk averse individual would 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 coping mechanism to natural hazards is generally accepted. Unfortunately, the issue is less widely discussed in the literature, with early studies largely ignoring the role of environmental factors for migration (Mallick and Etzold, 2015). Only a few recent studies have discussed migration as an alternative strategy to cope with the adverse effects of natural disasters (e.g., Blaikie et al., 2004; Black et al., 2011b; Naik, 2009; Poncelet et al., 2010). However, there is insufficient empirical evidence to identify the nature and extent of internal migration as a coping strategy against environmental shocks (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. He argued that the availability and the management of aid mitigate the effect of the disaster which allowed the victims to stay in their original location. The nature of environmental shocks can be transient or permanent and no studies specifically focused how the nature of shocks affect migration and the choice of destination. Again, while standard economic theories suggest that migrating households improve their well-being, only a few studies empirically confirmed this hypothesis.

Against this background, this study analyses internal migration as a coping mechanism against natural disasters in the south west coastal regions of Bangladesh. We explore whether riverbank erosion that leads to loss of lands and thus impose a permanent negative shock on households' economic status have higher influence on domestic migration decisions, compared to the transient shocks as represented by floods and cyclones. We also address whether such shocks differently influence households to migrate to the nearest city or to distant but bigger city. We further examine the impact of migration on household income and consumption. Our findings have significant implications for understanding whether migration can be used as an effective coping mechanism for people affected by natural disasters.

The remainder of this article is organized as follows. Section 2 discusses about the determinants of domestic migration in coastal Bangladesh with a particular focus on the nature of shocks and their effect on migration decision. Section 3 briefly describes the survey and the data. Section 4 presents the methodology, 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 be internal or international, slow or rapid, forced or motivated and temporary or permanent (Mallick and Vogt, 2012; Portes, 2010). Altogether, migration has a very complex set of determinants that can be economic, social, political, demographic or environmental while the last factor has the capacity to affect all the others (Black et al., 2011a,b; Bunea, 2012). Rural-urban (and in general internal) migration in Bangladesh is usually explained by the push and pull factors in which the former factor mostly refers to the desire for survival while the other refers to the attraction of better living and economic conditions (Poncelet et al., 2010; Barrios et al., 2006). Though it is commonly believed that economic pull factors have dominance over social or demographic factors of internal migration, with the recent global climate change, environmental push factors are becoming increasingly important to exert direct and indirect influences on internal migration decisions (Black et al., 2011a,b).

The shocks faced by households in developing countries, can be characterised 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. It can also be inferred that the managing covariate shocks are more challenging than idiosyncratic shocks as they affect a large proportion of households in the same community (Patnaik et al., 2016).

The coastal zone of Bangladesh, which makes up approximately 30% of the total area of the country, is particularly vulnerable to natural disasters. Its topographic and geo-physical location makes it prone to periodic cyclones, floods and riverbank erosion. 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.

Bangladesh is one of the most flood-prone countries in the world due to its unique geographical location, topography and exposure to monsoon rainfall. In the last 30 years, Bangladesh has experienced severe floods

during 1987-1988, 1998-1999, 2004-2005, 2007, 2010 and 2017. With 50% of the land less than 8 meters above sea level, and a coastline of 600 km, coastal flooding is an alarming problem for Bangladesh. This not only creates significant hardship for the people of coastal communities but also results in short-term and long-term population displacements (Poncelet et al., 2010).

Cyclones that are usually accompanied by high winds and storm-surges, hit Bangladesh every three years on average (Dasgupta et al., 2010; Mallick and Etzold, 2015). The coastal area of Bangladesh has witnessed several cyclones in the last 50 years. Among them, Bhola in 1970, Gorky in 1991, Sidr in 2007, Aila in 2009, and Komen in 2015 are the deadliest cyclones on record. Cyclones that destroy the homesteads and livelihoods of millions of people in the coastal areas of Bangladesh trigger internal migration. Studies have found that the victims of cyclones move away because of resource scarcity, infrastructure damages and absent social protection, as well as the unavailability of income-generating alternatives (Poncelet et al., 2010; Mallick et al., 2017).

2.2. Permanent shock

While events such as cyclones and floods may cause the affected households to leave their homes temporarily, hazards like riverbank erosion that causes landloss forces households to move permanently. Households living close to riverbanks often experience the loss of homestead and agricultural land which reduces their production and employment opportunities, and subsequently threaten their livelihood security (Alam et al., 2017, 2018). People living in the south west coastal belt are particularly exposed to permanent natural hazards like riverbank erosion and find migration a viable coping strategy (Poncelet et al., 2010; Brammer, 2014; Kabir et al., 2018; Mollah and Ferdaush, 2015). Among all the climate-induced migrants in Dhaka city, a significant proportion are from the coastal districts of Bangladesh such as Barguna, Patuakhali, Maheshkhali, Noakhali, Bhola, Satkhira and Jessore, 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 —have eroded several thousands hectares of floodplain and damaged extensive road and rail network, and displaced millions of people (Das et al., 2014). This process has a long-term impact on the livelihood of people, society and economy. However, due to the slow process and scattered incidences, this does not draw the attention of media and policy makers in the same way victims of flood 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 area on their own initiative 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 area of Bangladesh covers 19 districts, most of which are frequently affected by environmental shocks like cyclones, floods and riverbank erosions (Dasgupta et al., 2014; Brammer, 2014). In 2015, we conducted a survey—Coastal Vulnerability and Livelihood Security (CVLS) survey—to identify the link of transient and permanent environmental shocks with households' migration decision and the choice of destination (nearest small city vs. distant big city).[4] 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 south west districts in Khulna and Barisal divisions. To better understand the dynamics of internal migration scenario in Bangladesh, the CVLS survey tracked households of coastal area who were included in the Household Income and Expenditure Survey (HIES) 2000 but now migrated to the nearby metropolitan city Khulna (of Khulna district) or the distant capital city Dhaka (of Dhaka District) in Bangladesh. The origin and destination of migrant households are shown in Figure 1.

[Figure 1]

Based on the survey design of nationally representative HIES, the CVLS collected information of 2,096 households. The distribution of respondents among source and destination districts is shown in Table 1. The table shows that about 59 per cent of households in the survey migrated from one location to another.[5] Among them, around 39 per cent of households moved to the nearest Khulna city, 31 per cent migrated to the capital city Dhaka and 30 per cent settled down in 35 other districts in Bangladesh. On the other hand, the origin of most of the migrants were Bagerhat and Khulna (20 per cent each), followed by Satkhira (18 per cent), Bhola (12 per cent) and Borguna (6 per cent). The rest 25 per cent of the migrants came from 32

[4]The Evaluation and Consulting Services (ECONS) Limited implemented the CVLS survey on behalf of the research team led by Florida International University. The survey data was collected between August-December 2015. Additional information on the survey can be available from the authors upon request.

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

other districts, some of which are outside our surveyed area. These internal migrants are mostly permanent or long-term migrants who did not indicate any intention of returning to their location of origin.

[Table 1]

Information in our survey include data on the occurrence of internal migration as well as their destination. We also asked households whether they have suffered from any environmental shocks like floods, cyclones or riverbank erosions in recent years. Other important information collected in the survey include, households' socio-demographic condition, educational status of the household members, ownership of housing, land ownership and landholding, value of households' assets, whether received credit or relief support and other economic activities. We also collected information on household income by asking them about the components of earnings coming from different sources. We further computed household consumption by asking about their consumption of food items like rice, food crops, wheat, lentils, edible oil, vegetables, poultry items, dairy items, salt, sugar, dry food, beverages, among others that they have consumed as well as the non-food consumption like expenditure on fuel, house rent, transportation, educational, toiletries, clothing, utensils and medical items.

A number of sampled households have missing information on household size, gender and age of household head as well as land ownership, asset, income and consumption. We dropped such 287 households from our analysis.[6,7] Thus our final analysis sample consists of 1,809 households.

Table 2 presents the summary statistics of explanatory variables considered in our analysis. Regarding the exposure to natural disasters, about 28 per cent of the households experienced riverbank erosion, a permanent environmental shock, compared to transient environmental shocks like cyclones (12 per cent) and floods (8 per cent). In our sample, the majority of the households in Bhola district are affected by riverbank erosion while respondents from Barguna and Khulna districts experienced significant threats from cyclones Sidr and Aila, respectively.[8] Note that household income and consumption in Table 2 are reported in current prices which, when adjusted for inflation between 2000 and 2015, appear to be close between the two periods.[9]

[Table 2]

[6] We dropped households who reported zero income which, we believe, are implausible and represent missing income.

[7] We did not observe any systematic difference in the excluded sample and the analysis sample regarding their observed characteristics. As a result, we do not expect any selection bias in our sample.

[8] Data not reported.

