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Climate Change and Migration

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Do Natural Hazards Cause International Migration?*

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Abstract

The estimated amount of people affected by natural hazards stands at a staggering number of about 243 million people per year. While not all of the affected move across borders, international migration potentially provides an adaptation mechanism to natural hazards. The aim of this article is to assess whether natural hazards induce international migration from a macro perspective. We construct a stylized theoretical gravity model of migration that includes hazards as random shocks. To estimate this model, we deploy exogenous data on geological anzd meteorological hazards from 1980 to 2010. We combine these data with the World Bank's Global Bilateral Migration Database. Overall, our results suggest little evidence that natural hazards affect medium- to long-run international migration. However, considering heterogeneity across income groups, we find that particularly middle-income countries experience significant push and pull effects on migration from natural hazards. (JEL codes: F22, O15, Q54).

Key words: natural hazards, international migration, gravity model, heterogeneity across income groups

1. Introduction

According to the UN-DESA 2016 report on migration, 244 million international migrants are living in the world in 2015. In all, 157 million of these stem from middle-income countries with their numbers rising more rapidly than those from other income groups. Related to this, the amount of people affected by natural hazards stands at an estimated number of 243 million per year.[1] The reports by the IPCC (2012), by the World Bank (2012) and the

1 This was calculated by Diamond and Ganeshan (2009) in the Oxfam research report 'Forecasting the numbers of people affected annually by natural hazards up to 2015'. Other studies suggest

Stern Review (Stern 2006) particularly accentuate that climate change and natural hazards have become serious issues that are global in their consequences. If global warming progresses, it will become increasingly impossible to sustain livelihoods in some regions so that the numbers of those needing to relocate permanently will continue to increase (Stern 2006; Marchiori and Schumacher 2011; IPCC 2012; Economist 2012). Historically, the vast bulk of relocation of people caused by hazards has occurred within nations.[2] Even though not all of the affected move across borders, international migration might provide a potential adaptation mechanism in the presence of natural hazards (McLeman and Smit 2006; Tacoli 2009; Barnett and Webber 2010; Marchiori and Schumacher 2011).

On these grounds, the impact of increasingly extreme natural hazards on the worldwide relocation of people is one of the major potentially problematic issues that need scrutiny. Knowledge remains limited on the factors at work involving hazards as a cause of international migration. One potential strategy in coping with temporary events, such as earthquakes, might be temporary relocation. However, natural hazards related to climate change might lead to more permanent migration, as these events may strip individuals from their basis of existence. Two channels advocated by Marchiori and Schumacher (2011) may cause permanent relocation as an adaptation mechanism to natural hazards and climate change. First, if amenities at home change or more infectious diseases occur, this may directly lead to higher emigration abroad. Second, crop failure or aridification in rural areas force people to migrate to urban regions, which puts urban wages under pressure and might thus lead to higher international migration. The rural poor in developing economies are most affected by natural hazards. By contrast, they are often liquidity constraint and least able to insure themselves or adopt alternative adaptation strategies. Moreover unfettered migration to the global North is not always possible as industrialized nations get increasingly tough on migrants with stricter immigration policies (Boeri and Brücker 2005).[3]

The aim of this article is to assess whether natural hazards induce international migration from a macro perspective. We relate to the literature on the determinants of migration,[4] to the general empirical literature on bilateral migration,[5] and to the more specific subcategory on the relation between migration and natural hazards or climate change. Empirical research is often regionally constrained. Naudé (2010) and Drabo and Mbaye (2015) investigate the relation between hazards and international migration from Sub-Saharan Africa or developing countries to OECD economies, respectively. They find that hazards cause outmigration. Other studies look at single extreme disasters to evaluate their impact on migration. Ambrosetti and Petrillo (2016) examine intra-national migration flows after L'Aquila's earthquake of 2009, finding a strong increase of outflows from L'Aquila to other provinces and close regions. Yet another branch of literature focuses only on certain hazard types. Reuveny and Moore (2009), Coniglio and Pesce (2015), and

even higher numbers, finding that 135 million are at risk due to desertification alone (INCCCD 1994), while 200 million are at jeopardy due to sea-level rise (Myers and Myers 2002).

