Environmental change and migration aspirations: evidence from Bangladesh

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Abstract

The argument that environmental change is an important driving force of migration has experienced a strong revival in the climate change context. We examine whether and how different environmental stressors aspire people to move. The analysis relies on newly collected, cross-sectional survey data of 1594 households residing in 36 villages along the 250 kilometers of the Jamuna River in Bangladesh – an area affected primarily by floods and riverbank erosion. The results show that long-term environmental events, i.e., riverbank erosion, increase aspirations for internal, permanent migration, while short-term environmental events, i.e., floods, do not affect migration aspirations. These results suggest that depending on the type of environmental change, people might prefer migrating rather than staying put and thus, they entail important policy implications regarding the effects of climate change on future internal migration flows.

Keywords: Climate Change | Flood | Riverbank erosion | Environmental Perceptions | Migration Aspirations | Survey | Bangladesh

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Climate change is expected to increase the frequency and intensity of climate events such as storms, floods, and droughts, and contributes to sea level rise (IPCC, 2021b). In turn, these climatic changes may increase migration flows especially of vulnerable people (Foresight, 2011). According to the World Bank's latest Groundswell report, under a business-as-usual scenario (i.e., high greenhouse gas emissions and unequal development), slow-onset climatic changes could force 216 million people in six regions of the world (of which 13.5 million reside in Bangladesh) to move by 2050 to escape the impacts of climate change (Clement et al., 2021). Furthermore, there is sufficient evidence to claim that climate-related events make it more likely that people migrate mostly within their own country (e.g., Afifi et al., 2016; Clement et al., 2021; Foresight, 2011). Yet, this effect does not hold under all circumstances and a significant amount of variation persists in migration (or non-migration) patterns of people affected by the same climate event such as a drought or a flood (Koubi et al., 2022; Thiede et al., 2016). It thus remains not well understood whether and how environmental factors shape individuals' decisions to migrate (Black et al., 2011; Cattaneo et al., 2019; Koubi, Spilker, et al., 2016).

With this study, we aim to contribute to our understanding of environmental migration by examining the impact of environmental stress on people's perception of migration as something desirable or necessary, that is, their *migration aspirations* (Carling & Schewel, 2018, p. 946). Aspirations concern individuals' potential migration based on thoughts and feelings rather than their actual migration behavior, which depends on their capacity/ability to convert these psychological elements into reality (Carling & Collins, 2018; Carling & Schewel, 2018).[1] Migration aspirations "can take a variety of forms, from lifestyle-driven preferences to

[1] While the degree to which migration aspirations signal a person's actual migration behavior as opposed to pure wishful thinking constitutes a topic of ongoing discussion, migration aspirations and intentions have been shown to be good predictors of future actual migration in a variety of contexts (e.g., Docquier et al. (2014); Kang et al. (2007); Tjaden et al. (2019); van Hear et al. (2018); Williams et al. (2018)). Moreover, according to the theory of planned behavior, expectations about achieving valued goals and intentions are among the primary determinants of behavior (Ajzen (1991)).

urgencies to escape danger, with innumerable possibilities in between" (Carling & Schewel, 2018, p. 959). This implies that some individuals aspire to migrate due to the value they attach to the migration experience in and of itself, e.g., the joy and pleasure derived from exploring new places (intrinsic aspirations), while others do so in order to achieve higher income, social status, or better education, and/or to manage threats to their livelihood (instrumental aspirations) (Carling & Schewel, 2018; de Haas, 2021). In the extant literature, *migration aspirations* are mostly conceived as 'a means to an end' and, consequently, they tend to refer to the basic conviction that leaving a particular place would be better than staying (Carling & Schewel, 2018, p. 946).[2] In the context of environmental changes, we conceive migration aspirations "as urgencies to escape danger" (Carling & Schewel, 2018, p. 959).

Yet not everyone perceives equally 'the urgency to escape danger' in the presence of environmental changes. For instance, farmers/fishermen are more vulnerable to droughts and floods than civil servants and, hence, we may observe a greater probability of migration aspirations for the former compared to the latter. This implies that individuals' migration aspirations are strongly affected by their vulnerability to environmental changes, which is linked to how people perceive these events to affect their livelihoods (Carling & Schewel, 2018; Zickgraf, 2018). Thus, we assume that migration aspirations are more likely to be directly related to individual *perceptions* of environmental changes than to more objectively identified environmental stressors (Dessai et al., 2004).[3]

Moreover, we argue that different types of perceived environmental changes, in particular sudden/short-term and gradual/long-term environmental events affect migration aspirations in diverse ways (Black et al., 2013; Cattaneo et al., 2019; Koubi et al., 2022; Koubi, Spilker, et

[2] Other terms used include desires, wishes, expectations, and preferences (Carling and Collins (2018); Carling and Schewel (2018)).

[3] Whether individual environmental perceptions consistently match scientifically observed climate data forms a topic of ongoing discussion in the literature. Recent research shows that this is often the case for changes in the temperature but not regarding changes in precipitation (e.g., Linke et al. (2020); Madhuri and Sharma (2020)).

al., 2016; Koubi, Stoll, & Spilker, 2016; R. A. McLeman, 2014). This classification of environmental events, however, is based on the speed of their onset (sudden- versus gradual onset) and duration (short- versus long-term) and does not consider the impact the particular event type has on affected households. Consequently, we argue that migration aspirations (and migration behavior) of affected individuals/households depend also on the nature of the impact, that is, whether the impact caused by the specific environmental event is reversible or irreversible. [4]

Sudden/short-term environmental events, e.g., floods and storms, can have severe, immediate impacts on the well-being of individuals by inflicting injuries and casualties, and causing property damage, food insecurity, and economic disruption (Wallemacq & House, 2018). These events are thus easily recognizable as extreme and people might consider moving away from the affected areas (Warner, 2010, p. 405). And indeed, the IDMC (2019) reports that an average of 24 million people a year fled their homes during the 2008-2018 period due to disasters, with 98% of those caused by floods and storms. Moreover, an emerging literature on environmental migration suggests most migration in the aftermath of sudden environmental events is short-distance and short-duration (Cattaneo et al., 2019; Curtis et al., 2015), especially among individuals who fail to derive a secure income (Saha, 2017) and that the majority of those moved away return as soon as possible to rebuild their homes and livelihoods (Cattaneo et al., 2019). Consequently, we argue that in the presence of sudden/short-term events people aspire to migrate only temporarily since the impacts of these events are mostly reversible. We thus expect the 'aspiration to migrate' after floods to be high for internal, temporary moves.[5]

[4] The study has been pre-registered at OSF; details are provided in Appendix B of the Supplementary Information.

[5] However, it is unclear for how long such migration aspirations persist, whether they are still present several months into the natural disaster, when imminent environmental pressure on livelihoods has

Gradual/long-term events, e.g., riverbank erosion, soil/water salinity, and sea level rise, on the other hand, are usually not perceived as extreme due to their slow moving nature and hence, they tend to remain beneath the perceptual threshold of immediate risk (Howe et al., 2013) that would inspire 'a need to move'. Under those circumstances, people might be willing to implement some type of adaptation or mitigation strategy (Koubi et al., 2022). For instance, in Bangladesh, people plant water resistant rice varieties and horticultural crops in the case of droughts (Al-Amin et al., 2019) and build walls using bamboo or sandbags to protect the riverbanks from eroding (Mamun et al., 2022). Yet, when they materialize, the impacts of such events are usually irreversible: complete and permanent destruction of (agricultural) land, houses, and infrastructure. Consequently, we expect that people experiencing such events are likely to develop aspirations, which persist over extended period, to migrate permanently to compensate for the losses suffered and since there is nothing physical left for them to be attached to.

Acknowledging the fact that the migration aspirations are not determined only by perceptions of climate events, we also account for several socio-demographic factors that have been found to affect migration aspirations such as gender, age, education, socio-economic status, risk attitudes, place attachment, and the number of dependent children.

Our study extends the literature in several ways: First, although a growing body of literature has empirically explored the drivers of migration aspirations, e.g., individual/household characteristics such as gender, age, education and income as well as local/national socioeconomic and political/institutional factors such as economic development, governance, and corruption especially in the context of international migration (e.g., Marrow & Klekowski von Koppenfels, 2020; Méndez, 2020; Migali & Scipioni, 2019; Sadiddin et al.,

receded, and to what extent sudden-onset climate events also contribute to permanent, long-term migration aspirations.

2019), to the best of our knowledge there is little scholarly work addressing the impact of environmental stress on migration aspirations and intentions (Bertoli et al. (2021) and Helbling et al. (2021) are notable exceptions). Second, our measures for migration aspirations are stricter than pure migration considerations used in recent research since we directly ask respondents whether they desire (desired) to move at the time of the survey (during the last month) instead of whether they would (ideally) like to move permanently to another country (Bertoli et al., 2021). Furthermore, we explore additional dimensions of migration aspirations such as the intended destination (internal/international, rural/urban) and the duration of stay (temporary/permanent). Third, we focus on individual perceptions of environmental/climatic events rather than actual meteorological data, e.g., temperature and precipitation (see Bertoli et al. (2021) and Helbling et al. (2021)) as no two people experience environmental/climatic changes in the same manner due to a variety of objective individual-level characteristics (i.e., wealth, education, gender, etc.) and subjective realities (norms, emotions/place attachment, and risk propensities) (Koubi et al., 2022; Koubi, Stoll, & Spilker, 2016). Consequently, examining individual environmental perceptions, which are inherently subjective, can better help to explain migration aspirations, which are equally subjective but also a prerequisite for actual behavior in response to environmental changes. A better understanding of the formation of these aspirations is important as it permits an assessment of the migration propensities in a world experiencing environmental and climatic changes, which could in turn contribute to our knowledge of migrant selection and possible future migration dynamics and patterns.[6]

Design

To empirically examine the effect of environmental changes on migration aspirations, we use cross-sectional data from a panel survey of 1,594 household heads residing in 36 locations

[6] Aspirations refer to voluntary migration, and not to forced migration (displacement).

distributed along the whole 250 km of the Jamuna River in Bangladesh. We chose Bangladesh because the country is at the forefront of both climate/environmental changes with riverbank erosion and floods being the most impactful processes in terms of yearly damage (Ahmed, 2015) and migration (e.g. G. M. M. Alam et al., 2019; Gray & Mueller, 2012; R. Islam et al., 2020; Kabir et al., 2018; Khandker et al., 2012; Mallick & Vogt, 2014), and the Jamuna River because significant spatial, temporal, and inter-household variation for both riverbank erosion and floods exists along its length (see section "Case Study" in "Methods and Protocols"). The survey data were collected between January and March 2022 and are supplemented by pre-exposure measures of time-variant respondent attitudes and household characteristics from a survey conducted in June 2021 of the very same respondents (Fig.S1 and Table S1 in "Methods and Protocols"). Interviews were conducted face-to-face in Bangla by native interviewers and lasted for about 45-60 minutes. The questionnaires included both closed and open-ended questions pertaining to respondents' experience with environmental events and migration as well as personal and household information.

We selected participants in a multi-stage cluster design (see "Survey Overview" in "Methods and Protocols"). In the first stage, all survey locations (one-kilometer stretches) potentially at risk of slow- and sudden onset environmental stress along the easternmost riverbank line of the Jamuna River were identified; of all potential locations, 36 (86%) could be visited. At each of these 36 locations, households were sampled using a stratified random spatial sampling design to survey households located within three zones defined by distance from the shoreline. The three zones at each location were constructed by shifting the shoreline inland by 50 m (high risk), 100 m (medium risk) and 200 m (low risk), respectively to capture potential effects of different ex-ante erosion and flood risk levels on migration aspirations. Consequently, each sampling zone has an extent of 200 m inland and of 1 km in the direction of flow.

Within each of the three zones, we generated a spatially explicit sample following the procedure outlined by Crawford et al. (2020). In particular, we generated a set of 25 random latitude-longitude points per zone using ArcMap software (with a minimum distance of 10 m between points). In the field, enumerators navigated to these points using smartphones. Having arrived at the point, they selected the house closest to that point based on visual estimation. This household was subsequently interviewed. If a household declined participation or if the household head was not available at two contact attempts, the enumerator continued to the next closest household, in reference to the starting point. Within each household, the household head was interviewed, defined as the primary decision-maker within the household. Hence, we are confident that our respondents constitute a high-quality sample[7] of the riverbank population at risk of erosion and flood in Bangladesh.

We use two main dependent variables to capture migration aspirations (Carling and Collins (2018). The first, *current migration aspirations*, is a binary measure with a value of 1 if a respondent expresses a preference for migrating over remaining in the current location *right now* (0 otherwise), that is, at the time of the survey. While this is in principle what we want to capture, this measure can be highly volatile, depending on the mood of the day. Hence, we also ask about respondents' *last month's migration aspirations*, which are coded as a binary measure with a value of 1 if a respondent expresses that (s)he had thought about migrating during the last month. In additional analyses, we also use secondary dependent variables, namely the aspired duration (permanent vs. temporary) and the aspired destination (rural vs. urban) (see "Variables" in "Methods and Protocols"). We operationalize treatment as a binary indicator of whether a household reported affectedness by flood/erosion in the previous monsoon season,

[7] High response rate, very low attrition rate between survey waves 1 and 2, random GIS sample of households within villages, and surveying of almost all inhabited survey locations with erosion risk along the left bank of the 250 km of the Jamuna River.

i.e., four to six months prior to the survey. Additional models subdivide affectedness by four degrees of severity.

We employ linear probability models to estimate the effects for current/last month's aspirations. This facilitates the interpretation of coefficients, as the indicator of flood/erosion affectedness can be directly understood as a percentage point in-/decrease of migration aspirations with affectedness. We report logistic regression models in the Supplementary Information (with fundamentally identical results). We draw on multinomial models to estimate effects for the categorical dependent variables duration and destination. As risk of exposure to environmental stress and migration aspirations are likely endogenous, we employ the quasi-random exposure to erosion and flood within a sample of households at risk of these events in combination with entropy balancing weights to facilitate the interpretation of our estimates as causal effects; and we correct for sample selection effects due to migration with imputation and bounding of estimates (see subsequent section and "Estimation Strategy and Causal Identification" in "Methods and Protocols"). Standard errors are clustered at the village-level, as the treatment clusters at this level (Abadie et al., 2017).