[9] 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

$$Pr(M_i = 1|X) = \alpha + \beta E_i + \gamma H_i + \theta W_i + \psi Z_i + \lambda_d + \varepsilon_i \tag{1}$$

where, for each i, M takes the value of 1 if household head 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.[10] In some separate models E represents transient shocks (floods or cyclones) and permanent shock (riverbank erosions) that households experience. H is the vector of household characteristics that include household size, and sex, age, age squared, marital status and religion of household head. H also includes indicators for literacy of household head, whether household head has a personal phone and whether there is electricity connection in their residence. The income and wealth components are represented by the vector W that includes amount of land owned by the household, a dummy indicating house ownership, household income and asset value. The vector Z includes separate dummies for receiving credit or relief by the household that can be considered as coping instruments against natural hazards. Finally, we control for the district fixed effects λ_d in our model to net out the effect of time-invariant variables (such as the communication and job opportunity in a district) that are correlated with the explanatory variables, leading 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. Since alternative estimation techniques like logit and linear probability model (LPM) provide similar results, we only rely on the probit models for our conclusions and report them in our analysis.

We also examine the determinants of destination choices. In particular, we examine how factors like transient and permanent shock affect migration to different types of destinations. 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 location (Von Reichert and Rudzitis, 1992; Mollah and Ferdaush, 2015; Mishra, 2016). In

[10] 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 excluded separate controls for them. Our conclusions remain unchanged in case they are included in the model.

determining the choice of alternative locations, we use the the model given below[11]

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

where, in addition to the notations described earlier, for each i, M takes 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 cities. In that model we use a set of independent variables that are similar to our previous model including the district 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 analyse the impact of migration on household income and consumption. The availability of data in 2000 and 2015 for both group of households—who migrate and who do not—allow us to employ a difference-in-differences (DD) model as follows

$$Y_i = \alpha + \beta_1 M_i + \beta_2 Post_i + \beta_3 M_i \times Post + \gamma H_i + \theta W_i + \lambda_d + \varepsilon_i \tag{3}$$

where, for each i, Y represents income (or consumption in other models). M is a dummy for migration (reference group is no migration) and $Post$ is a dummy for 2015 values (reference year is 2000). The vectors H, W, Z and λ_d represents the same set of variables we defined earlier and they are included in the model to control for any difference between the two groups with regard to those characteristics. One obvious exception is the exclusion of household income when it is the dependent variable in the model. We employed the same model for investigating the impact on household consumption in which, we included household income as an explanatory variable.[12]

The identifying assumption in our DD estimation is the parallel trend of income (and consumption) between migrants and non-migrants. In other words, without migration, the difference in income (and consumption) between the two groups would have remained the same. We cannot test our identifying assumption directly but we are not aware of any reason that indicates different trends of consumption and income for these two groups.

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

[12] Income is the most important determinant of consumption and thus studies routinely employ household income in explaining consumption (see, e.g., Hasan, 2016b).

5. Estimation results and discussion

5.1. Types of shocks and migration

We start with identifying the links between different types of 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.[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 district fixed effects. It indicates a significant effect of all type of natural disasters that is lowest for cyclone (a transient shock) and highest for riverbank erosion (the permanent shock).[14]

[Table 3]

When we add additional control variables to the model, estimated marginal effects change (Column 2). Specifically, the effect of cyclone become insignificant while the effect of flood and riverbank erosion shrinks. Among the significant variables, age of household head negatively affects migration while migration is higher for married household heads. Such results are reasonable as older households are more attached to their location of origin and thus may have a tendency to migrate less. Also, in a finite work life, mature age workers are not as motivated as young workers since they have less time to accumulate income (Kennan and Walker, 2011). Married households, on the other hand, can be more desperate to improve their livelihood and therefore migrate more, as we find in our study.

Literacy can affect migration in both ways. In one hand, education may provide more opportunity to improve livelihood by migrating to a new place (Sandefur and Scott, 1981; De Jong, 2000). On the other hand, literate households may migrate less as they may have a better understanding of coping and mitigation mechanisms, allowing them to stay at their place of origin (Marshall and Rahman, 2013). Our study supports the latter hypothesis. Mobile phones may facilitate migration by allowing people to network with others living in potential migration destinations. Transferring property can be time-consuming in Bangladesh which can be relevant for house owners. Such households may also have enhanced capacity to cope up. Thus it is reasonable for people living in their own house to be less likely to migrate, as we see in our results. Lower migration of the people who receive credit can also be expected as they can spend

[13] Since the individual regression coefficients of probit models are difficult to interpret, we reported marginal effects. Full regression results are available from the authors upon request.

[14] All tests are conducted at the 5 per cent significance level.

the money on mitigating the negative effect of natural hazards as well as on coping up activities to allow them to stay at their place of origin. Assets discourage households to migrate, probably in the same way house ownership does. Interestingly, high income households are more likely to migrate. One potential explanation can be that higher income people can afford the cost of migration. It may also be the case that such households are more motivated to migrate to protect their income.

Column 3 of Table 3 presents the estimated results of the model that also controls for the fixed effects at the district level. The previous results largely remain unchanged in this model where, cyclone is not statistically significant while flooding increases the probability of migration by 24 per cent. The estimated effect of flood is similar to some previous findings. For example, Gray and Mueller (2012) observed flooding to have modest effect on internal mobility in Bangladesh, especially for the women and the poor. In this model, riverbank erosion, which washes away assets and homesteads of rural households, increases domestic migration by 43 per cent. The results reveal that riverbank erosion is the key driver of internal mobility since the victims of this hazard become destitute who eventually migrate. This pattern is also observed by Das et al. (2014). The only variable which is not significant in the previous model but significant in the model with district fixed effect is household size. 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). In contrast, the larger the family size, the more difficult it would be to migrate due to the associated cost (and management) of migration. Better coping by such households through job and income diversification and then not migrating can also be a possibility. The significantly negative effect of household size in our study indicates that the latter hypothesis can be more relevant for Bangladesh.

Next, we compare the effect of transient and permanent shocks. Column 4-6 repeats the previous analysis conducted in columns 1-3 but now include group shocks in the model while drop separate controls for cyclone, flood and riverbank erosion. Again, the results are largely similar. In the final model with all controls and district fixed effects, presented at column 6, people affected by transient shocks are 11 percent more likely to migrate. On the other hand, permanent shocks induce people to migrate more by 41 per cent compared to the people who do not suffer from any natural hazard. In summary, Table 3 demonstrates that transient and permanent shocks affect domestic migration differently with higher effects for permanent shock and lower effect for transient shock.

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.1). We also arrive at a similar conclusion

when we use logistic regression model 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).

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 BIC (Bayesian information criterion) compared to the values of the corresponding model.[15] As a result, we continue to use grouped shocks in the latter part of our study.

5.2. Choice of migration destination

At this stage, we start looking at how different type of shocks affect the choice of migration destination. We employ equation (2) and estimate it using multivariate probit regression. Table 4 presents the marginal effects estimated from the multivariate probit model, again calculated at the mean values of all other covariates. The determinants of migrating to Dhaka, presented at column 1, indicate that transient shocks do not induce people migrating to the big city. However, permanent shock is very important in explaining their migration to Dhaka city. On the other hand, both transient and permanent shocks significantly affect households to migrate to Khulna city but the latter has a much higher impact than the former (column 2). When we consider migration to other cities, we find a significant impact of permanent shock but no effect of temporary shock on their move (column 3).

[Table 4]

The effect of other variables, presented 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 particular type of destination. For instance, literacy of household head negatively affects migration to either Dhaka or Khulna (cities) but has no effect on migrating to other cities. This is consistent with the two hypotheses we discussed earlier—literacy can allow to people cope up and stay at the location of origin but also can offer better opportunity through migration. In particular, the former argument can be important for migrating Dhaka and Khulna while both (or none) can be relevant for migrating to other cities and thus producing a null result. As expected, mobile phone can affect migration to Dhaka by allowing to network with people in

[15] We prefer BIC over AIC as the former favours parsimonious models (Chakrabarti and Ghosh, 2011).

Dhaka while it may not be relevant for migrating nearby cities as networking with people from those cities is possible without phones. Living in own house, while has a significantly negative effect on migrating to cities in Dhaka and Khulna, the effect is significant for other cities only at the 10 per cent level of significant. The most interesting case is receiving credit which is considered as a coping instrument to natural disaster. Receiving credit negatively affects migrating to Dhaka city but positively affects migrating to Khulna and other cities. Receiving credit can be tied with the condition of not migrating to a distant place but may encourage migration to a nearby place as credit may allow them to expand income generating activities. Relief has no impact on migration to Dhaka and Khulna but impacts positively in migrating to other cities. This can be due to the fact that affected households, who receive relief, may have friends and relative to other cities where they can migrate easily. Non-land asset holding has a negative effect on migration but the impact is not statistically significant for migrating to khulna. One potential reason can be the inclusion of income, asset and land ownership in the model which, altogether over-controls household entitlement in our specification.