2 In this context, previous research found an effect of hazards in particular on migration from rural to urban areas within national boundaries (Barrios, Bertinelli and Strobl 2006; Beine and Parsons 2015).

3 For a survey on the measurement, determinants and outcomes of migration policies, see Ortega and Peri (2015) and further contributions in that issue.

4 Important contributions are Sjaastad (1962); Borjas (1987, 1989); Mincer (1978); Stark (1991).

5 Studies include Lewer and Van den Berg (2008); Pedersen et al. (2008); Letouzé et al. (2009); Ortega and Peri (2009); Mayda (2010); Beine et al. (2011), to name a few.

Backhaus et al. (2015) use a gravity framework to analyze the role of origin country climate anomalies on international migration to OECD countries. Their results suggest that an increase in weather-related hazards in the origin increases outmigration. Beine and Parsons (2015) use a comprehensive data set of global migration for 1960–2000. They find little direct effects of climate anomalies or disasters on international migration, but rather on migration from rural to urban areas. In a more recent paper, Beine and Parsons (2017) find some evidence of weather conditions on the variation in bilateral migrant stocks, suggesting that disasters affect credit constraints of individuals, deterring emigration from all origin countries but spurring emigration to neighboring countries. For middle-income origins, they find that natural disasters foster emigration to former colonial powers. Notably, Beine and Parsons (2017) highlight the importance of how differences in modeling climate change can lead to differing results.

A range of promising approaches to identify the link between hazards and migration exists, but the underlying data used in seeking answers often have their drawbacks,[6] which makes it difficult to generalize results and policy implications. As recapitulated by Mbaye and Zimmermann (2015) in a literature review, effects of environmental hazards on migration range from positive to neutral to negative outcomes. Above all, most of the empirical literature suffers from two major problems. First, they exclude migration toward non-OECD countries, which might induce a large measurement error. According to the Global Bilateral Migration Database, migration to non-OECD countries accounts for 51% of international migration. Piguet et al. (2011) note that hazards are unlikely to affect migration in rich and politically stable economies. Exceptions that also include non-OECD destinations are Beine and Parsons (2015, 2017), who find little effect of climate change on migration, and Cattaneo and Peri (2016), who find in a monadic regression that higher temperature increases migration to urban areas and middle-income countries, while poor countries are liquidity constrained. Second, studies have often used information on the incidence of disasters from databases drawn from insurance records or news. This introduces severe reporting and endogeneity biases, as both, insurance penetration and damage caused are correlated with development, which in turn affects migration patterns (for a detailed discussion, see Felbermayr and Gröschl 2014).

In this article, we construct a stylized theoretical gravity model of migration based on derivations by Anderson (2011) and includes hazards as random shocks. To estimate the implications of this model, we deploy a conditional fixed effects (FE) Poisson Pseudo Maximum Likelihood (PPML) approach advocated by Santos Silva and Tenreyro (2006). We offer two contributions beyond recent work: (i) we explicitly estimate the time-variant part of multilateral resistance (MR)[7] in bilateral migration, thereby allowing hazards in the origin and the destination to vary in impact; and (ii) we deploy updated and extended natural hazard data from the Ifo Database on Geological and Meteorological Events (Ifo GAME) based on exogenous intensity measures, thus we solve the endogeneity and reporting problems of insurance- and news-based disaster data.