Results

We start with the relation between aspirations and two indicators for flood and for erosion affectedness and present our results in six different models in Table 1 (last month's aspirations) and Table 2 (current aspirations) (see "Causal Identification" in "Methods and Protocols"). Specification (1) regresses migration aspirations on exposure to flood/erosion. For a causal interpretation, these estimates assume that exposure occurs quasi-randomly. In specifications (2) and (3), we additionally adjust with entropy balancing weights (Hainmueller, 2012) constructed from reweighting the control group such that it corresponds to the erosion treatment group (models 2) or flood treatment group (models 3) with respect to control variables that could correlate with exposure. This approach goes beyond a mere statistical control and

corresponds to a matching of observations in the group affected and unaffected by erosion/flood. As a major advantage of entropy balancing, we can select weights such that the treatment group corresponds to the control group on the first, second and third moments of the distribution of covariates. Implicitly, we thereby also restrict our inference to the region of the covariate space where treatment and control group have common support, improving inference (Lechner & Strittmatter, 2019). For a causal interpretation, these estimates assume selection-on-observables. Specifications (4) to (6) mirror specifications (1) to (3), but explicitly include control variables that could correlate with exposure. This also addresses endogeneity concerns (albeit under modeling assumptions) for specification (4) compared to specification (1), and improves efficiency, and tackles any remaining endogeneity for specifications (5) and (6) compared to (2) and (3).

In the presentation of results below, we draw on the sample of individuals that lived in villages in the month before monsoon onset, i.e., we include respondents who migrated. We impute values for the dependent variables under the assumption that these individuals would have held current and last month migration aspirations as indicated by their move away. Furthermore, we assume permanent/temporary and destination aspirations as observed. The robustness section reports estimates for the subsample of households that remained *in-situ*. With this approach, we estimate lower-bound effects by excluding all households that migrated out of their village and all households that shifted their location of residence within the village. Summary statistics for all variables are presented in Appendix A, Table A.18, in Supplementary Information.

Table 1 shows that erosion but not flood affectedness is related to increases in last month's migration aspirations on average. Erosion affectedness increases last month's migration aspirations by 22 percentage points (model 1, without controls or entropy balancing (EB) weights) to 16 percentage points (model 5, our preferred specification, with EB weights and controls). This effect is estimated to be statistically significant at the 1%-level. It is also

substantially highly relevant: Given the control group mean of 13 percentage points (see statistics for model 1), erosion affectedness leads to more than a doubling of migration aspirations (120%, model 5). Results are substantially similar, though slightly attenuated, for current aspirations (Table 2). For our preferred specification (model 5), we estimate the increase in aspirations to 12 percentage points (110% of control group mean).

Insert Table 1 and Table 2 about here

In the Supplementary Information, Tables A.2 and A.3 show the results for the covariates not displayed in models 4-6 of Tables 1 and 2. Both last month's (Table A.2) and current aspirations (Table A.3) increase significantly for men relative to women and decrease significantly and substantively as a respondent grows older relative to the baseline of 18 to 30 years old respondents. Both these relationships are in line with the literature. A higher number of children in the household is associated with higher last month's aspirations. One explanation for this could be that a larger household size increases the pressure to earn income, which might result in migration aspirations if the availability of work in the present location is limited.

Relative to a baseline of illiterate respondents, we observe a U-shaped relationship of education level to migration aspirations. While aspirations decrease among respondents who have some education (primary or secondary school completed), they increase for those who have completed higher education. The reason behind this could be that moderately educated respondents have multiple options *in situ* to change their income source when they experience environmental changes, whereas highly educated respondents are overqualified for the local job market and thus strive to move elsewhere for work. Both higher levels of place attachment and a larger amount of land owned decrease migration aspirations. This is not surprising, given that both variables can be seen as proxies for the ties which a respondent has to their current location. Lastly, respondents who indicated migration aspirations during the baseline survey in June 2021

(aspirations_present_all), show higher levels of aspirations at the time of the follow-up survey in January/February 2022.

Table 3 reports results by degree of affectedness. Strong self-reported affectedness of erosion increases last month's migration aspirations by 18 to 25 percentage points – with a similar interpretation as above. Similarly, moderate impacts increase migration aspirations, even though coefficients are slightly smaller (13 to 19 percentage points). Other types of impact result in substantively smaller effects (4 percentage points for model 5, our preferred specification, insignificant at conventional levels of statistical significance). By contrast, strong and moderate impacts of floods are not significantly related to migration aspirations. Notably, other impacts of floods (most frequently mentioned were difficulties with transport, reduced income, and reduced food intake), reduce last month's aspirations by 5 (model 6, our preferred specification, statistically insignificant) to 9 percentage points (model 3, significant at the 5%-level).[8] Results are substantively similar for current aspirations, Table 4. For erosion impact, as indicated by model 5, with decreasing affectedness, the relation with current migration aspirations becomes weaker: from 16 percentage points (strong impact) to 11 percentage points (some impact), while other impact is substantively not discernable from baseline respondents, who did not report any affectedness. For floods, effects are substantively small and statistically insignificant (model 6).[9]

Insert Table 3 and Table 4 about here

[8] These counterintuitive findings might also indicate that different impact categories are related to other potential confounders.

[9] Note that in model 1 and 3, strong flood impact is associated with substantively relevant, though statistically insignificant positive shifts in migration aspirations, while other flood impact is related to substantively relevant and statistically significant negative shifts in migration aspirations.

Finally, Tables 5 and 6 extend the picture and report the desired migration destination and duration, respectively, of those who indicated having migration aspirations.

Insert Table 5 and Table 6 about here

Being affected consistently increases the logit coefficients for aspirations to move to a rural destination, whereas for an urban destination, the coefficient reaches significance only for model 1 (relative to no aspiration). Flood affectedness is not significantly related to differences in the preferred migration destination. In terms of the aspired migration duration, erosion affectedness increases the logit coefficients for both aspirations for temporary and permanent moves (relative to no aspirations). Again, flood affectedness shows no significant relationship to the preferred migration duration.

Robustness tests

The robustness section Appendix A in the Supplementary Information presents additional evidence on four aspects, adding credibility to our proposed link between erosion affectedness and migration aspirations (and the inexistent link between flood affectedness and migration aspirations) as outlined above.

First, we present logit models for all estimates of the relationship between flood/erosion affectedness and last month's/current migration aspiration, as logit models are under certain conditions more appropriate for binary outcomes (Horrace & Oaxaca, 2006). As indicated in Tables A.4 to A.7, we derive substantively and statistically comparable results with this statistical set-up, indicating that our modeling choice does not affect our conclusions.

Second, as discussed in the research design section, our sample includes both migrants and non-migrants, imputing the aspirations of migrants with realized values. In order to also show a lower bound for the effect of affectedness on aspirations, we additionally estimate all models

excluding households that moved – i.e., all households which migrated permanently, temporarily, and even those that shifted their household location within the village. The corresponding results are presented in Tables A.8 to A.13. The general picture that emerges is that the erosion effects are attenuated. This is expected, given that we removed those households from the estimation for which migration aspirations were allegedly strongest, that is, they have materialized into actual moves. Notably, this attenuation is strongest for current aspirations (see Table A.8), i.e., when a respondent is directly asked whether (s)he would prefer to leave the village at this instant. We obtain no statistically discernable effect for erosion affectedness, and the coefficients are substantively close to zero (2 to 4 percentage points) in this case, and significant (at the 10%-level) for the simple OLS model only. For floods, the coefficients are of a similar magnitude, and throughout insignificant. However, this attenuation is only moderate for last month's aspirations. That is, when a respondent is asked whether (s)he had thought about migrating in the past month, erosion is still related to increased aspirations that are substantively relevant at 9 to 12 percentage points (which is substantial, with about a doubling of the control group mean of 10-12%), and statistically significant at least at the 5%-level. For floods, as in our main estimation models, the relationship is positive, but substantively much smaller (estimated to 1-4 percentage points) and statistically insignificant (see Table A.9). This picture holds for subgroups of the extent of erosion/flood impact – generally, stronger affectedness relates to stronger current aspirations. However, these relationships are not estimated at conventional levels of statistical significance (see Table A.10). Concerning last month's aspirations, erosion is linked to an increase in aspirations of about 15 to 17 percentage points for strong impact, and around 10-11 percentage points for some impact (at the 5% significance level). For floods, strong and some impact lead to increases in last month's aspirations of around 4 to 6 percentage points, once entropy balancing weights are included, where the effect for some impact is statistically significant at the 5%-level (see Table A.11). Also concerning destination and duration, our general findings hold: As indicated in Table

A.12, erosion affectedness is statistically significantly related to temporary *and* permanent migration aspirations. The link to temporary aspirations is stronger, though. Floods are, if anything, related to temporary aspirations. However, this effect is not statistically discernible in all models. As indicated in Table A.13, erosion affectedness is related to increased aspirations to rural, but not urban migrations (statistically significant, and independent of specification). For flood affectedness, no consistent pattern emerges.

Third, as our treatment is clustered at the village level, it might be a concern that not individual, but village level affectedness is driving the results. We show in Tables A.14 and A.15 that this is not the case. There, we add the extent of affectedness in the village level (percent of households reporting flood/erosion affectedness) as an additional explanatory factor. Notably, while this variable has a substantively relevant and statistically discernible effect on migration aspirations, individual household aspirations are still strongly affected by household-level exposure. This suggests an important venue for future research, that is, disentangling the potential effects of household and village level affectedness, where the former could be interpreted as realized, while the latter as potential risk of affectedness by environmental change.

Fourth, we re-estimate our main models with a specific recoding of aspirations to zero for all respondents who indicated that they wanted to change location but highlighted in the location-preference question that they would prefer to relocate within their own village. This reduces potential measurement error in our dependent variable, if households that do express aspirations for within-village mobility had erroneously indicated they have aspirations for out-of-village migration (due to a misunderstood question, for example). As reported in Tables A.16 and A.17, this does not substantively affect our results.

Discussion and Conclusion

Our study investigates how the perception of environmental changes, namely slow-onset riverbank erosion events and sudden-onset flood events affect migration aspirations. We argue that migration aspirations of affected households are considerably influenced by the type of the environmental event experienced and, in particular, by the impact, i.e., reversible versus irreversible impact, caused by the specific environmental event. We find that slow-onset events, i.e., riverbank erosion, affect last month's and current aspirations to a great extent, increasing these by 16 to 22 and 12 to 18 percentage points, respectively, compared to the control group without such experiences. These effects are substantively similar for strong and moderate impacts as compared to rather light affectedness of households by erosion. At the same time, sudden-onset events, i.e., floods, show no strong effect on migration aspirations *on average*. This indicates that the reversibility of damage, which we theorized as a relevant distinction between these events *on average* could drive responses, at least for aspirations at some temporal distance (4 to 6 months) to the event. However, while strong and moderate flooding impacts are not significantly related to migration, other impacts of floods, such as transportation difficulties and reduced income significantly reduce last month's migration aspirations.

This result might not be that surprising since in riverine environments like Bangladesh, small scale flooding is required to sustain the agricultural productivity, as sediment deposited by floodwater fertilizes fields. In other words, given the need for water to grow rice, which is the primary staple food and the most important crop in Bangladesh, natural flooding replaces artificial irrigation, which is time-consuming and costly to build. This implies that small floods should not exert any statistically significant influence on migration aspirations as flooding replenishes soil and nutrients to floodplains, making them ideal sites for agriculture. Furthermore, broader benefits even from extreme flooding could outweigh the short-term costs

by improving overall soil quality and yields in subsequent crop cycles, potentially increasing the opportunity cost of migration.[10]

Regarding the aspired destination, none of our respondents indicated an aspiration of an international move. This finding is not surprising given that the extant literature shows that environmental migration is mostly internal (Clement et al., 2021; Kumari Rigaud et al., 2018). Moreover, while flood affectedness is not significantly related to any preferred migration destination or duration, erosion affectedness increases aspirations to move both temporarily[11] and permanently, and predominantly to rural rather than to urban areas.[12]

Concerning the external validity of our findings, we have good reason to believe that our respondents constitute a high-quality sample of the riverbank population at risk of erosion in Bangladesh. To what extent our findings extend beyond the Bangladeshi context should be the subject of further research, and we hope that our study design can serve as a useful template for this. Having said that, it is worth noting that riverbank erosion and floods do not occur only along the Jamuna River and the other major rivers in Bangladesh but also along various major rivers worldwide (e.g. Mekong River, Yellow River, Mississippi River or Danube River), making the findings of our study relevant beyond the specific case study of Bangladesh. Hence, our case should also speak to related environmental changes such as sea-level rise, where populations try to cope and adapt to slowly changing, but long-lasting and permanent environmental changes, and where erosion/sea-level rise co-occurs with sudden-onset flood/storm events. That these populations can seemingly adapt by sustained proximate moves

[10] Indeed, recent studies from Bangladesh report either a negative relationship (Call et al. (2017); J. J. Chen et al. (2017)) or no effect (Lu et al. (2016)) of floods on migration. In particular, Lu et al. (2016) tracked population movements around the time Cyclone Mahasen stroke Bangladesh in 2013 using mobile phone network data and find that population flows were largely unchanged by this event, implying that no substantial migration took place.

[11] Temporal migration is a well-known adaptation strategy to economic stress (including environment-induced economic stress) of Bangladeshi households (Call et al. (2017)).

[12] The finding that erosion aspires rural and permanent moves is corroborated by the evidence provided by J. Chen and Mueller (2018), who show that in Bangladesh, soil salinity induces permanent migration, but mobility is restricted to certain locations mostly close to the affected areas. Kamal and Abedin (2019) also find that riverbank erosion leads to migration in India.

is a surprise finding, and it will be interesting to study whether there are potential tipping points when migration aspirations turn to more distant locations.