Our overall results in Table 4 indicate that permanent shocks have significant and positive impact on the choice of all the migration destinations. However, transient shock only affects migration to the nearby city Khulna and not migration to any other cities. We also arrive at similar conclusions when we employ independent probit regressions (see appendix Table A.2) or the multinomial logit regression to explain the choice of migration destinations. Such results are expected as people may like to stick at their location of origin or temporarily shift to nearby destinations when the shock is temporary. On the contrary, when any shock does a permanent damage to people's economic condition and livelihood 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.

5.3. Impact on income and consumption

Our last hunch is to look at the impact of migration on household income and consumption. Estimated results of the difference-in-difference model in equation (3) are presented at Table 5. Column 1 in the table estimates the model without any control variable and shows that, in 2000, there was no significant difference between the people who migrated (treatment group) and who did not (control group). Over time, income of both groups increased significantly. The DD estimate indicates that, the increase was nearly 44 percent 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 recognise that the effect can be due to the various macroeconomic and local factors occurred between 2010-2015 that are not controlled for in our model. However, our results may indicate that migration has been important for such income growth.

[Table 5]

Table 5, column 2 adds some additional controls into the model. It produces similar results like those in column 1. Significant explanatory variables in the model indicate that all of large, male headed, married, house owners and wealthy households benefit significantly from migration while households with electricity connection experience the opposite effect. Larger households may have more working members while male headed households may benefit more as females from conservative households are less likely to be in wage work or salaried jobs (Ahmed and Sen, 2018) and even if they work, women earn less due to the discrimination against women in Bangladesh (Ahmed and Maitra, 2010, 2015). On the other had, married households can be more desperate to improve their economic condition. Home ownership and asset holding can have a positive effect on income. The negative effect of electricity connection appears counter-intuitive but can be due to the intermittent electricity supply in Bangladesh (Hasan and Mozumder, 2017).

Model estimates largely remain unchanged when we add district fixed effects (Table 5, column 3). The two exceptions are significant and negative impact of the age of household head and the positive impact of receiving relief support. Older head may represent households with more elderly members who can be less productive (Kennan and Walker, 2011). On the other hand, receiving relief may enable households to avoid the negative shocks of natural disaster. For example, Hasan (2016a) finds that a negative income shock results in a significant reduction in food consumption that can eventually affect the health and thus future income.

We observe a similar picture when we conduct our analysis with household consumption (Table 5, columns 4-6). However, migrants (treatment group) start with a lower consumption in 2000—the reference period in our setting. In the model with district fixed effects (column 6), Muslim households have higher consumption which can be due to the religion-culture interaction (Cleveland et al., 2013). Households with mobile phones and electricity connections have higher consumption; land ownership and income also affect consumption positively. Since all these variables can be considered as proxies to wealth, such effects may reflect the positive effect of wealth on consumption. In summary, Table 5 indicates that households disproportionately benefit from migration compared to those who are left behind. Such findings are consistent with some previous studies (e.g., Beegle et al., 2011; De Brauw et al., 2017) who find large consumption growth after migration. This is expected as people optimally choose to migrate to maximise their future utility and both income and consumption can be considered as good proxies for household welfare.

All the models of income and consumption in Table 5 have reasonable goodness of fit and the results are robust to changes in model specification. For example, allowing differential impact for those suffered transient shock and those suffered permanent shock provides a similar conclusion (see appendix, Table A.3).

To examine whether migration locations have separate effects on household income and consumption, next we estimate a DD model with three treatment groups—migrating to Dhaka city, migrating to Khulna city and migrating to other cities—against the same reference group (no migration). Results in Table 6 indicate a similar impact we observed earlier. However, the table indicates that, the groups migrated to Dhaka or Khulna city benefited while those who migrated to other cities did not. Our conclusions remain unchanged if we allow for differential impact for transient and permanent shocks as well as for the migration destinations (see appendix, Table A.4).

[Table 6]

To sum up, Table 6 indicates that migration location was important for household welfare. Compared to people who did not migrate, households disproportionately benefited by migrating to Dhaka or Khulna city whereas those who migrated to other cities did not. Since the opportunity of working and earning is much higher in larger cities, people migrated there are expected to have higher income and consumption.

Our analysis primarily suggest that the government should assist in 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 the incentive induces 22 per cent of households to send a seasonal migrant and their consumption 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 adaptability 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' residences (Dustmann and Okatenko, 2014; Kirchberger, 2017; Depetris-Chauvin and Santos, 2018).

6. Conclusion

We explored the nexus of environmental disasters and internal migration in the south west 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 consumption 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. However, the influence of permanent shocks (riverbank erosions) on migration are much stronger than that of the transient shocks (cyclones or floods). We also find that households prefer to move into the nearest metropolitan city when the environmental shock is transient, whereas they tend to relocate to a distant city when it is permanent in nature. Our analysis on income and consumption indicates that migration can be an effective coping mechanism against environmental shocks as households' income and consumption increase following migration, compared to those who do not migrate.

Our analysis suggests that strengthening the adaptive capacity may include internal migration and thus the government should assist the migration process to cope with rising vulnerabilities of natural disasters. Migration, as a strategy of adaptation, is important as it benefits both who migrates as well as those who stay put by reducing the pressure at the origin. However, in formulating public policies to promote migration, it is important to be aware that a pro-poor adoption policy should consider the complementarity among markets, governments, and communities (Sawada and Takasaki, 2017).

Tables and Figures

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

	Migrated to				
Source district	Dhaka	Khulna	Other	No migration	Total
Bagerhat	26	90	127	330	573
Khulna	4	125	119	182	430
Satkhira	22	106	93	111	332
Bhola	127	13	19	97	256
Barguna	52	14	8	58	132
Other	149	140	13	71	373
Total	380	488	379	849	2,096

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 independent variables**

Variable definition	Mean	SD
Experienced cyclone in last 10yrs	0.12	0.32
Experienced flood in last 10yrs	0.08	0.27
Experienced river erosion in last 10yrs	0.28	0.45
Transinet shock	0.18	0.39
Permanent shock	0.28	0.45
Number of household members	4.91	2.18
Household head is male	0.94	0.23
Age of the household head in years	45.35	13.62
Household head is married	0.86	0.35
Household head is muslim	0.83	0.37
Literacy of household head	0.51	0.50
Household head has a personal phone	0.90	0.29
Electricity in home	0.55	0.50
Owned land in decimals	6.60	10.42
Lives in owned house	0.61	0.49
Received credit after disaster	0.49	0.50
Received relief after disaster	0.41	0.49
Non-land asset value (BDT)	4,204	13,930
Monthly household income before migration (BDT)	3,754	3,122
Monthly household income after migration (BDT)	12,348	7,755
Monthly consumption before migration (BDT)	4,126	5,852
Monthly consumption after migration (BDT)	15,873	18,792
N	1,809	

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 cyclone in last 10yrs	0.096**	-0.036	-0.023			
	(0.043)	(0.043)	(0.044)			
Experienced flood in last 10yrs	0.362***	0.262***	0.215***			
	(0.064)	(0.070)	(0.071)			
Experienced river erosion in last 10yrs	0.493***	0.357***	0.359***			
	(0.030)	(0.045)	(0.048)			
Transinet shock				0.249***	0.115***	0.105***
				(0.035)	(0.040)	(0.040)
Permanent shock				0.488***	0.340***	0.341***
				(0.031)	(0.045)	(0.047)
Number of household members		-0.013*	-0.020***		-0.013*	-0.021***
		(0.007)	(0.007)		(0.007)	(0.007)
Household head is male		0.039	0.013		0.028	0.003
		(0.069)	(0.068)		(0.069)	(0.068)
Age of the household head in years		-0.003***	-0.004***		-0.003***	-0.003***
		(0.001)	(0.001)		(0.001)	(0.001)
Household head is married		0.267***	0.296***		0.270***	0.300***
		(0.045)	(0.046)		(0.046)	(0.046)
Household head is muslim		0.061*	0.047		0.060*	0.045
		(0.031)	(0.032)		(0.031)	(0.032)
Literacy of household head		-0.063**	-0.065**		-0.067**	-0.068**
		(0.027)	(0.027)		(0.027)	(0.027)
Household head has a personal phone		0.139***	0.140***		0.149***	0.147***
		(0.042)	(0.043)		(0.043)	(0.043)
Electricity in home		-0.039	0.026		-0.036	0.030
		(0.030)	(0.031)		(0.030)	(0.031)
Owned land in decimals		-0.002*	-0.001		-0.003**	-0.002
		(0.001)	(0.001)		(0.001)	(0.001)
Lives in owned house		-0.252***	-0.249***		-0.245***	-0.240***
		(0.042)	(0.044)		(0.043)	(0.044)
Received credit after disaster		0.070***	0.053**		0.075***	0.058**
		(0.025)	(0.025)		(0.025)	(0.025)
Received relief after disaster		-0.013	0.017		-0.023	0.009
		(0.029)	(0.029)		(0.029)	(0.029)
Ln(non-land asset value)		-0.062***	-0.057***		-0.061***	-0.056***
		(0.014)	(0.015)		(0.014)	(0.015)
Ln(monthly income before migration)		0.093***	0.101***		0.084***	0.095***
		(0.017)	(0.018)		(0.017)	(0.018)
Constant	0.698***	0.718***	0.732***	0.695***	0.714***	0.730***
	(0.013)	(0.017)	(0.017)	(0.013)	(0.017)	(0.017)
District fixed effects	No	No	Yes	No	No	Yes
Psedu R^2	0.16	0.29	0.34	0.16	0.28	0.33
AIC	1969.13	1707.88	1605.58	1969.64	1719.23	1610.44
BIC	1991.13	1812.39	1743.09	1986.14	1818.24	1742.45
N	1,809	1,809	1,809	1,809	1,809	1,809