We use migration data constructed by the World Bank from decennial census information which captures temporary migration only to a very limited extend. Any kind of migration that takes place and is reverted within the 10 years between two census rounds is excluded, as these short-term migrants do not show up in census stocks. Moreover, the

6 Empirical economists face a lack of observational data and definitions for migration and hazards.

7 MR terms are adapted to the setup from the derivations of Baier and Bergstrand (2009) using a Taylor series expansion.

data extend almost exclusively to legal immigrants.[8] Therefore, our presented results hold almost only for legal medium- to long-run international migration, even though temporary or short-term migration present a very valid coping strategy in face of transit natural hazards, it cannot be captured with the available worldwide data.

Our results suggest little evidence for an impact of natural hazards on medium- to long-term international migration. Using the full sample and considering the timing of events combined with migration decisions, we find that a mean hazard event at origin leads to 1.7% more bilateral migration. The identification of statistically significant effects becomes very noisy if we do not consider timing. Moreover, decomposing hazards by type does not yield evidence for a clear pattern. When we distinguish countries by income levels, we do find heterogeneity across groups. Moreover, we find no evidence that individuals from low-income countries migrate internationally if struck by natural hazards. International migration or other adaptation strategies may not be feasible for financially constrained individuals (see also Cattaneo and Peri 2016 and Beine and Parsons 2017). If high-income countries experience hazards, their outmigration declines, possibly due to high insurance penetration rates. These may cause incentives to stay as insured capital is upgraded after a hazard. Middle-income countries show a clear pattern of migration due to hazards—which lead to international migration of 1.4%, while those at potential destinations decrease migration by 11.5%, both evaluated at the mean. Hence, examining the effect of natural hazards on migration using a full sample may lead to aggregation bias.

The remainder of the article is structured as follows. Section 2 provides a theoretical gravity model of migration. Section 3 describes details on the empirical strategy, and Section 4 addresses the data. Section 5 provides results and a sensitivity analysis. The last section concludes.

2. A Gravity Model of Migration

To provide a simple theoretical motivation for estimating bilateral migration in a gravity framework, we follow Anderson (2011). The decision to migrate is, in contrast to the decision to export, characterized by the choice over a discrete number of alternative locations on a global scale. The costs of migration are common to all migrants within a particular bilateral link, albeit migration costs may have an idiosyncratic component reflecting individual costs or utility from moving.

Consider a multi-country framework where $i, j = 1, \cdots, C$ denote countries, $h = 1, \cdots, H$ denotes individuals, and t denotes time. Each individual h has an idiosyncratic component of utility from migrating, $\xi_{ijh,t}$, which is unobservable and independently distributed across individuals with an iid extreme value distribution. In addition, individuals face costs of migration, which are the same for all workers who migrate in a particular migration corridor, $\kappa_{ij,t} = \kappa_{ji,t}$.[9]

8 The exact implications of this for our results remain unclear: Undocumented migrants may be more mobile after an exogenous shock but are also more likely to be financially constrained, potentially favoring less costly internal migration.

9 Note that migration costs may as well vary by skill levels. Migration costs could be lower for skilled workers and increase with decreasing skill level. Individuals with low skill levels may benefit more from migrating but also face relatively higher migration costs given their lower income and potential liquidity constraints they face in situations where they cannot save or borrow enough to pay the costs of migration. On the other hand, migrant networks may increase with skill and thus lead to lower migration costs for the more highly skilled. This implies selection mechanisms by skill,

Migration costs constitute an iceberg cost factor $\kappa_{ij,t} \geq 1$ and $\kappa_{ii,t} = 1$ at time t. Migration costs are a function of several factors, comprising time-invariant costs from the move, such as cultural proximity (common language, common colonizer) or geographic location (distance, common border), and time-variant factors, such as networks (stock of migrants), regional networks (regional trade agreements), immigration policies, political ties between country pairs, or benevolence of welfare states in receiving countries. In addition, migration costs may depend on unobserved bilateral determinants, such as historical affinity of country pairs, ethnic or business networks. Moreover, migration costs may also follow a common time trend t.