In terms of policy relevance, one of the core questions about migration aspirations is how many of those who aspire to migrate will indeed start moving. Linking aspirations to actual moves goes beyond the scope of this paper, and we will address this in future work. In our survey, however, we followed the three-step-approach suggested by Carling and Schewel (2018) and asked those respondents who expressed aspirations how likely it was that they would move within the upcoming twelve months, and if they had taken any concrete preparations. 55% of those who aspire to leave their village consider it likely or very likely that they will indeed move, and 20% have already made some preparations for the move, e.g., by buying land in another location. This decline in percentages from general aspirations to specific plans to concrete preparations is in line with other studies (e.g. OECD, 2015). Still, it highlights that those aspirations are not just about people's dreams under ideal conditions but will materialize into actual moves for a certain fraction. Consequently, aspirations might be a better indicator for policy needs than the actual, realized mobility outcome, especially since mobility outcomes do not tell us much about households' agency in the mobility decision and as a result, they tend to conflate aspirations and capabilities. Studying aspirations and their link to environmental changes is thus a worthwhile undertaking.

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Table 1: ***Last month's migration aspirations and erosion/flood affectedness (OLS models)***

	(1) Aspiration (past month)	(2) Aspiration (past month)	(3) Aspiration (past month)	(4) Aspiration (past month)	(5) Aspiration (past month)	(6) Aspiration (past month)
Erosion affected	0.22***	0.16***		0.18***	0.16***	
	(0.04)	(0.05)		(0.04)	(0.04)	
Flood affected	-0.01		-0.01	-0.02		-0.01
	(0.02)		(0.03)	(0.02)		(0.02)
Controls	No	No	No	Yes	Yes	Yes
N	1585	1271	1271	1271	1271	1271
Adj. R2	0.06	0.03	0.05	0.18	0.22	0.22
Mean erosion control group	0.13	0.19	0.26	0.13	0.19	0.26
SD erosion control group	0.34	0.39	0.44	0.34	0.39	0.44
Weights	No	Erosion	Flood	No	Erosion	Flood

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated (see Appendix A, Table A.2 for full display of results). Standard errors clustered by village. ** (***, *) indicates $p < 0.05$ (0.01, 0.10). Models 2 and 3 and 5 and 6 control for the respective other event that is not of primary interest for this regression (effect display omitted).

Table 2: ***Current migration aspirations and erosion/flood affectedness (OLS models)***

	(1) Aspiration (now)	(2) Aspiration (now)	(3) Aspiration (now)	(4) Aspiration (now)	(5) Aspiration (now)	(6) Aspiration (now)
Erosion affected	0.18***	0.12**		0.12***	0.12***	
	(0.04)	(0.05)		(0.04)	(0.04)	
Flood affected	0.00		0.00	-0.00		0.00
	(0.02)		(0.03)	(0.02)		(0.02)
Controls	No	No	No	Yes	Yes	Yes
N	1584	1270	1270	1270	1270	1270
Adj. R2	0.05	0.02	0.04	0.22	0.25	0.29
Mean erosion control group	0.11	0.18	0.22	0.11	0.18	0.22
SD erosion control group	0.32	0.38	0.41	0.32	0.38	0.41
Weights	No	Erosion	Flood	No	Erosion	Flood

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated (see Appendix A, Table A.3 for full display of results). Standard errors clustered by village. ** (***, *) indicates $p < 0.05$ (0.01, 0.10). Models 2 and 3 and 5 and 6 control for the respective other event that is not of primary interest for this regression (effect display omitted).

Table 3: ***Last month's migration aspirations and erosion/flood affectedness by impact category (OLS models)***

	(1) Aspiration (past month)	(2) Aspiration (past month)	(3) Aspiration (past month)	(4) Aspiration (past month)	(5) Aspiration (past month)	(6) Aspiration (past month)
Erosion: strong impact	0.25***	0.21***		0.21***	0.18**	
	(0.06)	(0.08)		(0.06)	(0.07)	
Erosion: some impact	0.19***	0.13***		0.17***	0.17***	
	(0.04)	(0.04)		(0.04)	(0.04)	
Erosion: other impact	0.15**	0.11		0.05	0.04	
	(0.07)	(0.08)		(0.07)	(0.07)	
Erosion: none reported	(ref)	(ref)		(ref)	(ref)	
	(.)	(.)		(.)	(.)	
Flood: strong impact	0.02		0.04	-0.05		-0.05
	(0.05)		(0.06)	(0.04)		(0.04)
Flood: some impact	0.01		-0.00	0.00		0.01
	(0.02)		(0.04)	(0.02)		(0.03)
Flood: other impact	-0.08**		-0.09**	-0.06*		-0.05
	(0.03)		(0.04)	(0.03)		(0.04)
Flood: none reported	(ref)		(ref)	(ref)		(ref)
	(.)		(.)	(.)		(.)
Flood affected		0.02			-0.00	
		(0.03)			(0.03)	
Erosion affected			0.20***			0.15***
			(0.05)			(0.04)
Controls	No	No	No	Yes	Yes	Yes
N	1585	1271	1271	1271	1271	1271
Adj. R2	0.06	0.03	0.06	0.18	0.22	0.22
Mean erosion control group	0.13	0.19	0.26	0.13	0.19	0.26
SD erosion control group	0.34	0.39	0.44	0.34	0.39	0.44
Weights	No	Erosion	Flood	No	Erosion	Flood

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ** (***, *) indicates $p < 0.05$ (0.01, 0.10).

Table 4: ***Current migration aspirations and erosion/flood affectedness by impact category (OLS models)***

	(1) Aspiration (now)	(2) Aspiration (now)	(3) Aspiration (now)	(4) Aspiration (now)	(5) Aspiration (now)	(6) Aspiration (now)
Erosion: strong impact	0.24***	0.20**		0.19***	0.16**	
	(0.06)	(0.08)		(0.06)	(0.08)	
Erosion: some impact	0.12***	0.07		0.10***	0.11***	
	(0.03)	(0.04)		(0.03)	(0.03)	
Erosion: other impact	0.15*	0.06		0.00	-0.00	
	(0.07)	(0.08)		(0.07)	(0.07)	
Erosion: none reported	(ref)	(ref)		(ref)	(ref)	
	(.)	(.)		(.)	(.)	
Flood: strong impact	0.06		0.09	-0.01		-0.01
	(0.06)		(0.06)	(0.05)		(0.05)
Flood: some impact	0.01		-0.00	0.01		0.00
	(0.02)		(0.04)	(0.02)		(0.03)
Flood: other impact	-0.05**		-0.07**	-0.03		-0.03
	(0.02)		(0.03)	(0.02)		(0.03)
Flood: none reported	(ref)		(ref)	(ref)		(ref)
	(.)		(.)	(.)		(.)
Flood affected		0.02			-0.01	
		(0.03)			(0.02)	
Erosion affected			0.15***			0.10***
			(0.05)			(0.03)
Controls	No	No	No	Yes	Yes	Yes
N	1584	1270	1270	1270	1270	1270
Adj. R2	0.05	0.02	0.04	0.22	0.26	0.29
Mean erosion control group	0.11	0.18	0.22	0.11	0.18	0.22
SD erosion control group	0.32	0.38	0.41	0.32	0.38	0.41
Weights	No	Erosion	Flood	No	Erosion	Flood

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ** (***, *) indicates $p < 0.05$ (0.01, 0.10).

Table 5: ***Destination of migration aspirations among those reporting these aspirations (multinomial logit models)***

	(1) asp_destin.	(2) asp_destin.	(3) asp_destin.	(4) asp_destin.	(5) asp_destin.	(6) asp_destin.
stay						
Erosion affected	(ref)	(ref)		(ref)	(ref)	
	(.)	(.)		(.)	(.)	
Flood affected	(ref)		(ref)	(ref)		(ref)
	(.)		(.)	(.)		(.)
rural						
Erosion affected	1.21***	0.95***		1.05***	1.12***	
	(0.17)	(0.24)		(0.20)	(0.21)	
Flood affected	0.00		0.08	-0.04		0.09
	(0.14)		(0.17)	(0.14)		(0.15)
urban						
Erosion affected	0.86***	0.15		0.45	0.35	
	(0.29)	(0.38)		(0.36)	(0.40)	
Flood affected	-0.07		-0.25	0.06		-0.06
	(0.21)		(0.44)	(0.29)		(0.35)
Controls	No	No	No	Yes	Yes	Yes
N	1566	1256	1256	1256	1256	1256
Pseudo R2	0.04	0.02	0.03	0.18	0.22	0.23
Mean erosion control group	0.20	0.30	0.36	0.20	0.30	0.36
SD erosion control group	0.49	0.60	0.61	0.49	0.60	0.61
Weights	No	Erosion	Flood	No	Erosion	Flood

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ** (***, *) indicates $p < 0.05$ (0.01, 0.10). Models 2 and 3 and 5 and 6 control for the respective other event that is not of primary interest for this regression (effect display omitted).

Table 6: ***Duration of migration aspirations among those reporting these aspirations (multinomial logit models)***

	(1) asp_durat.	(2) asp_durat.	(3) asp_durat.	(4) asp_durat.	(5) asp_durat.	(6) asp_durat.
stay						
Erosion affected	(ref)	(ref)		(ref)	(ref)	
	(.)	(.)		(.)	(.)	
Flood affected	(ref)		(ref)	(ref)		(ref)
	(.)		(.)	(.)		(.)
temporary						
Erosion affected	1.25***	0.87***		1.00***	1.12***	
	(0.26)	(0.30)		(0.34)	(0.34)	
Flood affected	0.00		0.05	-0.15		0.05
	(0.21)		(0.40)	(0.24)		(0.26)
permanent						
Erosion affected	1.08***	0.72**		0.88***	0.90***	
	(0.19)	(0.31)		(0.25)	(0.30)	
Flood affected	-0.05		-0.01	-0.01		0.03
	(0.16)		(0.17)	(0.17)		(0.16)
Controls	No	No	No	Yes	Yes	Yes
N	1566	1257	1257	1257	1257	1257
Pseudo R2	0.04	0.02	0.03	0.22	0.26	0.27
Mean erosion control group	0.28	0.38	0.48	0.28	0.38	0.48
SD erosion control group	0.66	0.74	0.80	0.66	0.74	0.80
Weights	No	Erosion	Flood	No	Erosion	Flood

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ** (***, *) indicates $p < 0.05$ (0.01, 0.10). Models 2 and 3 and 5 and 6 control for the respective other event that is not of primary interest for this regression (effect display omitted).

Methods and Protocols

The Case Study: Jamuna River in Bangladesh

Bangladesh is among the countries most susceptible to the adverse effects of climate change (Kumari Rigaud et al., 2018), due to its topography and its location in one of the largest river deltas of the world. Bangladesh is affected heavily by sea level rise, frequent cyclones, and high monsoon rainfall that increases river flow, which in turn contributes to extensive flooding and riverbank erosion (Hasan et al., 2018; M. A. Islam et al., 2021). The Intergovernmental Panel on Climate Change (IPCC, 2021a) predicts that all these climatic events will intensify in the future and will adversely affect people and their livelihoods by damaging their homesteads, agricultural land, and causing economic and social disruptions resulting in large migration flows (Kumari Rigaud et al., 2018). In Bangladesh, riverbank erosion and floods are the most impactful processes in terms of yearly damage (Ahmed, 2015).

Regarding riverbank erosion, around 20 out of 64 districts in the country are prone to erosion, which consumes around 8.700 ha of land each year and thereby affects around 200.000 people (G. M. M. Alam, 2017). While communities along the rivers are aware of erosion risks, yet people choose to settle next to rivers due to the high soil fertility and/or lack of other suitable space given the extreme population density in the country. Erosion (both coastal and riverbank) has several negative impacts on affected communities, including destruction of farmable land, housing, and infrastructure such as roads or schools. For example, along the 250 km long Jamuna River, our case study region, the net erosion was about 933 km² during the 1973-2017 period (CEGIS, 2018a).[13] This would

[13] Riverbank erosion occurs in two distinct but connected forms Grove et al. (2013): First, the flow of water continuously removes small amounts of sediment from the riverbank (*gradual erosion*). Second, if large patches of land become unstable, *mass wasting* occurs whereby up to several hundred square meters of land collapse into the river within days or weeks. While major mass wasting events occur during the rainy monsoon season (typically from June to October) primarily in hotspot areas, gradual erosion as well as smaller mass wasting events happen almost everywhere in the river system, including three major rivers, Jamuna, Ganges and Meghna.

correspond to an inland shift of the riverbank of more than four kilometers if the erosion were distributed equally along the river.