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

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

	Migrated to		
	Dhaka (1)	Khulna (2)	Other cities (3)
Transinet shock	0.078	0.670***	0.150
	(0.211)	(0.168)	(0.185)
Permanent shock	1.340***	1.308***	0.994***
	(0.208)	(0.195)	(0.222)
Number of household members	-0.079*	-0.087**	-0.058*
	(0.043)	(0.035)	(0.031)
Household head is male	0.116	-0.311	0.398
	(0.338)	(0.319)	(0.396)
Age of the household head in years	0.023	-0.043	-0.017
	(0.033)	(0.031)	(0.026)
Household head is married	1.167***	1.435***	0.862***
	(0.267)	(0.226)	(0.207)
Household head is muslim	0.399	0.428**	0.053
	(0.240)	(0.165)	(0.139)
Literacy of household head	-0.314**	-0.290**	-0.155
	(0.150)	(0.127)	(0.125)
Household head has a personal phone	1.276***	0.383*	0.289
	(0.340)	(0.210)	(0.197)
Electricity in home	0.294	0.440***	-0.272*
	(0.191)	(0.147)	(0.140)
Owned land in decimals	0.009	-0.018**	-0.006
	(0.007)	(0.008)	(0.006)
Lives in owned house	-0.926***	-1.081***	-0.349*
	(0.213)	(0.185)	(0.201)
Received credit after disaster	-0.299**	0.328***	0.404***
	(0.139)	(0.121)	(0.120)
Received relief after disaster	-0.319*	-0.006	0.341**
	(0.182)	(0.143)	(0.132)
Ln(non-land asset value)	-0.471***	-0.114	-0.180**
	(0.083)	(0.071)	(0.072)
Ln(monthly income before migration)	0.335***	0.147**	0.830***
	(0.089)	(0.072)	(0.139)
Constant	-0.074	0.289	-6.659***
	(1.143)	(1.026)	(1.384)
District fixed effects	Yes	Yes	Yes
N		1,809	

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 consumption: OLS estimates**

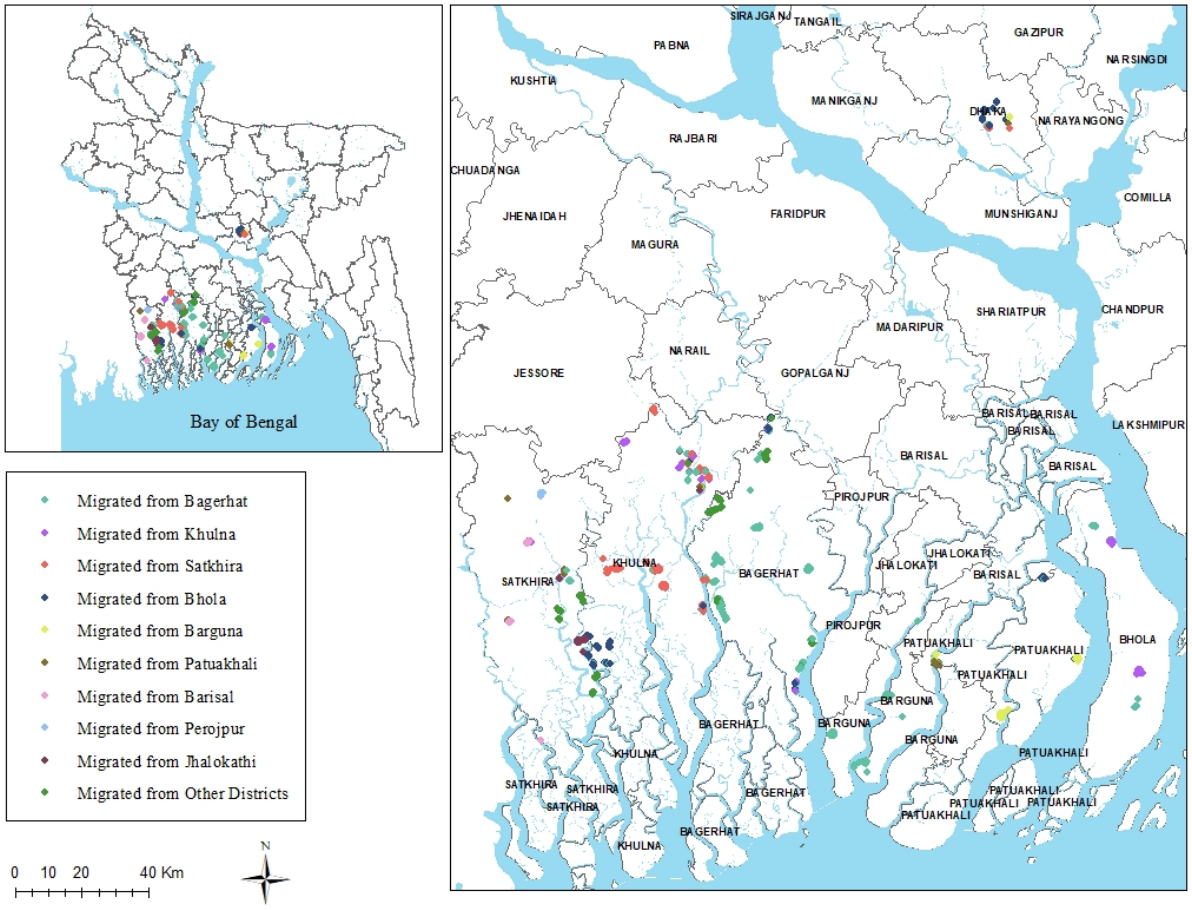
	Ln(household income)			Ln(household consumption)		
	(1)	(2)	(3)	(4)	(5)	(6)
Migrated to a	-0.075*	0.075*	0.086*	-0.620***	-0.514***	-0.471***
different location	(0.043)	(0.044)	(0.045)	(0.040)	(0.035)	(0.036)
Post migration	1.063***	1.063***	1.063***	1.119***	0.636***	0.630***
	(0.047)	(0.046)	(0.046)	(0.038)	(0.044)	(0.043)
Migrated to a different	0.366***	0.366***	0.366***	0.592***	0.426***	0.423***
location × post migration	(0.058)	(0.056)	(0.055)	(0.051)	(0.044)	(0.043)
Number of household		0.057***	0.057***		-0.002	0.004
members		(0.007)	(0.007)		(0.006)	(0.006)
Household head is		0.270***	0.282***		0.073	0.084
male		(0.077)	(0.078)		(0.057)	(0.055)
Age of the household		0.007	0.010		0.011**	0.009**
head in years		(0.007)	(0.007)		(0.005)	(0.005)
Age squared		-0.000*	-0.000**		-0.000**	-0.000**
		(0.000)	(0.000)		(0.000)	(0.000)
Household head is		0.132***	0.117**		0.066*	0.055
married		(0.048)	(0.048)		(0.038)	(0.037)
Household head is		-0.021	-0.018		0.072**	0.102***
muslim		(0.036)	(0.037)		(0.029)	(0.030)
Literacy of		-0.035	-0.020		0.041*	0.032
household head		(0.029)	(0.029)		(0.024)	(0.023)
Household head has		0.070	0.065		0.125***	0.128***
a personal phone		(0.047)	(0.047)		(0.039)	(0.038)
Electricity in home		-0.119***	-0.115***		0.075***	0.059**
		(0.033)	(0.033)		(0.027)	(0.027)
Owned land in		-0.002	-0.002		0.008***	0.008***
decimals		(0.002)	(0.002)		(0.001)	(0.001)
Lives in owned house		0.323***	0.284***		-0.002	-0.023
		(0.036)	(0.039)		(0.032)	(0.033)
Received credit		0.012	0.018		0.056**	0.040*
after disaster		(0.027)	(0.027)		(0.022)	(0.022)
Received relief		0.058*	0.084***		0.123***	0.074***
after disaster		(0.030)	(0.030)		(0.025)	(0.025)
Ln(non-land asset		0.044***	0.042***		0.125***	0.127***
value)		(0.016)	(0.016)		(0.014)	(0.014)
Ln(household income)					0.454***	0.461***
					(0.025)	(0.025)
District fixed effects	No	No	Yes	No	No	Yes
Adjusted R^2	0.39	0.45	0.46	0.50	0.68	0.69
N	3,618	3,618	3,618	3,618	3,618	3,618