When a natural hazard strikes, it damages and destroys both physical and human capital. It follows that hazards affect the migration decision by reducing the productivity of labor. By this they affect wages and eventually also the movement of population.[10] We formally introduce natural hazards as random shocks Φ, where $\Phi \geq 1$.[11] The occurrence of random shocks and the damage they cause are assumed to be idiosyncratic across locations. Random shocks have a transitive effect on labor productivity as they suddenly shift demand and/or supply structures. Let the wage net of migration costs and net of random shocks to labor productivity in the destination be $w_{j,t}/(\kappa_{ij,t}\Phi_{j,t})$, where $w_{j,t}$ denotes the wage in destination j at time t, and wage net of the labor productivity shock at home is $w_{i,t}/\Phi_{i,t}$, where $w_{i,t}$ denotes the wage at origin i at time t and $\kappa_{ii,t} = 1$. Then, an individual h migrates if the utility from migrating to some destination j at time t is larger than from staying at home, $(w_{j,t}/(\kappa_{ij,t}\Phi_{j,t}))\xi_{ijh,t} \geq w_{i,t}/\Phi_{i,t}$.[12]

To evaluate migration, suppose expected utility is a logarithmic constant relative risk aversion (CRRA) function.[13] Specifically, the observable component of log-linear utility from migrating is

$$\ln u_{ij,t} = \ln w_{j,t} - \ln \kappa_{ij,t} - \ln \Phi_{j,t} - [\ln w_{i,t} - \ln \Phi_{i,t}].^{14} \tag{1}$$

which we abstract from in this model as we cannot test implications empirically on the basis of our global migration data which does not allow us to distinguish migrants by skill level.

10 Note that natural hazards could also affect migration costs directly, such that migration costs would increase with natural hazards as, for instance, infrastructure or amenities get destroyed. This would make migration more costly and less likely. We abstain from modeling a direct effect; instead we consider that hazards change MR of countries, thus assuming an implicit effect on migration costs.

11 Random shocks may also incorporate civil or international war, changes in governance from autocracy to democracy or vice versa, etc.

12 The average expected gain in utility from not migrating (remaining in i) is zero for individuals that choose to stay in the origin (Ortega and Peri 2009). $w_{i,t}$ and $\Phi_{i,t}$ are constant across all destinations.

13 The CES utility function is given as $u_{ij,t} = \frac{1}{\sigma-1}\left(\frac{w_{j,t}/(\kappa_{ij,t}\Phi_{j,t})}{w_{i,t}/\Phi_{i,t}}\right)^{\sigma-1}$, where σ is the elasticity of substitution for wages in different locations (also called the coefficient of relative risk aversion). Compared to partial equilibrium Random Utility Maximization (RUM) models—an alternative theoretical foundation used widely in the migration literature (see Beine et al. (2016) for a discussion and related literature)—our approach features a similar setup, yields a similarly tractable gravity equation, but allows us to theoretically trace the wage effects of natural hazards, which drive the migration decision while simultaneously accounting for counterveiling general equilibrium labor market effects induced by changes in the labor stocks.

14 Utility may also be derived from country characteristics C that denote benefits such as public infrastructure, amenities, and the welfare state (see for instance Beine and Parsons (2015) for a more detailed discussion). We do not specifically model these benefits here as we do not devote particular attention to country-specific factors which do not alter the prediction of our random

Note that individual decisions can be aggregated up to a representative individual (McFadden 1974), as migrants are assumed to be homogeneous except for the random term $\xi_{ijh,t}$. To retrieve a tractable gravity equation, we assume that the aggregated level of the discrete choice probability is equal to migration flows from source i to destination j at time t. Aggregate bilateral migration is then given as

$$M_{ij,t} = P(u_{ij,t})N_{i,t}, \tag{2}$$

where the population in the source country takes a decision on migration and, with $\xi_{ijh,t}$ following an iid extreme value distribution, the probability $P(u_{ij,t})$[15] is given by

$$P(u_{ij,t}) = P(u_{ij,t} = \max_{\mathrm{k}} u_{ik,t}) = \frac{e^{u_{ij,t}}}{\sum_k e^{u_{ik,t}}} \quad \text{for} \quad ik \neq ij. \tag{3}$$