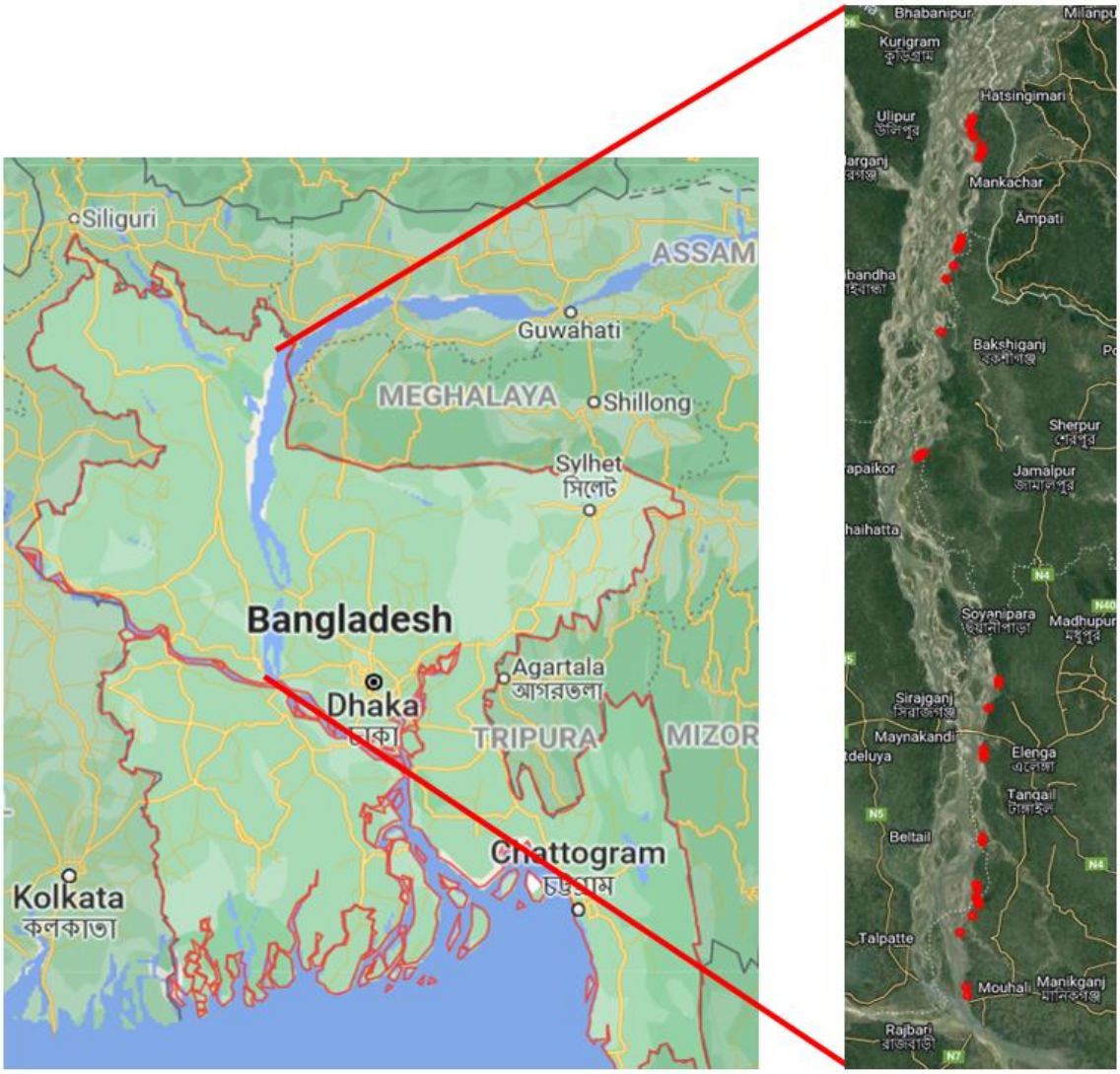
Concerning floods, they also occur mostly during the monsoon period, when water levels of the Jamuna River rise to a point where most land – and accordingly, most villages – on its riverbanks are flooded. This regular flooding has an important function in the livelihood cycle of riverine populations, providing humidity and nutrients for their agricultural plots. Only when a flood becomes too severe – either because the water rises too high or because it stays too long –, a flood may turn into a disaster which damages crops, houses or infrastructure (S. M. N. Alam, 1990). Riverbank erosion and flooding are closely linked, given that severe erosion typically occurs when the force of the flowing water increases during the monsoon season.

The impact of floods and erosion is not uniform along and across the river, but varies depending on local natural and anthropogenic characteristics such as elevation or embankments (Ferdous et al., 2018). These characteristics vary not only in space, but also in time, given that the Jamuna River is among the most dynamic river systems in the world (Oberhagemann et al., 2020). Lastly, variation also occurs between households in their ability to cope with environmental change. The populations residing next to the rivers have developed a range of coping strategies to minimize the damage resulting from floods and erosion (Paul & Routray, 2010). Since coping strategies are usually related to socio-economic status, not all households are equally capable of adopting these strategies.

Survey overview

For the empirical analysis, we use cross-sectional data on migration aspirations and exposure to environmental change from a panel survey of 1,594 household heads from 36 locations distributed along the whole length of the Jamuna River in Bangladesh (Fig S1).

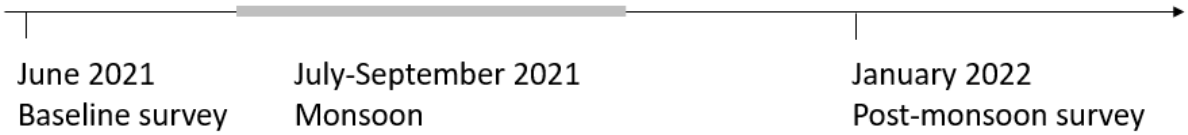
Figure S1: Overview of the 36 study locations



Copyright map: Google. Copyright satellite image: TerraMetrics, 2022

The survey data were collected between January and March 2022 and are supplemented by pre-exposure measures of time-variant respondent attitudes and household characteristics from a survey conducted in June 2021 of the very same respondents (Table S1). Interviews were conducted face-to-face in Bangla by native interviewers and lasted for about 45-60 minutes. The questionnaires included both closed and open-ended questions pertaining to respondents' experience with environmental events and migration as well as personal and household information.

Table S1: Timeline of survey waves and the monsoon season



We selected participants in a multi-stage cluster design. In the first stage, we selected 36 locations along the easternmost riverbank line of the Jamuna because the rates of riverbank erosion are higher along the eastern than along the western riverbank due to differences in floodplain materials (CEGIS, 2018b; Sarker et al., 2014). We identified this line using the most recent satellite imagery available. Villages on islands in the river (so-called *chars*) were not considered since *char* populations have adapted their livelihoods to the yearly recurring flood and erosion events (G. M. M. Alam et al., 2017; M. S. Islam et al., 2015).

Along this line, we started by defining 250 sampling points with a one-kilometer distance along the whole stretch of the river (from the border with India in the north to the convergence of Ganges and Jamuna in the south). Ideally, we would have drawn the 36 study locations randomly from this pool of 250 stretches. However, a visual, satellite-based analysis revealed that not all of these 250 stretches were suitable for our study purpose. Therefore, we evaluated each of the 250 stretches with respect to the following two criteria: First, survey feasibility, that is, whether there were enough settlements (= at least

75 houses) in the 200 m stretch inland. And second, the ex-ante risk for riverbank erosion, in particular, whether there was a clear indication of a permanent embankment structure that prevents erosion and whether there was a *char*/large sandbank in front of the stretch that blocks erosion.

Stretches for which the satellite analysis showed that at least one of these criteria was violated were excluded from the pool. This reduced the pool size from 250 to 79 stretches. For some of these 79 stretches, not all criteria could be clearly evaluated from the satellite images due to insufficient image resolution. Therefore, the final screening was done on the ground during a field visit. Six stretches could not be visited due to their remote location. Of the remaining 73 stretches, 30 were excluded after the field visit due to a violation of at least one of the three criteria. One stretch was used for training the enumerators, leaving 42 stretches suitable for our sample. Due to time constraints during the fieldwork, not all 42 stretches could be included in the sample. Therefore, we chose 36 stretches such that they were well distributed along the entire length of the Jamuna. Table S2 provides a list of all 79 stretches initially in the sample, including whether they were part of the final sample and – if not – the reason for their exclusion.

Table S2: List of 79 stretches initially in the sample. Coordinates refer to the midpoint of the respective stretch.

Site	Latitude	Longitude	District	Sampled	Reason for exclusion
1	23.84858386	89.77728293	Manikganj	Yes	
2	23.85741259	89.7761692	Manikganj		Suitable, excluded for time constraints
3	23.8659592	89.77336891	Manikganj	Yes	
4	23.8741437	89.7696434	Manikganj		Training site
5	23.88306306	89.76938992	Manikganj		Suitable, excluded for time constraints
6	23.89188075	89.77113454	Manikganj		Embankment
7	23.93977265	89.77300493	Manikganj		Not visited
8	23.96265272	89.75980911	Manikganj		Char/sandbank
9	23.971464	89.75801152	Manikganj		Char/sandbank
10	23.97946232	89.76071457	Manikganj	Yes	
11	23.98646574	89.76636763	Manikganj		Not enough settlement
12	23.99336663	89.77212095	Manikganj		Not enough settlement
13	24.00092974	89.77700303	Manikganj		Not enough settlement
14	24.0080967	89.78240531	Manikganj		Not enough settlement
15	24.01468743	89.78848452	Tangail	Yes	
16	24.01998107	89.79575917	Tangail		Not visited
17	24.02782786	89.79999907	Tangail		Not visited
18	24.03669272	89.80143637	Tangail	Yes	
19	24.04554666	89.80018357	Tangail	Yes	
20	24.05359151	89.79620979	Sirajganj	Yes	
21	24.06191619	89.79537304	Sirajganj		Not enough settlement; char/sandbank
22	24.07061319	89.79705522	Sirajganj	Yes	
23	24.07936755	89.79571167	Sirajganj	Yes	
24	24.08826802	89.79443957	Sirajganj		Not enough settlement; char/sandbank

25	24.09651555	89.79100124	Sirajganj		Char/sandbank
26	24.10416064	89.78625988	Sirajganj		Char/sandbank
27	24.11252358	89.78760715	Sirajganj		Not enough settlement; embankment
28	24.1199595	89.79245961	Sirajganj		Embankment
29	24.12686204	89.79824051	Sirajganj		Embankment
30	24.13388967	89.80382386	Sirajganj		Embankment
31	24.14197229	89.80777083	Sirajganj		Embankment
32	24.15055663	89.81028585	Tangail		Not enough settlement; embankment
33	24.15953767	89.81062441	Tangail		Suitable, excluded for time constraints
34	24.16836954	89.80947906	Tangail	Yes	
35	24.17727796	89.80949719	Tangail	Yes	
36	24.2295696	89.78659759	Tangail		Not visited
37	24.23854823	89.7860587	Tangail		Not visited
38	24.34224707	89.81162957	Tangail	Yes	
39	24.35117757	89.81254109	Tangail	Yes	
40	24.36017152	89.81221315	Tangail	Yes	
41	24.36889043	89.81040512	Tangail		Not enough settlement; embankment
42	24.38032687	89.8048785	Tangail		Embankment
43	24.43313402	89.8199736	Tangail		Char/sandbank
44	24.44195819	89.82141819	Tangail	Yes	
45	24.45047689	89.82397444	Tangail	Yes	
46	24.49471362	89.84519411	Tangail	Yes	
47	24.50358737	89.84590586	Tangail	Yes	
48	24.51181581	89.84245001	Tangail		Embankment
49	24.58706697	89.81975046	Jamalpur		Not enough settlement; embankment
50	24.59501471	89.81563181	Jamalpur		Not enough settlement; embankment
51	24.60315021	89.81184187	Jamalpur		Embankment
52	24.61077011	89.80728877	Jamalpur		Embankment

53	24.61961004	89.80620216	Jamalpur		Embankment
54	24.9010855	89.65554932	Bogra		Not visited
55	24.96551006	89.66537782	Bogra	Yes	
56	24.97114163	89.67177488	Bogra	Yes	
57	24.9745598	89.68009865	Jamalpur		Not enough settlement
58	24.98684177	89.69272319	Jamalpur		Not enough settlement
59	25.00071823	89.70405209	Jamalpur		Char/sandbank
60	25.21211443	89.72276084	Jamalpur		Not enough settlement
61	25.22079034	89.7204164	Jamalpur	Yes	
62	25.22963506	89.7196273	Jamalpur	Yes	
63	25.33554382	89.72866088	Gaibandha	Yes	
64	25.36243599	89.7450544	Jamalpur	Yes	
65	25.38816632	89.74946849	Kurigram		Suitable, excluded for time constraints
66	25.39617635	89.75357157	Kurigram	Yes	
67	25.40397791	89.75805218	Kurigram	Yes	
68	25.41161802	89.76276468	Kurigram	Yes	
69	25.42006097	89.76266573	Kurigram	Yes	
70	25.58524338	89.80014675	Kurigram	Yes	
71	25.59256635	89.80534785	Kurigram	Yes	
72	25.60067086	89.80889396	Kurigram	Yes	
73	25.60950232	89.80727078	Kurigram	Yes	
74	25.62799682	89.78911681	Kurigram	Yes	
75	25.63403951	89.78356735	Kurigram	Yes	
76	25.64292418	89.78384213	Kurigram	Yes	
77	25.65177817	89.78241922	Kurigram	Yes	
78	25.66053126	89.78367557	Kurigram	Yes	
79	25.66861671	89.78750184	Kurigram	Yes	

At each of the 36 locations, we sampled households using a stratified random spatial sampling design to survey households located within three zones defined by distance from the shoreline. This design allowed capturing potential effects of different ex-ante erosion risk levels on migration aspirations. We constructed the three zones at each location by shifting the shoreline inland by 50 m (high risk), 100 m (medium risk) and 200 m (low risk), respectively. Since the zones are narrow and there are no significant natural elevation differences within the study villages, we assume risk levels to be constant within each zone. The downstream extent of each zone was determined by the midpoint between the sampling location and the two closest points up- and down-stream, respectively. This implies that each sampling zone has an extent of 1 km in the direction of flow.

Within each of the three zones, we generated a spatially explicit sample following the procedure outlined by Crawford et al. (2020): We generated a set of 25 random latitude-longitude points per zone using ArcMap software (with a minimum distance of 10 m between points). In the field, enumerators navigated to these points using smartphones. Having arrived at the point, they selected the house closest to that point based on visual estimation. This household was subsequently interviewed. If a household declined participation or if the household head was not available at two contact attempts, the enumerator continued to the next closest household, in reference to the starting point. Within each household, the household head was interviewed, defined as the primary decision-maker within the household. Hence, we are confident that our respondents constitute a high-quality sample of the riverbank population at risk of erosion in Bangladesh.