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 6: **Impacts of migration location on household income and consumption: OLS estimates**

	Ln(household income)			Ln(household consumption)		
	(1)	(2)	(3)	(4)	(5)	(6)
Migrated to Dhaka	-0.397***	-0.158***	-0.184***	-0.886***	-0.595***	-0.474***
	(0.057)	(0.061)	(0.064)	(0.056)	(0.050)	(0.054)
Migrated to Khulna	-0.269***	-0.118**	-0.101*	-0.824***	-0.659***	-0.615***
	(0.059)	(0.058)	(0.060)	(0.059)	(0.044)	(0.045)
Migrated to other	0.503***	0.453***	0.456***	-0.086*	-0.296***	-0.288***
city	(0.045)	(0.047)	(0.047)	(0.047)	(0.044)	(0.044)
Post migration	1.063***	1.063***	1.063***	1.119***	0.657***	0.648***
	(0.047)	(0.046)	(0.045)	(0.038)	(0.043)	(0.043)
Migrated to Dhaka	0.737***	0.737***	0.737***	0.776***	0.455***	0.449***
× post migration	(0.072)	(0.069)	(0.069)	(0.067)	(0.057)	(0.056)
Migrated to Khulna	0.451***	0.451***	0.451***	0.877***	0.681***	0.677***
× post migration	(0.075)	(0.072)	(0.071)	(0.070)	(0.055)	(0.054)
Migrated to other	-0.121*	-0.121*	-0.121*	0.040	0.093	0.094
location × post migration	(0.066)	(0.065)	(0.064)	(0.063)	(0.059)	(0.058)
Number of household		0.056***	0.056***		-0.001	0.005
members		(0.007)	(0.007)		(0.006)	(0.006)
Household head is		0.253***	0.262***		0.076	0.086
male		(0.076)	(0.077)		(0.056)	(0.054)
Age of the household		0.007	0.009		0.011**	0.010**
head in years		(0.007)	(0.006)		(0.005)	(0.005)
Age squared		-0.000*	-0.000**		-0.000**	-0.000**
		(0.000)	(0.000)		(0.000)	(0.000)
Household head is		0.143***	0.136***		0.074*	0.060
married		(0.047)	(0.047)		(0.038)	(0.037)
Household head is		0.001	-0.001		0.080***	0.104***
muslim		(0.036)	(0.036)		(0.029)	(0.030)
Literacy of		-0.037	-0.025		0.037	0.032
household head		(0.028)	(0.028)		(0.023)	(0.023)
Household head has		0.072	0.073		0.136***	0.128***
a personal phone		(0.047)	(0.047)		(0.039)	(0.038)
Electricity in home		-0.094***	-0.085***		0.085***	0.061**
		(0.032)	(0.032)		(0.027)	(0.027)
Owned land in		-0.002	-0.002		0.008***	0.008***
decimals		(0.002)	(0.002)		(0.001)	(0.001)
Lives in owned house		0.264***	0.229***		-0.022	-0.024
		(0.037)	(0.039)		(0.033)	(0.033)
Received credit		0.013	0.015		0.047**	0.042*
after disaster		(0.027)	(0.027)		(0.022)	(0.022)
Received relief		0.045	0.069**		0.115***	0.074***
after disaster		(0.030)	(0.031)		(0.025)	(0.025)
Ln(non-land asset		0.045***	0.041***		0.122***	0.129***
value)		(0.016)	(0.015)		(0.013)	(0.013)
Ln(household income)					0.435***	0.443***
					(0.025)	(0.025)
District fixed effects	No	No	Yes	No	No	Yes
Adjusted R^2	0.44	0.48	0.48	0.54	0.68	0.69
N	3,618	3,618	3,618	3,618	3,618	3,618

Note: See footnotes in Table 5.



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

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

References

Adri, N. and Simon, D. (2018). A tale of two groups: focusing on the differential vulnerability of "climate-induced" and "non-climate-induced" migrants in Dhaka City. *Climate and Development*, 10(4):321–336.

Agrawal, A. and Perrin, N. (2008). Climate adaptation, local institutions and rural livelihoods. IFRI Working Paper W08I-6, School of Natural Resources and Environment, University of Michigan, MI, USA.

Agrawal, A., Perrin, N., Chhatre, A., Benson, C. S., and Kononen, M. (2012). Climate policy processes, local institutions, and adaptation actions: Mechanisms of translation and influence. *Wiley Interdisciplinary Reviews: Climate Change*, 3(6):565–579.

Ahmed, S. and Maitra, P. (2010). Gender wage discrimination in rural and urban labour markets of Bangladesh. *Oxford Development Studies*, 38(1):83–112.

Ahmed, S. and Maitra, P. (2015). A distributional analysis of the gender wage gap in Bangladesh. *The Journal of Development Studies*, 51(11):1444–1458.

Ahmed, T. and Sen, B. (2018). Conservative outlook, gender norms and female wellbeing: Evidence from rural Bangladesh. *World Development*, 111:41–58.

Alam, G. M., Alam, K., and Mushtaq, S. (2017). Climate change perceptions and local adaptation strategies of hazard-prone rural households in Bangladesh. *Climate Risk Management*, 17:52–63.

Alam, G. M., Alam, K., Mushtaq, S., and Leal Filho, W. (2018). How do climate change and associated hazards impact on the resilience of riparian rural communities in Bangladesh? Policy implications for livelihood development. *Environmental Science & Policy*, 84:7–18.

Bangladesh Bank (2018). Monthly Economic Trends. Monthly report, Bangladesh Bank, Dhaka, Bangladesh.

Bangladesh Bureau of Statistics (2011). Statistical Year Book Bangladesh 2010. Report, BBS, Ministry of Planning, Government of the People's Republic of Bangladesh, Dhaka, Bangladesh.

Bangladesh Bureau of Statistics (2018). Statistical Year Book Bangladesh 2017. Report, BBS, Ministry of Planning, Government of the People's Republic of Bangladesh, Dhaka, Bangladesh.

Barrios, S., Bertinelli, L., and Strobl, E. (2006). Climatic change and rural–urban migration: The case of sub-Saharan Africa. *Journal of Urban Economics*, 60(3):357–371.

Beegle, K., De Weerdt, J., and Dercon, S. (2011). Migration and economic mobility in Tanzania: Evidence from a tracking survey. *Review of Economics and Statistics*, 93(3):1010–1033.

Black, R., Adger, W. N., Arnell, N. W., Dercon, S., Geddes, A., and Thomas, D. (2011a). The effect of environmental change on human migration. *Global Environmental Change*, 21:S3–S11.

Black, R., Kniveton, D., and Schmidt-Verkerk, K. (2011b). Migration and climate change: Towards an integrated assessment of sensitivity. *Environment and Planning A*, 43(2):431–450.

Blaikie, P., Cannon, T., Davis, I., and Wisner, B. (2004). *At risk: Natural hazards, people's vulnerability and disasters*. Routledge, NY, USA.

Brammer, H. (2014). Bangladesh's dynamic coastal regions and sea-level rise. *Climate Risk Management*, 1:51–62.

Brown, P., Daigneault, A. J., Tjernström, E., and Zou, W. (2018). Natural disasters, social protection, and risk perceptions. *World Development*, 104:310–325.

Bryan, G., Chowdhury, S., and Mobarak, A. M. (2014). Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh. *Econometrica*, 82(5):1671–1748.

Bunea, D. (2012). Modern gravity models of internal migration: The case of Romania. *Theoretical and Applied Economics*, 4(4):127.

Caruso, G. D. (2017). The legacy of natural disasters: The intergenerational impact of 100 years of disasters in Latin America. *Journal of Development Economics*, 127:209–233.

Cattaneo, t. and Peri, G. (2016). The migration response to increasing temperatures. *Journal of Development Economics*, 122:127–146.

Chakrabarti, A. and Ghosh, J. K. (2011). AIC, BIC, and recent advances in model selection. In Bandyopadhyay, P. S. and Forster, M. R., editors, *Philosophy of Statistics*, volume 7 of *Handbook of the Philosophy of Science*, pages 583–605. North-Holland, Amsterdam, the Netherlands.

Chen, J. J. and Mueller, V. (2018). Salt of the earth: Migration, adaptation, and soil salinity in coastal Bangladesh. Conference Paper, Presented at the ASSA 2018 Annual Meeting in Philadelphia, PA, USA. Available from: https://goo.gl/YDWZBy [Accessed: 15 March 2018].

Chen, J. J., Mueller, V., Jia, Y., and Tseng, S. K.-H. (2017). Validating migration responses to flooding using satellite and vital registration data. *American Economic Review*, 107(5):441–45.

Cleveland, M., Laroche, M., and Hallab, R. (2013). Globalization, culture, religion, and values: Comparing consumption patterns of lebanese muslims and christians. *Journal of Business Research*, 66(8):958–967.