Since the Φ's and κ's enter the model multiplicatively through their effect on wages, they combine into a shock-cost measure $\theta_{ij,t}$ that represents both migration costs and random shocks from natural hazards or similar factors on labor productivity.[16] Both migration costs and random shocks to labor productivity operate in combination with given wages to generate the allocation of migrants. The combined shock-cost measure is then given as $\theta_{ij,t} = \kappa_{ij,t}\Phi_{j,t}/\Phi_{i,t}$.

With logarithmic utility, the structure of the migration equation corresponds to

$$M_{ij,t} = \frac{(w_{j,t}/\theta_{ij,t})^{\sigma-1}}{\sum_k (w_{k,t}/\theta_{ik,t})^{\sigma-1}} N_{i,t}. \tag{4}$$

To derive a tractable gravity equation, define $\Gamma_{i,t} \equiv \sum_k (w_{k,t}/\theta_{ik,t})^{\sigma-1}$ and specify the aggregated labor market clearing condition as $N_{j,t} \equiv \sum_i M_{ij,t}$. The clearing condition is then $N_{j,t} = w_{j,t}^{\sigma-1} \sum_i (\theta_{ij,t}^{1-\sigma}/\Gamma_{i,t})N_{i,t}$. In equilibrium, wages are

$$w_{j,t}^{\sigma-1} = \frac{N_{j,t}}{N_t \Gamma_{j,t}} \tag{5}$$

with total world population $N_t \equiv \sum_i N_{i,t} \equiv \sum_j N_{j,t}$ and $\Gamma_{j,t} = \sum_i \frac{\theta_{ij,t}^{1-\sigma}}{\Gamma_{i,t}} \frac{N_{i,t}}{N_t}$. Substituting for the equilibrium wage in equation (4) using equation (5) yields the tractable gravity specification of migration

$$M_{ij,t} = \frac{N_{i,t}N_{j,t}}{N_t} \left(\frac{\theta_{ij,t}}{\tilde{\Gamma}_{i,t}\tilde{\Gamma}_{j,t}} \right)^{1-\sigma}, \tag{6}$$

shock variable. The role of these factors for migration will in our empirical section be considered by country dummies (time-invariant) and also by controls and MR terms (time-varying).

15 For examples of bilateral migration discrete choice models that build on a multinominal logit function, see Beine, Docquier and Özden (2011); Grogger and Hanson (2011); Gibson and McKenzie (2011); or Beine and Parsons (2015).

16 This useful simplification follows Anderson (2009) and is exploited in what follows. It can be decomposed at any point into its components.

with the outward migration friction price index $\tilde{\Gamma}_{i,t} = \left[\sum_j \frac{N_{j,t}}{N_t}\left(\frac{\theta_{ij,t}}{\tilde{\Gamma}_{j,t}}\right)^{1-\sigma}\right]^{1/1-\sigma}$ and the inward migration friction price index of $\tilde{\Gamma}_{j,t} = \left[\sum_i \frac{N_{i,t}}{N_t}\left(\frac{\theta_{ij,t}}{\tilde{\Gamma}_{i,t}}\right)^{1-\sigma}\right]^{1/1-\sigma}$.