Variables

We use two main dependent variables to capture migration aspirations (Carling and Collins (2018). The first, *current migration aspirations*, is a binary measure with a value of 1 if a respondent expresses a preference for migrating over remaining in the current location *right now* (0 otherwise), that is, at the time of the survey. The survey question asked: "Right now, if you could choose, would you stay here in your current location or would you prefer to move to another place?" with answer options "stay in this location" or "move to another place". While this is in principle what we want to capture, yet this measure can be highly volatile, depending on the mood of the day. Hence, we also ask about respondent's *last month's migration aspirations* (as advised by Carling and Collins (2018)), which are coded as a binary measure with a value of 1 if a respondent expresses that (s)he had thought about migrating during the last month. The question was stated as follows: "During the last month, have you thought seriously about leaving [location name]?" with answer options "yes" or "no". In additional analyses, we also use secondary dependent variables, namely the aspired duration (permanent vs. temporary) and the aspired destination (rural vs. urban). Specifically, we first asked: "Would you like to leave for a certain period of time or permanently with no intention of coming back?" with answer options "certain period of time" or "permanently with no intention of coming back", and then "Would you like to go to a city or to a village?" with answer options "city" or "village". Note that this question was preceded by a question for aspired international migration, to which none of the households answered "yes". The destination question was followed by a question about the name of the specific location the respondent aspired to move to, including whether the respondent aspired to move to the very same village. Although these more particular patterns of mobility aspirations are not the focus of this article, yet, we provide for additional analyses in the robustness section to exclude that these very specific aspirations to shift household location within the village are driving the effects (which they are not).

We operationalize treatment as a binary indicator of whether a household reported affectedness by flood/erosion in the previous monsoon season, i.e., four to six months prior to the survey. Specifically, we asked: “Did the erosion (flood) in 2021 have an impact on your household?” with answer options “yes” or “no”. Additional models subdivide affectedness by four degrees of severity. In particular, *Strong impact* is coded if the respondent reported: loss of house, permanent displacement, total loss of land; *medium impact*: damage to house, temporal displacement, partial loss of land, total loss of crop, death/disease of animals, loss of assets; *some impact*: partial loss of crop, decrease of soil quality, difficulties with transport, disease/injury of household members, reduced income, reduced food intake, mental health impacts, other impact/inconvenience; *no impact*: no impact reported.

We employ linear probability models to estimate the effects for current/last month’s aspirations. This facilitates the interpretation of coefficients, as the indicator of flood/erosion affectedness then can be directly understood as a percentage point in-/decrease of migration aspirations with affectedness. We report logistic regression models in the supplementary material (with fundamentally identical results). We draw on multinomial models to estimate effects for the categorical dependent variables duration and destination. Standard errors are clustered at the village-level, as the treatment clusters at this level (Abadie et al., 2017). We also used a more fine-grained approach of clustering at the zone-village level (with 85 clusters), as each village is divided into three zones (depending on proximity to the river (0-50, 50-100, 100+ meters)), hence clustering at the level where we sampled also within village. Standard errors were only marginally different with this approach (results available upon request).

Estimation Strategy and Causal identification

Identifying the causal effect of flood and erosion exposure on migration aspirations six months after these occurred is empirically challenging for three main reasons: First, migration aspirations, by definition, can only be measured for the population *in-situ* at the time of conducting the survey. However, wherever exposure-induced migration aspirations have already translated into actual migration, this leads to unobserved values for this migrated population, in turn introducing a downward bias to any estimates (Knox et al., 2020), if a positive relation between migration aspirations and actual migration is assumed. Second, as the causal path between erosion exposure and migration aspirations is complex, any control for post-treatment indicators of household characteristics or respondent attitudes might induce collider bias and/or the estimation of indirect effects (of conditioning on mediators) (Elwert & Winship, 2014). Third, additional variables might be related both to migration aspirations and erosion exposure, confounding the observed relationship. Below, we discuss how we deal with these issues.

Imputing migration aspirations for migrated population subsets

Concerning unobserved values for the population already migrated, there are two ways to deal with the potential sample selection bias introduced by this: A first possibility would start with the (reasonable) assumption that migration aspirations can only be positively correlated to actual migration behavior, and consequently, we have uni-directional bias. Jointly with knowledge on the size of the unobserved population, we could then derive bounds that correct for selection bias (Knox et al., 2020), or simply observe the naively estimated effect as a downwardly biased (and hence conservative) estimate. It would be even better if we could, as a second possibility, directly enrich the dataset with the unobserved outcomes of migrated individuals. This could allow for the estimation of the effects on a firmer basis, and it thus constitutes our preferred strategy. We are in the rare position of being able to take this latter route, as we know who resided in the study area before the monsoon onset. Importantly, we have measured all relevant indicators for these households at that time. As we also know the migration status

of these individuals and their households, we can impute migration aspirations for migrated respondents. For this, we assume that any respondent who actually migrated (hence, for whom we cannot measure migration aspirations at the time of the follow-up survey) would also hold migration aspirations at that time.[14] Following this second strategy hence allows us to estimate the relationship between exposure and aspirations without sampling bias. Additionally, with the first strategy, we can provide for the treatment effect on the subsample of households *not* moving, which gives us the lower bound for any treatment effect.

Post-treatment indicators

Any control for post treatment characteristics and attitudes of the survey household heads potentially introduces bias in two respects: Any control for mediators (variables on the causal pathway between exposure and aspirations) would control away these indirect linkages and lead to bias for our goal of estimating the total effect of exposure on aspirations. An example for such a mediator could be household wealth, which might be negatively affected by exposure, and in turn indirectly affect aspirations. Any control for colliders (i.e., factors that are directly affected by the independent *and* the dependent variable) similarly introduces bias in the observed association between exposure and erosion. An example here could be place attachment, which might potentially be suppressed by both migration aspirations and exposure to environmental change. We can circumvent all these issues by drawing, in all models that include any control variables, on pre-treatment measures of the control variables from the pre-monsoon survey. As these variables were measured before flood and erosion exposure, they are by definition unrelated to this exposure.[15]

[14] This assumption exactly stated, implies that: Had a household of the migrated subset not migrated, this household would hold migration aspirations in January/February 2022 (at the time of the survey). Obviously, this assumption is impossible to test. Still, the actual migration clearly indicates that a strong migration aspiration was there at some point between the two survey waves.
[15] Under the assumption of no structurally different anticipation effects between survey locations.

Endogeneity

The third crux for causally identifying changes in migration aspirations is whether occurrence of and degree of affectedness by floods or riverbank erosion correlates with pre-existing population attitudes. If so, the association between affectedness and aspirations could be mere confounding, an actual causal effect, or a mixture of both. Hence, causal claims require careful attention to potential confounders. As with most research on observational data, this is not a clear call. However, natural processes always have an element of inherent randomness – while prior risk of affectedness may ex-ante be unevenly distributed in space, the actual occurrence and extent of occurrence has quasi-random variation (given that it relies on a naturally generated process). We therefore propose that, by drawing on this exogenous element in erosion/flood-occurrence, conditional on observable covariates, we can try to isolate the causal effect. This would indicate that already the mere association between erosion/flood affectedness, the perception thereof, and migration aspirations has some causal interpretation – but only if erosion/flood perceptions are not strongly correlated to pre-existing population attitudes that also relate to aspirations. In Appendix A.1 in Supplementary Information, we discuss the potential for such selection effects. In short, we cannot exclude that a correlation between erosion/flood affectedness and pre-existing attitudes exists. Most importantly, and as expected, affectedness is unevenly distributed in space – even though it is important to keep in mind that we pre-selected study regions where all survey locations had a relevant risk of exposure. Pre-treatment differences on non-geographic pre-treatment indicators of socio-demographic conditions and migration behavior and aspirations are, assuredly, small, and largely non-significant. However, (as expected) some relationships between covariates (e.g., proximity to river, past aspirations, and place attachment) and later exposure are significant. We thus propose that considering selection into treatment, as a function of observable covariates (also known as the conditional independence assumption) improves the credibility of a causal interpretation of our estimates. Consequently, we match treatment and control group observations on pre-treatment measures of geographic, socio-demographic, and attitudinal variables at the individual and household levels. We use entropy balancing (Hainmueller, 2012) to achieve balance in the distribution of the first, second and third moments of these covariates for both the erosion control and treatment groups and the flood erosion

and treatment group. We assume that treatment status then is more plausibly assigned *as if random* for both floods and erosion.

As exposure to flood/erosion has a strong spatial component, we first draw on aggregate-level geographic confounders, namely district and distance to river (in three zones). Secondly, we also include potential individual-level predictors of migration aspirations (gender, age and education of household head, number of children, income source of household, wealth of households (based on land size, livestock units, as well as PCA indicators of asset ownership and house quality), risk attitudes, place attachment, migration history (binary) and past migration aspirations). By comparing households similar on these dimensions, we aim to address key aspects of remaining endogeneity. Appendix Table A.1 displays summary statistics for these variables by respective treatment and control group as well as differences-in-means between groups. Importantly, all these control variables have been measured pre-treatment, during the first survey wave in May/June 2021 (that is, before respondents experienced any environmental change[16]). This temporal structure of our measures is an important feature of our research design and improves over current cross-sectional studies. Many of these control variables could otherwise be directly or indirectly affected by the treatment and this would introduce bias into the estimated flood/erosion effect on migration aspirations. Lastly, we include reported flood exposure in the construction of the entropy balancing weights for erosion affectedness, and vice versa, as both events are likely correlated, and we are interested in the direct effects of these environmental changes.

Generally, the socio-demographic control variables have been selected based on other studies of individual-level migration aspirations. First, (household head) respondents' *age* and *sex* are included since younger individuals and men are more likely to possess migration aspirations, which could be explained by gender norms that favor men's income-earning work away from home (Migali & Scipioni, 2019; Ruyssen & Salomone, 2018). Sex is coded as 1 for males (0 otherwise). Second, we include the *number of dependent children* since children might dampen migration aspirations especially for women,

[16] We do not deem necessary to control for past exposure since we are not interested in the effects of compounding vs. singular environmental stress and assume that these disasters are not necessarily temporally related. In additional analyses, we include reported 2019 and 2020 flood as well as erosion exposure into the balancing and as control variable, without any change in the results presented in Tables 2 and 3 and A.8 and A.9 (results available upon request).

although desires to provide for children or to give them a better future might increase migration aspirations especially for men (Creighton, 2013; Migali & Scipioni, 2019). Number of dependent children is also an indicator of household size; we expect that individuals living in larger households have a higher propensity of aspiring to migrate since migration of a household member could assure income for the household through remittances (Cai et al., 2014). Fourth, *education* is proxied by years of schooling. Hence, we use a categorical indicator ranging from no education to higher education. Education should exert a positive influence on migration aspirations because migration is viewed as more achievable (Creighton, 2013; Migali & Scipioni, 2019). Fifth, the *socioeconomic status* of individuals and whether their income is dependent on the environment are likely to influence migration aspirations and the extent to which households are affected by (perceived) environmental changes – hence, we include the relation of respondents' occupation to potential environmental change as a readily available proxy to this end. Sixth, wealth of households is measured by land size, livestock ownership (measured in livestock units[17]) and the first component of a PCA on asset ownership as well as on the quality of housing construction materials.

We also include a variable indicating respondents' emotional connection to their place of residence, namely *place attachment*, which ranges from 1 (not attached at all) to 5 (very attached). Place attachment is generally stronger in rural than in urban areas because rural people deliberately choose their home or decide to stay based on factors other than the proximity to services and access to employment, such as culture and ancestors, which strengthen their sense of belonging (Lewicka, 2011). Past migration aspirations (binary variable), risk preferences (5-point Likert scale), and past migration history (binary variable) serve as additional proxies for the general mobility potential of households, irrespective of affectedness by the 2021 erosion/flood events.

[17] See https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Livestock_unit_(LSU).

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Supplementary Information

Appendix A

A.1 Balance tests

In order to analyze the relationship between environmental/climatic changes, namely riverbank erosion and floods, and migration aspirations, we have to assume (conditional) exogeneity of the occurrence of erosion and flood at the household level in relation to the household's migration aspirations (our core dependent variable). Table A.1 reports the mean of household heads in the control group C (no erosion (model 1) or no flood (model 2)) and treatment group T (erosion or flood reported), the difference in means (including their statistical significance based on two-sided t-tests) and the number of observations in each group.

Comparisons are conducted for geospatial factors (district the household is located in; zone the household is located in (i.e., distance to river pre-monsoon)), demographic characteristics, income-related characteristics and past migration behavior and past migration aspirations. We propose that this comparison captures the most important potential confounders.

As can be seen, both the erosion and the flood groups differ only in few respects – as it would be expected from a natural process such as erosion or floods which unsystematically affect households. However, a few notable differences can be discerned: First, some districts are more likely to be affected and, subsequently, also households within districts. We observe variation in all districts, though. Second, proximity to the river matters for erosion affectedness (though not for floods). Third, several of the pre-treatment measures of demographic or income-related variables are correlated (at the 5 or 1% level) with flood/erosion experience. Concerning erosion, we observe correlations with education, housing quality, place attachment, and migration aspirations. Concerning floods, we observe correlations with place attachment. However, given the large number of statistical tests, while some relationships might just be significant due to chance, still endogeneity cannot be excluded. Consequently, we infer that geographical location and socio-demographic covariates should be taken into account as potential confounders. Hence, we provide for cautionary estimates by matching the treatment and control groups for the distribution of these variables.