Coronese, M., Lamperti, F., Chiaromonte, F., Roventini, A., et al. (2018). Natural disaster risk and the distributional dynamics of damages. Working Paper 2018/22, Laboratory of Economics and Management (LEM), SantÁnna School of Advanced Studies, Pisa, Italy. Available from: https://goo.gl/te3iKL [Accessed: 23 August 2018].

Das, T. K., Haldar, S. K., Gupta, I. D., and Sen, S. (2014). River bank erosion induced human displacement and its consequences. *Living Review of Landscape Research*, 8(3):1–35.

Dasgupta, S. (2018). Burden of climate change on malaria mortality. *International Journal of Hygiene and Environmental Health*, 221(5):782–791.

Dasgupta, S., Akhter Kamal, F., Huque Khan, Z., Choudhury, S., and Nishat, A. (2014). River salinity and climate change: Evidence from coastal Bangladesh. Policy Research Working Paper 6817, World Bank, Washington DC, USA.

Dasgupta, S., Huq, M., Khan, Z. H., Ahmed, M. M. Z., Mukherjee, N., Khan, M., and Pandey, K. D. (2010). Vulnerability of Bangladesh to cyclones in a changing climate: Potential damages and adaptation cost. Policy Research Working Paper 5280, World Bank, Washington DC, USA.

Davies, P. S., Greenwood, M. J., and Li, H. (2001). A conditional logit approach to US state-to-state migration. *Journal of Regional Science*, 41(2):337–360.

De Brauw, A., Mueller, V., and Woldehanna, T. (2017). Does internal migration improve overall well-being in Ethiopia? *Journal of African Economies*, 27(3):347–365.

De Jong, G. F. (2000). Expectations, gender, and norms in migration decision-making. *Population Studies*, 54(3):307–319.

Depetris-Chauvin, E. and Santos, R. J. (2018). Unexpected guests: The impact of internal displacement inflows on rental prices in Colombian host cities. *Journal of Development Economics*, 134:289–309.

Desmet, K., Kopp, R. E., Kulp, S. A., Nagy, D. K., Oppenheimer, M., Rossi-Hansberg, E., and Strauss, B. H. (2018). Evaluating the Economic Cost of Coastal Flooding. Working Paper 24918, National Bureau of Economic Research, Cambridge, MA, USA.

Dustmann, C. and Okatenko, A. (2014). Out-migration, wealth constraints, and the quality of local amenities. *Journal of Development Economics*, 110:52–63.

FAO (2018). The impact of disasters on agriculture and food security. Technical Paper, Food and Agriculture Organisation (FAO), Rome, Italy. Available from: https://goo.gl/b9TEvf [Accessed: 5 March 2018].

Felbermayr, G., Gröschl, J. K., Sanders, M., Schippers, V., and Steinwachs, T. (2018). Shedding light on the spatial diffusion of disasters. CESifo Working Paper No. 7146, Munich Society for the Promotion of Economic Research - CESifo, Munich, Germany. Available from: https://goo.gl/wVqf4Q [Accessed: 30 August 2018].

Fischer, A. P. (2018). Pathways of adaptation to external stressors in coastal natural-resource-dependent communities: Implications for climate change. *World Development*, 108:235–248.

Gemenne, F. (2011). Why the numbers don't add up: A review of estimates and predictions of people displaced by environmental changes. *Global Environmental Change*, 21:S41–S49.

Gray, C. L. and Mueller, V. (2012). Natural disasters and population mobility in Bangladesh. Proceedings, National Academy of Sciences, Washington DC, USA.

Grillos, T. (2018). Women's participation in environmental decision-making: Quasi-experimental evidence from northern Kenya. *World Development*, 108:115–130.

Hasan, S. A. (2016a). Engel curves and equivalence scales for Bangladesh. *Journal of the Asia Pacific Economy*, 21(2):301–315.

Hasan, S. A. (2016b). The impact of the 2005-10 rice price increase on consumption in rural Bangladesh. *Agricultural Economics*, 47(4):423–433.

Hasan, S. A. and Mozumder, P. (2017). Income and energy use in Bangladesh A household level analysis. *Energy Economics*, 65:115–126.

IPCC (2007). Impacts, Adaptation and Vulnerability. Contribution of working group II to the fourth assessment report of the intergovernmental report on climate change, Intergovernmental Panel on Climate Change (IPCC), Cambridge University Press, NY, USA. Available from: https://goo.gl/xmT7uQ [Accessed: 3 August 2018].

Ishtiaque, A. and Nazem, N. I. (2017). Household-level disaster-induced losses and rural–urban migration: Experience from world's one of the most disaster-affected countries. *Natural Hazards*, 86(1):315–326.

Islam, A. and Nguyen, C. (2018). Do networks matter after a natural disaster? A study of resource sharing within an informal network after Cyclone Aila. *Journal of Environmental Economics and Management*, 90:249–268.

Kabir, M. E., Serrao-Neumann, S., Davey, P., Hossain, M., and Alam, M. T. (2018). Drivers and temporality of internal migration in the context of slow-onset natural hazards: Insights from north-west rural Bangladesh. *International Journal of Disaster Risk Reduction*, 31:617–626.

Kabir, R., Khan, H. T., Ball, E., and Caldwell, K. (2016). Climate Change Impact: The experience of the coastal areas of Bangladesh affected by Cyclones Sidr and Aila. *Journal of Environmental and Public Health*, 2016:1–9.

Karanja Ng'ang'a, S., Bulte, E. H., Giller, K. E., McIntire, J. M., and Rufino, M. C. (2016). Migration and self-protection against climate change: A case study of Samburu County, Kenya. *World Development*, 84:55–68.

Karim, A. (2018). The household response to persistent natural disasters: Evidence from Bangladesh. *World Development*, 103:40–59.

Kellenberg, D. and Mobarak, A. M. (2011). The economics of natural disasters. *Annual Review of Resource Economics*, 3:297–312.

Kennan, J. and Walker, J. R. (2011). The effect of expected income on individual migration decisions. *Econometrica*, 79(1):211–251.

Khandker, S. R. (2012). Seasonality of income and poverty in Bangladesh. *Journal of Development Economics*, 97(2):244–256.

Kirchberger, M. (2017). Natural disasters and labor markets. *Journal of Development Economics*, 125:40–58.

Kreft, S., Eckstein, D., Dorsch, L., and Fischer, L. (2016). Global climate risk index 2016: Who suffers most from extreme weather events? Weather-related loss events in 2014 and 1995 to 2014. Briefing Paper, Germanwatch, Berlin, Germany. Available from: https://goo.gl/UKo9Ri [Accessed: 3 August 2018].

Li, Y., López-Carr, D., and Chen, W. (2014). Factors affecting migration intentions in ecological restoration areas and their implications for the sustainability of ecological migration policy in arid Northwest China. *Sustainability*, 6(12):8639–8660.

Lynham, J., Noy, I., and Page, J. (2017). The 1960 Tsunami in Hawaii: Long-Term Consequences of a Coastal Disaster. *World Development*, 94:106–118.

Mallick, B. (2014). Cyclone-induced migration in southwest coastal Bangladesh. *ASIEN*, 130:60–81.

Mallick, B., Ahmed, B., and Vogt, J. (2017). Living with the risks of cyclone disasters in the south-western coastal region of Bangladesh. *Environments*, 4(1):13.

Mallick, B. and Etzold, B. (2015). *Environment, Migration, and Adaptation: Evidence and of Climate Change in Bangladesh.* AH Development Publishing House, Dhaka, Bangladesh.

Mallick, B. and Vogt, J. (2012). Cyclone, coastal society and migration: Empirical evidence from Bangladesh. *International Development Planning Review*, 34(3):217–240.

Marshall, R. and Rahman, S. (2013). Internal migration in Bangladesh: Character, drivers and policy issues. Technical Paper, United Nations Development Programme (UNDP), NY, USA. Available from: https://goo.gl/kKjLhB [Accessed: 3 August 2018].

Mejia, S. A., Mrkaic, M., Novta, N., Pugacheva, E., and Topalova, P. (2018). The effects of weather shocks on economic activity: What are the channels of impact? IMF Working Papers 18/144, International Monetary Fund, Washington DC, USA. Available from: https://goo.gl/NT5NiX [Accessed: 30 August 2018].

Mirza, M. M. Q. (2003). Climate change and extreme weather events: Can developing countries adapt? *Climate Policy*, 3(3):233–248.

Mirza, M. M. Q., Warrick, R., and Ericksen, N. (2003). The implications of climate change on floods of the Ganges, Brahmaputra and Meghna rivers in Bangladesh. *Climatic Change*, 57(3):287–318.

Mishra, D. K. (2016). *Internal Migration in Contemporary India.* SAGE Publications, India.

Mollah, T. H. and Ferdaush, J. (2015). Riverbank Erosion, Population Migration and Rural Vulnerability in Bangladesh (A Case Study on Kazipur Upazila at Sirajgonj District). *Environment and Ecology Research*, 3(5):125–131.