To make the impact of random shocks visible in the gravity equation of migration, we decompose θ_{ij}. This gives

$$M_{ij,t} = \frac{N_{i,t}N_{j,t}}{N_t}\left(\frac{\kappa_{ij,t}}{\tilde{\Gamma}_{i,t}\tilde{\Gamma}_{j,t}}\right)^{1-\sigma}\Phi_{i,t}^{\sigma-1}\Phi_{j,t}^{1-\sigma}, \tag{7}$$

and MR terms are $\tilde{\Gamma}_{i,t} = \left[\sum_j \frac{N_{j,t}}{N_t}\left(\frac{\kappa_{ij,t}}{\tilde{\Gamma}_{j,t}}\right)^{1-\sigma}\left(\frac{\Phi_{j,t}}{\Phi_{i,t}}\right)^{1-\sigma}\right]^{1/1-\sigma}$ and $\tilde{\Gamma}_{j,t} = \left[\sum_i \frac{N_{i,t}}{N_t}\left(\frac{\kappa_{ij,t}}{\tilde{\Gamma}_{i,t}}\right)^{1-\sigma}\left(\frac{\Phi_{j,t}}{\Phi_{i,t}}\right)^{1-\sigma}\right]^{1/1-\sigma}$.

The first term of equation (7) denotes bilateral migration in a world without frictions, where migrants are found in equal shares relative to the population in all destinations. The second term denotes the impact of frictions in a world that entails costs to migration. The larger the bilateral migration costs $\kappa_{ij,t}$, the lower are the migration flows. Albeit, in a world in which migrants choose from a set of alternative destinations, migration also depends on MR, which captures worldwide bilateral migration costs. The third term indicates that random shocks to labor productivity in the origin and in the receiving country affect migration. The larger the shock in the origin $\Phi_{i,t}$, the higher are migration flows. The larger the shock in the destination j at time t, the lower are migration flows.

3. Empirical Strategy

To test the predictions of the previous section regarding the effect of hazards on bilateral migration patterns, we outline a full-fledged gravity model on a panel of bilateral migration and primary hazard data. Estimating an augmented gravity specification, we examine how natural hazard in the origin ($\Phi_{i,t}$) and in the destination ($\Phi_{j,t}$) affect bilateral migration rates ($M_{ij,t}/N_{ii,t}$).

To get an estimable equation on migration rates, we take logs of equation (7) and obtain

$$\ln\frac{M_{ij,t}}{N_{ii,t}} = (1-\sigma)\ln\ \kappa_{ij,t} + (\sigma-1)\ln\ \tilde{\Gamma}_{i,t} + (\sigma-1)\ln\ \tilde{\Gamma}_{j,t} + (\sigma-1)\ln\ \Phi_{i,t} + (1-\sigma)\ln\ \Phi_{j,t}.^{17} \tag{8}$$

As discussed earlier in Section 2, migration costs comprise time-invariant and time-variant components. We empirically model our cost function as

$$\kappa_{ij,t} = g(\ln\ (DIST_{ij}), ADJ_{ij}, LAN_{ij}, COL_{ij}, RTA_{ij,t}, MigStock_{ij,t-1}, \nu_t, \nu_i, \nu_j) \tag{9}$$

which is a function of controls for time-invariant historical or cultural country characteristics, such as bilateral distance ln $(DIST_{ij})$, adjacency ADJ_{ij}, common language LAN_{ij}, and

17 Note that N_t is constant, ln $N_{j,t}$ is omitted, and ln $N_{i,t}$ is transformed to ln $N_{ii,t}$ (the non-migrant population of i) to obtain migration rates as the dependent variable rather than migration flows. With using migration rates we follow for instance Mayda (2010); Beine and Parsons (2015).

colonial heritage COL_{ij}. The cost function also comprises time-varying components, such as regional trade agreements $RTA_{ij,t}$ that account for the fact that more integrated countries or regions might also experience higher migration flows.[18] $MigStock_{ij,t-1}$ is the stock of migrants from country i residing in j at time $t-1$, which captures network effects.[19] ν_t are time-specific dummies that account for common trends. ν_i and ν_j are a complete collection of origin and destination country dummies which account for all time-invariant country characteristics. MR terms have a time-invariant and a time-variant component. While the time-invariant component of MR is fully captured by origin and destination country FE, the time-variant component of MR is captured by $\tilde{\Gamma}_{i,t}$ and $\tilde{\Gamma}_{j,t}$ in equation (8).[20] As in the traditional gravity model, price indexes are computable once migration costs $\kappa_{ij,t}$ are constructed econometrically.