Table A.1: ***Balance tests (two-sided t-test) for control vs. treatment group for geographic and socio-demographic indicators by erosion affectedness (model 1) and flood affectedness (model 2)***

	(1) Erosion C/mean	T/mean	Diff-In-Means/se	N C	N T	(2) Flood C/mean	T/mean	Diff-In-Means/se	N C	N T
district==Kurigram	0.04	0.03	0.00 (0.01)	1071	521	0.04	0.03	0.01 (0.01)	821	770
district==Tangail	0.04	0.01	0.03*** (0.01)	1071	521	0.04	0.02	0.01* (0.01)	821	770
district==Manikganj	0.10	0.04	0.06*** (0.01)	1071	521	0.12	0.04	0.08*** (0.01)	821	770
district==Shirajganj	0.10	0.11	-0.02 (0.02)	1071	521	0.09	0.12	-0.03* (0.02)	821	770
district==Tangail	0.12	0.27	-0.15*** (0.02)	1071	521	0.12	0.22	-0.10*** (0.02)	821	770
district==Bogra	0.08	0.12	-0.05*** (0.02)	1071	521	0.10	0.09	0.01 (0.01)	821	770
district==Gaibandha	0.09	0.09	-0.00 (0.02)	1071	521	0.08	0.10	-0.01 (0.01)	821	770
district==Kurigram	0.44	0.31	0.13*** (0.03)	1071	521	0.41	0.39	0.02 (0.02)	821	770
zone==zone: 0 to 50m	0.30	0.32	-0.02	1050	504	0.31	0.30	0.01	804	749

			(0.02)					(0.02)		
zone==zone: 50 to 100m	0.30	0.35	-0.05*	1050	504	0.31	0.32	-0.01	804	749
			(0.03)					(0.02)		
zone==zone: 100 plus	0.41	0.34	0.07***	1050	504	0.38	0.38	-0.00	804	749
			(0.03)					(0.02)		
sex	0.88	0.89	-0.02	1071	521	0.88	0.88	0.00	821	770
			(0.02)					(0.02)		
age_cat==age: 18 to 30	0.12	0.12	-0.00	1069	520	0.12	0.11	0.01	820	768
			(0.02)					(0.02)		
age_cat==age: 31 to 40	0.26	0.26	0.00	1069	520	0.26	0.26	0.00	820	768
			(0.02)					(0.02)		
age_cat==age: 41 to 50	0.24	0.25	-0.01	1069	520	0.26	0.23	0.03	820	768
			(0.02)					(0.02)		
age_cat==age: 51 to 60	0.20	0.19	0.01	1069	520	0.18	0.22	-0.04*	820	768
			(0.02)					(0.02)		
age_cat==age: 61 plus	0.18	0.18	-0.00	1069	520	0.18	0.18	-0.00	820	768
			(0.02)					(0.02)		
kids_num==kids: 0	0.05	0.05	0.00	988	497	0.06	0.04	0.02*	755	729
			(0.01)					(0.01)		
kids_num==kids: 1 to 2	0.31	0.28	0.03	988	497	0.31	0.29	0.02	755	729
			(0.03)					(0.02)		

kids_num==kids: 3 to 5	0.51	0.54	-0.04 (0.03)	988	497	0.50	0.54	-0.04 (0.03)	755	729
kids_num==kids: 6 plus	0.13	0.12	0.01 (0.02)	988	497	0.13	0.13	-0.00 (0.02)	755	729
education==edu: illiterate	0.59	0.64	-0.05** (0.03)	1070	521	0.58	0.62	-0.04* (0.02)	821	769
education==edu: signature	0.17	0.12	0.05*** (0.02)	1070	521	0.16	0.15	0.02 (0.02)	821	769
education==edu: some primary	0.12	0.13	-0.01 (0.02)	1070	521	0.12	0.12	0.00 (0.02)	821	769
education==edu: primary compl.	0.04	0.03	0.01 (0.01)	1070	521	0.05	0.04	0.01 (0.01)	821	769
education==edu: secondary compl.	0.04	0.04	-0.00 (0.01)	1070	521	0.04	0.04	0.00 (0.01)	821	769
education==edu: higher	0.04	0.03	0.00 (0.01)	1070	521	0.04	0.03	0.01 (0.01)	821	769
income_source == income: dep. on env.	0.43	0.41	0.02 (0.03)	1055	514	0.44	0.40	0.04 (0.02)	810	758
income_source == income: indep. on env.	0.54	0.56	-0.02 (0.03)	1055	514	0.53	0.56	-0.03 (0.03)	810	758
income_source ==	0.02	0.03	-0.01	1055	514	0.02	0.03	-0.00	810	758

income: other			(0.01)					(0.01)		
income_source == income: none	0.01	0.01	0.00 (0.00)	1055	514	0.01	0.01	-0.00 (0.00)	810	758
land size	0.22	0.25	-0.03 (0.06)	1042	503	0.24	0.21	0.03 (0.05)	795	749
housing quality (pca)	6.40	6.26	0.14** (0.06)	993	477	6.34	6.37	-0.03 (0.06)	761	708
livestock units	0.53	0.57	-0.04 (0.03)	1046	514	0.55	0.53	0.03 (0.02)	803	756
assets (pca)	0.59	0.63	-0.04 (0.06)	988	497	0.63	0.57	0.06 (0.05)	755	729
risk preference (1-5)	3.40	3.48	-0.08 (0.07)	1054	518	3.43	3.42	0.02 (0.07)	809	762
place attachement (1-5)	4.36	4.17	0.19*** (0.04)	1071	521	4.37	4.23	0.14*** (0.04)	821	770
past migration (0-1)	0.24	0.26	-0.02 (0.02)	987	496	0.26	0.23	0.03 (0.02)	753	729
migration aspirations	0.19	0.29	-0.10*** (0.02)	1071	521	0.21	0.24	-0.03 (0.02)	821	770
Observations	1592					1591				

Sample: HH that did and did not move within 6 months after potential exposure. All variables measured pre-treatment (May/June 2021). * 0.10 ** 0.05 *** 0.01

A.2 Additional results

Table A.2: ***Past migration aspirations and erosion/flood affectedness (OLS models. Full results.)***

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)
Erosion affected	0.22***	0.16***	0.21***	0.18***	0.16***	0.16***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Flood affected	-0.01	0.02	-0.01	-0.02	-0.01	-0.01
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
Manikganj				0.00	0.00	0.00
				(.)	(.)	(.)
Shirajganj				0.17	0.21	0.18
				(0.15)	(0.17)	(0.17)
Tangail				0.03	0.11*	0.06
				(0.06)	(0.06)	(0.06)
Bogra				0.05	0.04	0.08
				(0.09)	(0.11)	(0.10)
Gaibandha				0.06	0.03	0.00
				(0.07)	(0.06)	(0.08)
Kurigram				0.05	0.08	0.06
				(0.05)	(0.06)	(0.06)
zone: 0 to 50m				0.00	0.00	0.00
				(.)	(.)	(.)
zone: 50 to 100m				-0.01	0.01	-0.03
				(0.04)	(0.05)	(0.06)
zone: 100 plus				0.02	0.05	0.01
				(0.03)	(0.04)	(0.04)
female				0.00	0.00	0.00
				(.)	(.)	(.)

male				0.06	0.11**	0.07
				(0.04)	(0.05)	(0.05)
age: 18 to 30				0.00	0.00	0.00
				(.)	(.)	(.)
age: 31 to 40				-0.03	-0.06	-0.02
				(0.04)	(0.05)	(0.06)
age: 41 to 50				-0.03	-0.06	-0.06
				(0.04)	(0.05)	(0.05)
age: 51 to 60				-0.08*	-0.17***	-0.09
				(0.05)	(0.06)	(0.06)
age: 61 plus				-0.06	-0.15**	-0.12*
				(0.04)	(0.06)	(0.06)
kids: 0				0.00	0.00	0.00
				(.)	(.)	(.)
kids: 1 to 2				0.08*	0.14**	0.10
				(0.04)	(0.06)	(0.06)
kids: 3 to 5				0.08	0.17*	0.12
				(0.06)	(0.08)	(0.08)
kids: 6 plus				0.09	0.19**	0.14
				(0.06)	(0.08)	(0.09)
edu: illiterate				0.00	0.00	0.00
				(.)	(.)	(.)
edu: signature				-0.02	-0.05	-0.04
				(0.03)	(0.04)	(0.04)
edu: some primary				0.02	0.02	0.10
				(0.05)	(0.06)	(0.07)

edu: primary compl.				-0.06	-0.17**	-0.12
				(0.04)	(0.08)	(0.07)
edu: secondary compl.				-0.08**	-0.06	-0.06
				(0.03)	(0.04)	(0.05)
edu: higher				0.06	0.11	0.08
				(0.06)	(0.07)	(0.07)
income: dep. on env.				0.00	0.00	0.00
				(.)	(.)	(.)
income: indep. on env.				-0.02	-0.01	-0.00
				(0.02)	(0.04)	(0.02)
income: other				-0.02	0.03	0.06
				(0.07)	(0.09)	(0.08)
income: none				0.02	-0.14	-0.02
				(0.12)	(0.14)	(0.07)
place attachement (1-5)				-0.15***	-0.18***	-0.17***
				(0.01)	(0.01)	(0.02)
past migration (0-1)				0.01	-0.01	-0.01
				(0.03)	(0.03)	(0.04)
aspirations_ past				0.02	0.01	0.02
				(0.03)	(0.04)	(0.04)
aspirations_ present_all				0.08*	0.08*	0.06
				(0.04)	(0.04)	(0.06)

risk preference (1-5)				-0.00	-0.00	-0.01
				(0.01)	(0.01)	(0.01)
land size				-0.02**	-0.02**	-0.03**
				(0.01)	(0.01)	(0.01)
housing quality (pca)				-0.01	-0.03	-0.02
				(0.01)	(0.02)	(0.02)
livestock units				-0.02	-0.01	-0.01
				(0.02)	(0.03)	(0.03)
assets (pca)				-0.01	-0.01	-0.01
				(0.01)	(0.01)	(0.01)
Constant	0.14***	0.18***	0.16***	0.75***	0.86***	0.84***
	(0.02)	(0.04)	(0.02)	(0.11)	(0.16)	(0.13)
N	1585	1271	1271	1271	1271	1271
r2_a	0.06	0.03	0.05	0.18	0.22	0.22
control_mean	0.13	0.19	0.26	0.13	0.19	0.26
control_sd	0.34	0.39	0.44	0.34	0.39	0.44
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did and did not move within 6 months, i.e. recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ** (***, *) indicates $p < 0.05$ (0.01, 0.10).

Table A.3: ***Present migration aspirations and erosion/flood affectedness (OLS models. Full results.)***

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)
Erosion affected	0.18***	0.12**	0.16***	0.12***	0.12***	0.10***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Flood affected	0.00	0.02	0.00	-0.00	-0.01	0.00
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
Manikganj				0.00	0.00	0.00
				(.)	(.)	(.)
Shirajganj				0.13	0.16	0.16
				(0.11)	(0.14)	(0.13)
Tangail				0.01	0.08*	0.03
				(0.04)	(0.04)	(0.06)
Bogra				-0.04	-0.07	-0.02
				(0.05)	(0.08)	(0.08)
Gaibandha				-0.02	-0.05	-0.06
				(0.04)	(0.03)	(0.05)
Kurigram				-0.03	-0.03	-0.04
				(0.04)	(0.05)	(0.06)
zone: 0 to 50m				0.00	0.00	0.00
				(.)	(.)	(.)
zone: 50 to 100m				0.01	0.02	0.01
				(0.03)	(0.04)	(0.05)
zone: 100 plus				0.03	0.06*	0.02
				(0.03)	(0.03)	(0.03)
female				0.00	0.00	0.00
				(.)	(.)	(.)
male				0.08**	0.08*	0.11**

				(0.03)	(0.04)	(0.05)
age: 18 to 30				0.00	0.00	0.00
				(.)	(.)	(.)
age: 31 to 40				-0.03	-0.07	-0.02
				(0.04)	(0.06)	(0.05)
age: 41 to 50				-0.03	-0.09	-0.06
				(0.04)	(0.06)	(0.04)
age: 51 to 60				-0.09**	-0.18***	-0.11**
				(0.04)	(0.06)	(0.05)
age: 61 plus				-0.10**	-0.19**	-0.16***
				(0.04)	(0.07)	(0.04)
kids: 0				0.00	0.00	0.00
				(.)	(.)	(.)
kids: 1 to 2				0.07*	0.14*	0.05
				(0.04)	(0.07)	(0.06)
kids: 3 to 5				0.08*	0.15**	0.07
				(0.05)	(0.07)	(0.06)
kids: 6 plus				0.09*	0.22***	0.10
				(0.05)	(0.07)	(0.07)
edu: illiterate				0.00	0.00	0.00
				(.)	(.)	(.)
edu: signature				-0.05	-0.07*	-0.07
				(0.03)	(0.04)	(0.04)
edu: some primary				0.04	0.01	0.03
				(0.04)	(0.06)	(0.05)

edu: primary compl.				-0.04	-0.12	-0.10
				(0.05)	(0.08)	(0.07)
edu: secondary compl.				0.00	-0.04	-0.02
				(0.05)	(0.05)	(0.05)
edu: higher				0.08	0.12**	0.08
				(0.05)	(0.06)	(0.06)
income: dep. on env.				0.00	0.00	0.00
				(.)	(.)	(.)
income: indep. on env.				0.01	0.02	0.00
				(0.02)	(0.03)	(0.02)
income: other				0.01	0.05	0.04
				(0.07)	(0.09)	(0.08)
income: none				0.05	-0.08	0.00
				(0.11)	(0.13)	(0.07)
place attachement (1-5)				-0.18***	-0.19***	-0.20***
				(0.01)	(0.02)	(0.02)
past migration (0-1)				0.00	-0.01	0.01
				(0.02)	(0.03)	(0.03)
aspirations _past				-0.01	-0.04	-0.02
				(0.03)	(0.04)	(0.03)
aspirations _present_all				0.06*	0.08**	0.03

				(0.03)	(0.04)	(0.04)
risk preference (1-5)				0.01	0.00	0.00
				(0.01)	(0.01)	(0.01)
land size				-0.01*	-0.02**	-0.02**
				(0.01)	(0.01)	(0.01)
housing quality (pca)				-0.01	-0.03	-0.02
				(0.01)	(0.02)	(0.02)
livestock units				0.00	0.02	0.02
				(0.02)	(0.02)	(0.03)
assets (pca)				-0.02*	-0.01	-0.01
				(0.01)	(0.01)	(0.01)
Constant	0.11***	0.16***	0.13***	0.80***	0.97***	1.01***
	(0.01)	(0.03)	(0.02)	(0.09)	(0.14)	(0.13)
N	1584	1270	1270	1270	1270	1270
r2_a	0.05	0.02	0.04	0.22	0.25	0.29
control_mean	0.11	0.18	0.22	0.11	0.18	0.22
control_sd	0.32	0.38	0.41	0.32	0.38	0.41
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

A.3 Robustness

A.3.1 Logit estimation

Table A.4: Logit models for past migration aspirations, full sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)
Erosion affected	1.28***	0.84***	1.13***	1.12***	1.08***	1.03***
	(0.17)	(0.25)	(0.22)	(0.21)	(0.24)	(0.24)
Flood affected	-0.06	0.11	-0.05	-0.08	-0.02	-0.02
	(0.13)	(0.16)	(0.18)	(0.13)	(0.17)	(0.16)
Controls	No	No	No	Yes	Yes	Yes
N	1585	1271	1271	1271	1271	1271
r2_p	0.06	0.03	0.05	0.19	0.22	0.22
control_mean	0.13	0.19	0.26	0.13	0.19	0.26
control_sd	0.34	0.39	0.44	0.34	0.39	0.44
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate $p < 0.01, 0.05, 0.10$.