Mottaleb, K. A., Mohanty, S., and Mishra, A. K. (2015). Intra-household resource allocation under negative income shock: A natural experiment. *World Development*, 66:557–571.

Mozumder, P., Bohara, A. K., Berrens, R. P., and Halim, N. (2009). Private transfers to cope with a natural disaster: Evidence from Bangladesh. *Environment and Development Economics*, 14(2):187–210.

Mutton, D. and Haque, C. E. (2004). Human vulnerability, dislocation and resettlement: Adaptation processes of river-bank erosion-induced displacees in Bangladesh. *Disasters*, 28(1):41–62.

Myers, N. (2002). Environmental refugees: A growing phenomenon of the 21st century. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 357(1420):609–613.

Naik, A. (2009). Migration and natural disasters. In Laczko, F. and Aghazarm, C., editors, *Migration, Environment and Climate Change: Assessing the Evidence*, pages 247–317. International Organization for Migration (IOM), Geneva, Switzerland. Available from: https://goo.gl/JMrNUS [Accessed: 3 August 2018].

O'neill, B. C. and Oppenheimer, M. (2002). Dangerous climate impacts and the Kyoto Protocol. *Science*, 296(5575):1971–1972.

Para-PeñaS, R. I. and Reilly, B. (2018). Climate variability and theft in Colombia. Document 481, Directorate of Economic Studies, National Planning Department (DNP), Government of Colombia, Bogota, Colombia. Available from: https://goo.gl/ohGYhB [Accessed: 30 August 2018].

Patnaik, U., Das, P. K., and Bahinipati, C. S. (2016). Coping with climatic shocks: Empirical evidence from rural coastal Odisha, India. *Global Business Review*, 17(1):161–175.

Paul, B. K. (2005). Evidence against disaster-induced migration: The 2004 tornado in north-central Bangladesh. *Disasters*, 29(4):370–385.

Planning Commission (2015). Seventh Five Year Plan (FY2016 - FY2020): Accelerating Growth, Empowering Citizens. Final version, Planning Commission, Bangladesh Government. Available from: https://goo.gl/iWmHUN [Accessed: 23 August 2018].

Planning Commission (2017). Bangladesh Delta Plan 2100. Draft, Planning Commission, Bangladesh Government. Available from: https://goo.gl/5StZsk [Accessed: 23 August 2018].

Poncelet, A., Gemenne, F., Martiniello, M., and Bousetta, H. (2010). A country made for disasters: Environmental vulnerability and forced migration in Bangladesh. In Afifi, Tamer, J. J., editor, *Environment, forced migration and social vulnerability*, pages 211–222. Springer, NY, USA.

Portes, A. (2010). Migration and social change: Some conceptual reflections. *Journal of Ethnic and Migration Studies*, 36(10):1537–1563.

Sandefur, G. D. and Scott, W. J. (1981). A dynamic analysis of migration: An assessment of the effects of age, family and career variables. *Demography*, 18(3):355–368.

Sawada, Y. and Shimizutani, S. (2008). How do people cope with natural disasters? Evidence from the great Hanshin-Awaji (Kobe) earthquake in 1995. *Journal of Money, Credit and Banking*, 40(2-3):463–488.

Sawada, Y. and Shimizutani, S. (2011). Changes in durable stocks, portfolio allocation, and consumption expenditure in the aftermath of the Kobe earthquake. *Review of Economics of the Household*, 9(4):429.

Sawada, Y. and Takasaki, Y. (2017). Natural disaster, poverty, and development: An introduction. *World Development*, 94:2–15.

Shayegh, S. and Casey, G. (2017). To go or not to go: Migration alleviates climate damages even for those who stay behind. Technical report.

Skoufias, E. (2003). Economic crises and natural disasters: Coping strategies and policy implications. *World Development*, 31(7):1087–1102.

Stern, N. (2008). The economics of climate change. *American Economic Review*, 98(2):1–37.

Takasaki, Y. (2011). Do the commons help augment mutual insurance among the poor? *World Development*, 39(3):429–438.

Takasaki, Y. (2014). How is disaster aid allocated within poor communities? Risk sharing and social hierarchy. *Journal of International Development*, 26(8):1097–1114.

Takasaki, Y. (2017). Do natural disasters decrease the gender gap in schooling? *World Development*, 94:75–89.

Tian, Q. and Lemos, M. C. (2018). Household livelihood differentiation and vulnerability to climate hazards in rural China. *World Development*, 108:321–331.

Von Reichert, C. and Rudzitis, G. (1992). Multinomial logistic models explaining income changes of migrants to high-amenity counties. *The Review of Regional Studies*, 22(1):25.

Zaber, M., Nardi, B., and Chen, J. (2018). Responding to Riverbank Erosion in Bangladesh. In *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies*, page 27. ACM. Available from: https://doi.org/10.1145/3209811.3209823 [Accessed: 4 September 2018].

Appendix A: Tables

TABLE A.1: **Effect on internal migration: Marginal effects from OLS estimates**

	All shocks			Grouped shocks		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced cyclone in last 10yrs	0.106***	0.007	0.007			
	(0.033)	(0.030)	(0.030)			
Experienced flood in last 10yrs	0.280***	0.198***	0.173***			
	(0.031)	(0.033)	(0.033)			
Experienced river erosion in last 10yrs	0.393***	0.233***	0.232***			
	(0.018)	(0.027)	(0.027)			
Transinet shock				0.230***	0.115***	0.106***
				(0.025)	(0.026)	(0.026)
Permanent shock				0.391***	0.225***	0.223***
				(0.018)	(0.027)	(0.027)
Number of household members		-0.012**	-0.018***		-0.012**	-0.018***
		(0.005)	(0.005)		(0.005)	(0.005)
Household head is male		0.005	-0.018		0.003	-0.021
		(0.055)	(0.054)		(0.054)	(0.053)
Age of the household head in years		-0.002***	-0.003***		-0.002***	-0.003***
		(0.001)	(0.001)		(0.001)	(0.001)
Household head is married		0.236***	0.253***		0.238***	0.255***
		(0.036)	(0.036)		(0.036)	(0.035)
Household head is muslim		0.066**	0.061**		0.064**	0.057*
		(0.030)	(0.029)		(0.030)	(0.029)
Literacy of household head		-0.050**	-0.050**		-0.051**	-0.051**
		(0.021)	(0.020)		(0.021)	(0.020)
Household head has a personal phone		0.126***	0.128***		0.132***	0.133***
		(0.039)	(0.038)		(0.040)	(0.038)
Electricity in home		-0.061**	-0.006		-0.058**	-0.005
		(0.028)	(0.028)		(0.028)	(0.028)
Owned land in decimals		-0.003**	-0.002		-0.003**	-0.002
		(0.001)	(0.001)		(0.001)	(0.001)
Lives in owned house		-0.217***	-0.215***		-0.209***	-0.204***
		(0.033)	(0.034)		(0.034)	(0.034)
Received credit after disaster		0.064***	0.051***		0.068***	0.055***
		(0.020)	(0.019)		(0.020)	(0.019)
Received relief after disaster		-0.003	0.026		-0.013	0.017
		(0.026)	(0.026)		(0.026)	(0.025)
Ln(non-land asset value)		-0.043***	-0.039***		-0.043***	-0.039***
		(0.011)	(0.012)		(0.011)	(0.012)
Ln(monthly income before migration)		0.074***	0.075***		0.067***	0.069***
		(0.013)	(0.013)		(0.012)	(0.012)
Constant	0.651***	0.654***	0.651***	0.651***	0.654***	0.651***
	(0.010)	(0.013)	(0.013)	(0.010)	(0.013)	(0.013)
District fixed effects	No	No	Yes	No	No	Yes
R^2	0.18	0.31	0.36	0.18	0.31	0.36
AIC	2108.38	1810.25	1696.49	2101.30	1818.37	1701.41
BIC	2124.89	1909.26	1823.00	2112.30	1911.87	1822.42
N	1,809	1,809	1,809	1,809	1,809	1,809

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

TABLE A.2: **Choice of location for internal migrants: Marginal effects from independent probit models**