Table A.5: Logit models for present migration aspirations, full sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)
Erosion affected	1.17***	0.66**	1.00***	0.86***	0.84***	0.74***
	(0.19)	(0.28)	(0.24)	(0.25)	(0.29)	(0.26)
Flood affected	0.02	0.12	0.00	0.02	-0.04	0.06
	(0.14)	(0.19)	(0.21)	(0.16)	(0.19)	(0.19)
Controls	No	No	No	Yes	Yes	Yes
N	1584	1270	1270	1270	1270	1270
r2_p	0.05	0.02	0.04	0.24	0.26	0.30
control_mean	0.11	0.18	0.22	0.11	0.18	0.22
control_sd	0.32	0.38	0.41	0.32	0.38	0.41
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

Table A.6: Logit models for past migration aspirations, full sample, by impact extent

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)
Aspiration (past month)						
strong impact	1.40***	1.03***		1.27***	1.13***	
	(0.28)	(0.36)		(0.32)	(0.41)	
some impact	1.14***	0.71***		1.12***	1.15***	
	(0.18)	(0.23)		(0.24)	(0.23)	
other impact	0.94***	0.58		0.38	0.37	
	(0.33)	(0.37)		(0.37)	(0.39)	
missing	0.00	0.00		0.00	0.00	
	(.)	(.)		(.)	(.)	
strong impact	0.08		0.20	-0.30		-0.33
	(0.27)		(0.28)	(0.23)		(0.22)
some impact	0.05		-0.00	0.05		0.08
	(0.15)		(0.20)	(0.14)		(0.17)
other impact	-0.63*		-0.67*	-0.48		-0.41
	(0.33)		(0.35)	(0.31)		(0.34)
missing	0.00		0.00	0.00		0.00
	(.)		(.)	(.)		(.)

Flood affected		0.11			0.01	
		(0.16)			(0.17)	
Erosion affected			1.09***			1.02***
			(0.23)			(0.24)
Controls	No	No	No	Yes	Yes	Yes
N	1585	1271	1271	1271	1271	1271
r2_a						
control_mean	0.13	0.19	0.26	0.13	0.19	0.26
control_sd	0.34	0.39	0.44	0.34	0.39	0.44
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

Table A.7: Logit models for present migration aspirations, full sample, by impact extent

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)
Aspiration (now)						
strong impact	1.42***	1.01**		1.25***	1.08**	
	(0.31)	(0.39)		(0.39)	(0.47)	
some impact	0.88***	0.39		0.74***	0.78***	
	(0.19)	(0.24)		(0.25)	(0.25)	
other impact	0.99***	0.38		0.05	0.06	
	(0.38)	(0.47)		(0.49)	(0.53)	
missing	0.00	0.00		0.00	0.00	
	(.)	(.)		(.)	(.)	
strong impact	0.31		0.47	-0.11		-0.12
	(0.30)		(0.30)	(0.35)		(0.32)
some impact	0.08		-0.01	0.10		0.10
	(0.17)		(0.24)	(0.18)		(0.22)
other impact	-0.42*		-0.59**	-0.21		-0.22
	(0.21)		(0.26)	(0.24)		(0.27)
missing	0.00		0.00	0.00		0.00
	(.)		(.)	(.)		(.)

Flood affected		0.13			0.01	
		(0.19)			(0.17)	
Erosion affected			0.95***			0.74***
			(0.24)			(0.25)
Controls	No	No	No	Yes	Yes	Yes
N	1584	1270	1270	1270	1270	1270
r2_a						
control_mean	0.11	0.18	0.22	0.11	0.18	0.22
control_sd	0.32	0.38	0.41	0.32	0.38	0.41
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate $p < 0.01, 0.05, 0.10$.

A.3.2 Reduced sample

Table A.8: OLS models for present migration aspirations, reduced sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)
Erosion affected	0.04*	0.02	0.02	0.02	0.02	0.02
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Flood affected	0.02	0.04	0.03	0.02	0.02	0.03
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Controls	No	No	No	Yes	Yes	Yes
N	1309	1040	1040	1040	1040	1040
r2_a	0.01	0.00	0.00	0.02	0.05	0.03
control_mean	0.08	0.10	0.08	0.08	0.10	0.08
control_sd	0.27	0.30	0.27	0.27	0.30	0.27
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did not move within 6 months, i.e., excluding temporary and permanent migrants, as well as households that 'shifted' within village. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

Table A.9: OLS models for past migration aspirations, reduced sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)
Erosion affected	0.12***	0.11***	0.09**	0.11***	0.11***	0.09**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Flood affected	0.01	0.05	0.04	0.01	0.03	0.04
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Controls	No	No	No	Yes	Yes	Yes
N	1308	1039	1039	1039	1039	1039
r2_a	0.03	0.02	0.02	0.04	0.07	0.04
control_mean	0.10	0.11	0.12	0.10	0.11	0.12
control_sd	0.30	0.31	0.32	0.30	0.31	0.32
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did not move within 6 months, i.e., excluding temporary and permanent migrants, as well as households that 'shifted' within village. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

Table A.10: OLS models for present migration aspirations, reduced sample, by impact extent

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)
strong impact	0.06	0.04		0.03	0.03	
	(0.05)	(0.06)		(0.06)	(0.05)	
some impact	0.02	0.01		0.01	0.01	
	(0.02)	(0.03)		(0.03)	(0.03)	
other impact	0.10	0.04		0.01	0.02	
	(0.06)	(0.08)		(0.07)	(0.07)	
missing	0.00	0.00		0.00	0.00	
	(.)	(.)		(.)	(.)	
strong impact	0.04		0.07	0.04		0.04
	(0.05)		(0.07)	(0.06)		(0.06)
some impact	0.03		0.03	0.03		0.03
	(0.02)		(0.03)	(0.02)		(0.03)
other impact	-0.01		-0.02	-0.01		-0.01
	(0.02)		(0.03)	(0.02)		(0.03)
missing	0.00		0.00	0.00		0.00
	(.)		(.)	(.)		(.)

Flood affected		0.04			0.02	
		(0.03)			(0.03)	
Erosion affected			0.01			0.01
			(0.03)			(0.03)
Controls	No	No	No	Yes	Yes	Yes
N	1309	1040	1040	1040	1040	1040
r2_a	0.01	0.00	0.00	0.02	0.05	0.03
control_mean	0.08	0.10	0.08	0.08	0.10	0.08
control_sd	0.27	0.30	0.27	0.27	0.30	0.27
Weights_flood	No	No	Yes	No	No	Yes
Weights_erosion	No	Yes	No	No	Yes	No

Sample: HH that did not move within 6 months, i.e., excluding temporary and permanent migrants, as well as households that 'shifted' within village. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

Table A.11: OLS models for past migration aspirations, reduced sample, by impact extent

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)
strong impact	0.17***	0.16***		0.15***	0.15**	
	(0.06)	(0.06)		(0.05)	(0.06)	
some impact	0.11***	0.10**		0.10**	0.11**	
	(0.03)	(0.04)		(0.04)	(0.04)	
other impact	0.11*	0.11		0.07	0.09	
	(0.06)	(0.08)		(0.06)	(0.06)	
missing	0.00	0.00		0.00	0.00	
	(.)	(.)		(.)	(.)	
strong impact	0.00		0.05	0.00		0.04
	(0.04)		(0.04)	(0.05)		(0.06)
some impact	0.03		0.06*	0.03		0.06**
	(0.02)		(0.03)	(0.02)		(0.03)
other impact	-0.04		-0.02	-0.04		-0.01
	(0.04)		(0.04)	(0.03)		(0.04)
missing	0.00		0.00	0.00		0.00
	(.)		(.)	(.)		(.)

Flood affected		0.05			0.03	
		(0.03)			(0.03)	
Erosion affected			0.08**			0.08**
			(0.04)			(0.04)
Controls	No	No	No	Yes	Yes	Yes
N	1308	1039	1039	1039	1039	1039
r2_a	0.03	0.02	0.02	0.04	0.07	0.04
control_mean	0.10	0.11	0.12	0.10	0.11	0.12
control_sd	0.30	0.31	0.32	0.30	0.31	0.32
Weights_flood	No	No	Yes	No	No	Yes
Weights_erosion	No	Yes	No	No	Yes	No

Sample: HH that did not move within 6 months, i.e., excluding temporary and permanent migrants, as well as households that 'shifted' within village. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

Table A.12: Multinomial logit for destination, reduced sample

	(1)	(2)	(3)	(4)	(5)	(6)
	asp_destination	asp_destination	asp_destination	asp_destination	asp_destination	asp_destination
stay						
Erosion affected	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)
Flood affected	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)
rural						
Erosion affected	0.78***	0.67**	0.61**	0.75***	0.81***	0.67**
	(0.19)	(0.27)	(0.25)	(0.27)	(0.27)	(0.27)
Flood affected	0.15	0.35	0.26	0.14	0.18	0.28
	(0.17)	(0.26)	(0.22)	(0.16)	(0.22)	(0.21)
urban						
Erosion affected	0.43	0.36	-0.04	0.23	0.40	-0.03
	(0.30)	(0.36)	(0.37)	(0.41)	(0.49)	(0.46)
Flood affected	-0.06	0.46	0.20	0.11	0.59	0.32
	(0.36)	(0.54)	(0.43)	(0.50)	(0.65)	(0.46)
Controls	No	No	No	Yes	Yes	Yes
N	1293	1027	1027	1027	1027	1027
r2_p	0.02	0.02	0.01	0.11	0.14	0.11
control_mean	0.15	0.16	0.17	0.15	0.16	0.17
control_sd	0.42	0.43	0.43	0.42	0.43	0.43
Weights_erosio	No	Yes	No	No	Yes	No

n						
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did not move within 6 months, i.e., excluding temporary and permanent migrants, as well as households that 'shifted' within village. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate $p < 0.01, 0.05, 0.10$.

Table A.13: Multinomial logit for duration, reduced sample

	(1)	(2)	(3)	(4)	(5)	(6)
	asp_duration	asp_duration	asp_duration	asp_duration	asp_duration	asp_duration
stay						
Erosion affected	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)
Flood affected	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)
temporary						
Erosion affected	1.21***	1.59**	0.89	1.39**	1.91***	0.92
	(0.47)	(0.66)	(0.56)	(0.56)	(0.72)	(.)
Flood affected	0.22	1.03***	0.81**	0.33	1.17*	0.84
	(0.34)	(0.39)	(0.32)	(0.36)	(0.63)	(.)
permanent						
Erosion affected	0.63***	0.50*	0.44*	0.57**	0.59**	0.52
	(0.18)	(0.26)	(0.27)	(0.28)	(0.26)	(.)
Flood affected	0.09	0.30	0.18	0.11	0.10	0.20
	(0.19)	(0.30)	(0.26)	(0.19)	(0.23)	(.)
Controls	No	No	No	Yes	Yes	Yes
N	1294	1029	1029	1029	1029	1029
r2_p	0.02	0.03	0.01	0.12	0.19	0.13
control_mean	0.24	0.26	0.28	0.24	0.26	0.28
control_sd	0.64	0.66	0.69	0.64	0.66	0.69
Weights_erosio	No	Yes	No	No	Yes	No

n						
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did not move within 6 months, i.e., excluding temporary and permanent migrants, as well as households that 'shifted' within village. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate $p < 0.01, 0.05, 0.10$.

A.3.3 Village level affectedness

Table A.14: OLS models for present migration aspirations, full sample, controlling for village level affectedness

	(1)	(2)	(3)	(4)
	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)
Erosion affected	0.11***	0.05	0.11***	0.05*
	(0.03)	(0.03)	(0.03)	(0.03)
Flood affected	-0.00	-0.00	-0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Erosion: HH affected in %	0.26**	0.34***		
	(0.09)	(0.09)		
Flood: HH affected in %	-0.04	-0.17		
	(0.09)	(0.11)		
affected: below 25%			0.00	0.00
			(.)	(.)
affected: 25 to 50%			0.02	-0.01
			(0.03)	(0.05)
affected: above 50%			0.14**	0.20***
			(0.06)	(0.06)
affected: below 25%			0.00	0.00

			(.)	(.)
affected: 25 to 50%			-0.04	-0.07**
			(0.03)	(0.03)
affected: above 50%			-0.00	-0.06
			(0.04)	(0.05)
Controls	No	Yes	No	Yes
N	1584	1270	1584	1270
r2_a	0.07	0.24	0.07	0.24
control_mean	0.10	0.10	0.10	0.10
control_sd	0.31	0.31	0.31	0.31
Weights	No	No	No	No

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

Table A.15: OLS models for past migration aspirations, full sample, controlling for village level affectedness

	(1)	(2)	(3)	(4)
	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)
Erosion affected	0.13***	0.08**	0.14***	0.09**
	(0.03)	(0.03)	(0.03)	(0.04)
Flood affected	-0.01	-0.01	-0.02	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Erosion: HH affected in %	0.32***	0.45***		
	(0.10)	(0.12)		
Flood: HH affected in %	-0.05	-0.25*		
	(0.10)	(0.13)		
affected: below 25%			0.00	0.00
			(.)	(.)
affected: 25 to 50%			0.07	0.05
			(0.05)	(0.08)
affected: above 50%			0.19***	0.26**
			(0.07)	(0.10)
affected: below 25%			0.00	0.00
			(.)	(.)

affected: 25 to 50%			0.01	-0.01
			(0.03)	(0.05)
affected: above 50%			0.00	-0.08
			(0.05)	(0.06)
Controls	No	Yes	No	Yes
N	1585	1271	1585	1271
r2_a	0.09	0.21	0.08	0.21
control_mean	0.12	0.12	0.12	0.12
control_sd	0.32	0.32	0.32	0.32
Weights	No	No	No	No

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village. ***, **, * indicate p < 0.01, 0.05, 0.10.

A.3.4 Excluding shifting aspirations

Table A.16: OLS models for present migration aspirations, full sample, recoding respondents with aspirations to zero aspirations

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)	Aspiration (now)
Erosion affected	0.16***	0.11***	0.15***	0.11***	0.11***	0.09***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Flood affected	-0.01	0.00	-0.01	-0.02	-0.02	-0.01
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Controls	No	No	No	Yes	Yes	Yes
N	1584	1270	1270	1270	1270	1270
r2_a	0.04	0.02	0.04	0.25	0.29	0.33
control_mean	0.09	0.13	0.18	0.09	0.13	0.18
control_sd	0.28	0.34	0.39	0.28	0.34	0.39
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village.***, **, * indicate p < 0.01, 0.05, 0.10. Aspirations recoded to zero if respondent indicates within-village shifting aspirations.

Table A.17: OLS models for past migration aspirations, full sample, recoding respondents with aspirations to zero aspirations

	(1)	(2)	(3)	(4)	(5)	(6)
	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)	Aspiration (past month)
Erosion affected	0.18***	0.14***	0.17***	0.14***	0.14***	0.13***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)
Flood affected	-0.01	0.02	-0.00	-0.01	-0.00	-0.00
	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)
Controls	No	No	No	Yes	Yes	Yes
N	1585	1271	1271	1271	1271	1271
r2_a	0.05	0.03	0.04	0.20	0.23	0.26
control_mean	0.10	0.15	0.21	0.10	0.15	0.21
control_sd	0.30	0.35	0.41	0.30	0.35	0.41
Weights_erosion	No	Yes	No	No	Yes	No
Weights_flood	No	No	Yes	No	No	Yes

Sample: HH that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Entropy balancing weights and control variables used as indicated. Standard errors clustered by village.***, **, * indicate p < 0.01, 0.05, 0.10. Aspirations recoded to zero if respondent indicates within-village shifting aspirations.

A.4 Additional statistics

Table A.18: Summary statistics for all major variables

	mean	sd	min	max	count
Migrant	.0840652	.2775727	0	1	1594
House shifted	.097867	.297228	0	1	1594
Shifting aspiration	.0608532	.2391359	0	1	1594
Aspiration (past month)	.2044025	.4033912	0	1	1590
Aspiration (now)	.1724355	.3778774	0	1	1589
Erosion affected	.3272613	.469361	0	1	1592
Flood affected	.4839723	.4999002	0	1	1591
erosion2021_impactcat==strong impact	.1136935	.3175383	0	1	1592
erosion2021_impactcat==some impact	.1771357	.3819034	0	1	1592
erosion2021_impactcat==other impact	.0351759	.184282	0	1	1592
erosion2021_impactcat==missing	.673995	.4688964	0	1	1592
flood2021_impactcat==strong impact	.0534255	.2249512	0	1	1591
flood2021_impactcat==some impact	.3438089	.4751276	0	1	1591
flood2021_impactcat==other impact	.0842238	.2778104	0	1	1591
flood2021_impactcat==missing	.5185418	.4998132	0	1	1591
Erosion: HH affected in %	.3274327	.2642363	.016129	1	1594
Flood: HH affected in %	.4843627	.1898651	.125	.88	1594
asp_duration==stay	.7695735	.4212399	0	1	1571
asp_duration==temporary	.0706556	.2563303	0	1	1571
asp_duration==permanent	.1597708	.3665101	0	1	1571
asp_destination==stay	.7695735	.4212399	0	1	1571
asp_destination==rural	.1826862	.3865321	0	1	1571

asp_destination==urban	.0477403	.2132841	0	1	1571
district==Kurigram	.0376412	.1903865	0	1	1594
district==Tangail	.0294856	.1692162	0	1	1594
district==Manikganj	.0828105	.2756821	0	1	1594
district==Shirajganj	.1010038	.3014283	0	1	1594
district==Tangail	.1681305	.3740995	0	1	1594
district==Bogra	.0915935	.2885418	0	1	1594
district==Gaibandha	.0909661	.2876512	0	1	1594
district==Kurigram	.3983689	.4897158	0	1	1594
zone==zone: 0 to 50m	.3033419	.4598494	0	1	1556
zone==zone: 50 to 100m	.3136247	.4641149	0	1	1556
zone==zone: 100 plus	.3830334	.4862826	0	1	1556
sex	.8826851	.3218962	0	1	1594
age_cat==age: 18 to 30	.1181647	.3229045	0	1	1591
age_cat==age: 31 to 40	.2614708	.4395739	0	1	1591
age_cat==age: 41 to 50	.2426147	.4287988	0	1	1591
age_cat==age: 51 to 60	.1986172	.3990846	0	1	1591
age_cat==age: 61 plus	.1791326	.3835839	0	1	1591
kids_num==kids: 0	.0531271	.2243624	0	1	1487
kids_num==kids: 1 to 2	.3019502	.4592582	0	1	1487
kids_num==kids: 3 to 5	.5178211	.4998504	0	1	1487
kids_num==kids: 6 plus	.1271015	.3331987	0	1	1487
education==edu: illiterate	.6026365	.489506	0	1	1593
education==edu: signature	.1563089	.3632619	0	1	1593
education==edu: some primary	.1242938	.33002	0	1	1593
education==edu: primary compl.	.0408035	.1978969	0	1	1593
education==edu: secondary compl.	.0408035	.1978969	0	1	1593
education==edu: higher	.0351538	.1842263	0	1	1593

income_source1_coded==income: dep. on env.	.4232973	.494239	0	1	1571
income_source1_coded==income: indep. on env.	.5448759	.4981407	0	1	1571
income_source1_coded==income: other	.0241884	.1536827	0	1	1571
income_source1_coded==income: none	.0076384	.0870915	0	1	1571
place attachement (1-5)	4.297365	.8130484	1	5	1594
past migration (0-1)	.2478114	.4318872	0	1	1485
past aspirations (in pre-monsoon survey)	.3146853	.4645381	0	1	1573
current aspirations (in pre-monsoon survey)	.2227102	.4161959	0	1	1594
risk preference (1-5)	3.425032	1.324773	1	5	1574
land size	.2256772	1.061743	0	24.28116	1547
housing quality (pca)	6.35428	1.07739	2	10	1472
livestock units	.5414033	.4786132	0	1	1562
assets (pca)	.5995293	1.009634	0	5.5	1487
Observations	1594				

Appendix B

A.1 Modifications to the pre-analysis plan

Following Banerjee et al. (2020), we partially adapted our pre-analysis plan but report the differences here for transparency. In order to better characterize the types of the environmental/climatic events we study, namely sudden/short-term and gradual/long-term events whose initial classification was based on the speed of their onset and their duration, we now add the extent of their impact on affected households. Specifically, we argue that migration aspirations and migration behavior depend also on the nature of the impact, i.e., reversible versus irreversible impacts caused by the specific environmental event on the affected households.

In particular, we argue that sudden and rapid (short-term) environmental/climate events, such as floods, storms, and typhoons, can have severe impacts – at least in the short-run – on the well-being of individuals. These events cause casualties or injuries, property damage (e.g., houses, machinery, crops, etc.), or social and economic disruption. Such events are likely to produce the greatest aspirations to migrate, because they are above the perceptual threshold of direct human experience and are easily recognizable as extreme events with the potential to inflict a lot of (human and property) cost on individuals. Affected individuals may thus want to migrate in the aftermath of such environmental/climate events, as the costs of migration are lower than the costs of staying at this location. However, given that the impact of such events on affected households is reversible, for instance when floodwaters recede, people come back to their homes and rebuild their lives, we argue that in the presence of sudden/short-term events, people aspire to migrate only temporarily and in short distance.

H1: Perceptions of sudden-onset environmental events positively affect individuals' aspirations to migrate temporarily and inside the borders of their own country.

In contrast, gradual/long-term events, e.g., riverbank erosion, water/soil salinity, are usually not perceived as extreme due to their slow moving nature and hence tend to remain beneath the perceptual threshold of immediate risk (Howe et al., 2013) that would inspire 'a need to flee'. Under those circumstances, people might be willing to implement some type of adaptation or mitigation strategy, e.g., investments in irrigation systems or the use of drought or water resistant plants. The implementation of (actual or anticipated) adaptation strategies is then likely to weaken the relationship between environmental change and aspirations to migrate. Yet, when such events materialize, their impacts are irreversible: complete and permanent destruction of (agricultural) land, houses, and infrastructure. Consequently, we expect that people experiencing such events are likely to develop aspirations to migrate

permanently to compensate for the losses suffered and since there is nothing physical left for them to be attached to.

H2: Perceptions of slow-onset, gradual environmental events positively affect individuals' aspirations to migrate permanently.

Operationalization and empirical strategy

We use the following conceptualizations and classification of event types:

- Sudden-onset event: an event which occurs rapidly – in our case study: floods
- Gradual event: an event which occurs in a progressive, creeping manner over an extended period of time – in our case study: riverbank erosion
- Impact: erosion: strong impact, some impact, other impact, no impact; floods: strong impact, some impact, other impact, no impact.

A.2 Anonymized version of pre-analysis plan

Perceptions of environmental change & their influence on migration aspirations

The debate on whether and how environmental changes impair human security and, ultimately, force people to leave their homes and migrate to places more conducive to their wellbeing has experienced a strong revival in the climate change context. While various studies predict large, predominantly internal, environmental migration flows due to climate change (Kumari Rigaud et al. 2018), the ex post empirical evidence for such migration is mixed (Cattaneo et al. 2019). In this part of the project, we examine the following question:

RQ: How do individual perceptions of different types of environmental/climate events – notably short- vs. long-term environmental/climate events – affect their aspiration to migrate or stay?

In particular, we argue that environmental/climatic changes, by negatively affecting personal income and the opportunity for future employment, increase the likelihood that affected individuals would consider migration (Harris and Todaro 1970; Todaro 1969). Furthermore, and in line with existing studies (Koubi et al. 2016b), we argue that migration decisions are likely to be affected to a large degree by individual perceptions of environmental change, rather than environmental change identified objectively with "scientific risk analysis, performed by experts, of system characteristics of the physical or social world" (Dessai et al. 2004, p. 11). Research has confirmed that people's actions depend heavily upon their perceptions (Tanner et al. 2015).

We further argue that the specific characteristics of environmental/climate change affect the aspirations to migrate or stay. In terms of these characteristics, we focus on the distinction between sudden (short-term) and slow-onset, gradual (long-term) environmental events (see

also Cattaneo et al. 2019; Koubi et al. 2016a; McLeman 2014). Sudden and rapid (short-term) environmental/climate events, such as floods, storms, typhoons and sudden riverbank erosion, can have severe impacts – at least in the short-run – on the well-being of individuals. These events cause casualties or injuries, property damage (e.g., houses, machinery, crops, etc.), or social and economic disruption. Such events are likely to produce the greatest aspirations to migrate, because they are above the perceptual threshold of direct human experience and are easily recognizable as extreme events with the potential to inflict a lot of (human and property) cost on individuals. Affected individuals may thus want to migrate in the aftermath of such environmental/climate events, as the costs of migration are lower than the costs of staying at this location.

H1: Perceptions of sudden-onset environmental events positively affect individuals' aspirations to migrate.

In contrast, slow-onset and long-term environmental events, e.g., droughts, desertification, water/land salinity, or gradual riverbank erosion, even in the presence of short-term seasonal and/or annual variability, are not usually regarded as extreme enough to be significant, because they are likely to have a smaller (immediate) impact on individuals. Consequently, people will try to adjust their productive strategies over time when experiencing such environmental events by implementing a variety of adaptive techniques, e.g., investments in irrigation systems or the use of drought or water-resistant plants. The implementation of (actual or anticipated) adaptation strategies is then likely to weaken the relationship between environmental change and aspiration to migrate. Thus, we expect:

H2: Perceptions of slow-onset, gradual environmental events are unlikely to positively affect individuals' aspirations to migrate.

Furthermore, while existing research posits that sex, age, remittances, and social networks are important confounding factors in environmental migration, we argue that additional individual level characteristics, namely individuals' risk orientation, knowledge of future climate risks, and desire to migrate, condition this relationship. These latter individual attributes have been identified in the existing literature as being important mediators, yet they have not been so far considered in empirical research (Black et al. 2011a; Black and Collyer 2014).

Operationalization and empirical strategy

We use the following conceptualizations and classification of event types:

- Sudden-onset event: an event which occurs rapidly – in our case study: floods and sudden-onset erosion (mass failure)

- Gradual event: an event which occurs in a progressive, creeping manner over an extended period of time – in our case study: gradual riverbank erosion

In the previous paper project (section 5.1), we examine whether perceptions of environmental events match actual occurrences. Building on the hypotheses from that section, we assume that environmental perceptions are a good proxy for actual environmental exposure. Therefore, we regress migration aspirations on perceptions of floods and erosion. We define migration aspirations if a respondent expressed a wish to move after experiencing flood or erosion. Our estimation strategy relies on the panel nature of our dataset, where we can assess within-household variation over time. Additional characteristics to include in the regression as covariates are individual level characteristics, individuals' risk orientation and knowledge of future climate risks.