	Migrated to		
	Dhaka (1)	Khulna (2)	Other cities (3)
Transinet shock	0.301	0.564***	0.033
	(0.205)	(0.145)	(0.182)
Permanent shock	1.452***	0.991***	0.318
	(0.183)	(0.168)	(0.206)
Number of household members	-0.048	-0.068**	-0.036
	(0.039)	(0.032)	(0.025)
Household head is male	0.141	-0.176	0.470
	(0.304)	(0.265)	(0.328)
Age of the household head in years	0.042	-0.040	-0.023
	(0.030)	(0.026)	(0.022)
Household head is married	0.764***	1.158***	0.642***
	(0.229)	(0.186)	(0.160)
Household head is muslim	0.404*	0.230	0.118
	(0.217)	(0.141)	(0.110)
Literacy of household head	-0.213	-0.248**	-0.064
	(0.152)	(0.115)	(0.103)
Household head has a personal phone	0.718**	0.420**	0.153
	(0.272)	(0.181)	(0.163)
Electricity in home	0.383**	0.320**	-0.272**
	(0.170)	(0.129)	(0.112)
Owned land in decimals	0.005	-0.012**	-0.005
	(0.006)	(0.006)	(0.005)
Lives in owned house	-0.758***	-0.874***	0.081
	(0.179)	(0.156)	(0.152)
Received credit after disaster	-0.025	0.120	0.292***
	(0.139)	(0.106)	(0.097)
Received relief after disaster	-0.470**	-0.015	0.387***
	(0.185)	(0.119)	(0.108)
Ln(non-land asset value)	-0.315***	-0.130**	-0.130**
	(0.076)	(0.061)	(0.059)
Ln(monthly income before migration)	0.284***	0.094	0.787***
	(0.093)	(0.061)	(0.148)
Constant	-1.038	0.947	-6.991***
	(1.110)	(0.872)	(1.368)
District fixed effects	Yes	Yes	Yes
Psedu R^2	0.64	0.46	0.27
N	996	1,087	988

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.3: **Impacts of migration on household income and consumption by types of shocks experienced: OLS estimates**

	Ln(household income)			Ln(household consumption)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post transient shock	0.645***	0.837***	0.827***	0.544***	0.251*	0.181
induced migration	(0.186)	(0.232)	(0.227)	(0.106)	(0.143)	(0.146)
Post permanent shock	0.371**	0.552***	0.560***	0.603***	0.393***	0.314***
induced migration	(0.167)	(0.196)	(0.194)	(0.104)	(0.118)	(0.116)
Migrated to a	-0.147***	0.083**	0.091**	-0.670***	-0.453***	-0.418***
different location	(0.039)	(0.041)	(0.042)	(0.038)	(0.032)	(0.033)
Post transient shock induced migration	0.313	0.549**	0.584**	0.821***	0.662***	0.690***
× migrated to a different location	(0.193)	(0.236)	(0.231)	(0.116)	(0.148)	(0.151)
Post permanent shock induced migration	0.604***	0.936***	0.945***	0.669***	0.476***	0.589***
× migrated to a different location	(0.171)	(0.200)	(0.199)	(0.111)	(0.124)	(0.123)
Number of household		0.067***	0.068***		-0.005	0.001
members		(0.008)	(0.008)		(0.006)	(0.006)
Household head is		0.277***	0.294***		0.039	0.051
male		(0.089)	(0.090)		(0.064)	(0.062)
Age of the household		0.007	0.009		0.009*	0.008
head in years		(0.008)	(0.008)		(0.005)	(0.005)
Age squared		-0.000	-0.000*		-0.000*	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Household head is		0.098*	0.086		0.026	0.019
married		(0.057)	(0.057)		(0.043)	(0.042)
Household head is		-0.071	-0.051		0.045	0.085**
muslim		(0.045)	(0.045)		(0.033)	(0.033)
Literacy of		-0.017	-0.000		0.056**	0.048*
household head		(0.033)	(0.033)		(0.025)	(0.025)
Household head has		0.006	0.006		0.078*	0.083**
a personal phone		(0.058)	(0.058)		(0.042)	(0.042)
Electricity in home		-0.200***	-0.181***		0.041	0.032
		(0.038)	(0.038)		(0.031)	(0.031)
Owned land in		-0.002	-0.002		0.009***	0.008***
decimals		(0.002)	(0.002)		(0.002)	(0.002)
Lives in owned house		0.737***	0.663***		0.193***	0.155***
		(0.048)	(0.049)		(0.038)	(0.039)
Received credit		0.030	0.027		0.064***	0.042*
after disaster		(0.032)	(0.032)		(0.024)	(0.023)
Received relief		0.085**	0.113***		0.129***	0.080***
after disaster		(0.036)	(0.036)		(0.028)	(0.028)
Ln(non-land asset		0.044**	0.042**		0.118***	0.122***
value)		(0.018)	(0.018)		(0.015)	(0.014)
Ln(household income)					0.611***	0.613***
					(0.020)	(0.020)
District fixed effects	No	No	Yes	No	No	Yes
Adjusted R^2	0.12	0.28	0.29	0.21	0.63	0.64
N	3,618	3,618	3,618	3,618	3,618	3,618

Note: See footnotes in Table 5.

TABLE A.4: **Impacts of migration location on household income and consumption by types of shocks experienced: OLS estimates**

	Ln(household income)			Ln(household consumption)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post transient shock induced migration	0.283***	0.313***	0.297***	0.190***	0.031	-0.027
	(0.087)	(0.100)	(0.099)	(0.062)	(0.070)	(0.072)
Post permanent shock induced migration	0.172	0.298	0.324*	0.467***	0.362***	0.314**
	(0.173)	(0.197)	(0.195)	(0.114)	(0.124)	(0.122)
Migrated to Dhaka	-0.639***	-0.182***	-0.172***	-1.130***	-0.513***	-0.376***
	(0.059)	(0.059)	(0.062)	(0.059)	(0.046)	(0.050)
Migrated to Khulna	-0.399***	-0.140***	-0.136**	-0.959***	-0.587***	-0.557***
	(0.056)	(0.054)	(0.057)	(0.056)	(0.037)	(0.040)
Migrated to other city	0.397***	0.342***	0.333***	-0.111***	-0.340***	-0.344***
	(0.041)	(0.045)	(0.046)	(0.043)	(0.039)	(0.039)
Post transient shock induced migration × migrated Dhaka	1.248***	1.461***	1.525***	1.505***	0.799***	0.846***
	(0.118)	(0.125)	(0.128)	(0.112)	(0.113)	(0.114)
Post permanent shock induced migration × migrated Dhaka	1.355***	1.512***	1.480***	1.104***	0.434***	0.519***
	(0.183)	(0.203)	(0.201)	(0.130)	(0.135)	(0.133)
Post transient shock induced migration × migrated Khulna	0.836***	1.147***	1.178***	1.509***	1.108***	1.129***
	(0.114)	(0.125)	(0.125)	(0.090)	(0.092)	(0.093)
Post permanent shock induced migration × migrated Khulna	0.831***	1.086***	1.108***	1.260***	0.875***	0.972***
	(0.183)	(0.204)	(0.203)	(0.127)	(0.133)	(0.133)
Post transient shock induced migration × migrated other districts	0.385**	0.468***	0.487***	0.593***	0.433**	0.432**
	(0.165)	(0.167)	(0.164)	(0.150)	(0.173)	(0.173)
Post permanent shock induced migration × migrated other districts	0.221	0.132	0.112	-0.002	-0.137	-0.085
	(0.215)	(0.241)	(0.236)	(0.133)	(0.152)	(0.148)
Number of household members		0.066***	0.067***		-0.004	0.002
		(0.008)	(0.008)		(0.006)	(0.006)
Household head is male		0.266***	0.277***		0.053	0.064
		(0.087)	(0.087)		(0.063)	(0.061)
Age of the household head in years		0.008	0.010		0.009*	0.007
		(0.008)	(0.008)		(0.005)	(0.005)
Age squared		-0.000*	-0.000*		-0.000*	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Household head is married		0.113**	0.109*		0.035	0.024
		(0.056)	(0.056)		(0.043)	(0.042)
Household head is muslim		-0.030	-0.016		0.051	0.091***
		(0.044)	(0.045)		(0.033)	(0.034)
Literacy of household head		-0.019	-0.005		0.046*	0.043*
		(0.032)	(0.032)		(0.025)	(0.025)
Household head has a personal phone		0.021	0.021		0.097**	0.089**
		(0.058)	(0.057)		(0.043)	(0.042)
Electricity in home		-0.185***	-0.164***		0.031	0.015
		(0.038)	(0.038)		(0.032)	(0.031)
Owned land in decimals		-0.002	-0.002		0.009***	0.008***
		(0.002)	(0.002)		(0.002)	(0.002)
Lives in owned house		0.630***	0.567***		0.171***	0.146***
		(0.048)	(0.049)		(0.038)	(0.038)
Received credit after disaster		0.029	0.025		0.045*	0.036
		(0.032)	(0.032)		(0.024)	(0.024)
Received relief after disaster		0.081**	0.110***		0.133***	0.098***
		(0.036)	(0.037)		(0.028)	(0.028)
Ln(non-land asset value)		0.046**	0.044**		0.112***	0.123***
		(0.018)	(0.018)		(0.014)	(0.014)
Ln(household income)					0.599***	0.602***
					(0.020)	(0.020)
District fixed effects	No	No	Yes	No	No	Yes
Adjusted R^2	0.20	0.31	0.32	0.29	0.64	0.65
N	3,618	3,618	3,618	3,618	3,618	3,618

Note: See footnotes in Table 5.