Zero bilateral migration flows make up about 65% of observations. To account for these zero migration flows and to correct for heteroskedastic error terms, we choose a conditional FE PPML approach advocated by Santos Silva and Tenreyro (2006).[21] Based on equation (8), we estimate a gravity equation of the form

$$\frac{M_{ij,t}}{N_{ii,t}} = \exp\ [\alpha_1\Phi_{i,t} + \alpha_2\Phi_{j,t} + \alpha_3 \ln\ (GDP_{j,t}/GDP_{i,t}) + \alpha_4 \text{Civil War}_{i,t} + \alpha_5 \text{Civil War}_{j,t} + \alpha_6\kappa_{ij}, t + \alpha_7 \mathbf{MR_{ij,t}}] + \varepsilon_{ij,t}\,. \tag{10}$$

where $\frac{M_{ij,t}}{N_{ii,t}}$ is the decennial bilateral migration rate calculated as the migration flow from i to j at decade t divided by the domestic non-migrant population in country i. $\Phi_{i,t}$ ($\Phi_{j,t}$) capture the physical intensity of natural hazards in the origin (destination) in a given decade. These may be included as an index variable or separately for specific types (see data section for more detail). As common in the migration-hazard literature, we include two country-specific controls directly that vary over time. $GDP_{j,t}/GDP_{i,t}$ is the ratio of destination to origin decennial average per capita gross domestic product (GDP) and proxies average wage differences. Civil War $_{n,t}$ with $n=i,j$ are count variables of the number of years in which civil wars took place in the source or the receiving country, respectively, within the last 10 years of observation. κ_{ij}, t is a vector of migration costs as outlined in equation (9). It includes time constant and time-varying costs including a complete collection of origin and destination country dummies and time-specific FE. The constructed MR terms $\mathbf{MR_{ij,t}} = \tilde{\Gamma}_{i,t}, \tilde{\Gamma}_{j,t}$ capture the time-variant component of MR (for example, immigration policies or benevolence of the welfare state). We derive MR indices from a first-order Taylor series

18 Our RTA variable incorporates free trade agreements, currency unions, and customs unions.

19 We follow the recent literature on migration, which identifies migrant networks to promote bilateral migration flows, trade, and capital flows (Rauch and Trindade 2002; Munshi 2003; Kugler and Rapoport 2007; Docquier and Lodigiani 2010; Bertoli and Fernández-Huertas Moraga 2012; Patel and Vella 2013; Docquier et al. 2014). In particular, Beine, Docquier and Özden (2011) find that migrant networks significantly increase migration flows to OECD countries. To address potential endogeneity concerns pointed out by Munshi (2014), we exclude lagged migration stocks as a robustness check from our baseline specification.

20 Ideally, the time-variant component of MR is controlled for using time-varying country FE. Since our hazard variables are country-time specific, this approach is unfeasible. The FE would pick up the variation in our variables of interest.

21 If zeros are prevalent in the data and error terms are heteroscedastic, PPML generates consistent estimates even when the underlying distribution is not strictly Poisson.

expansion of the gravity equation following an approach by Baier and Bergstrand (2009). We approximate MR terms based on distance ($\text{MRDIST}_{ij,t}$), adjacency ($\text{MRADJ}_{ij,t}$), common language ($\text{MRLAN}_{ij,t}$), colonial relationship ($\text{MRCOL}_{ij,t}$), and RTAs ($\text{MRRTA}_{ij,t}$) which we weight by population over world population (a proxy for a country's relative migrant potential). For details see Appendix A. This econometric approach allows us to control simultaneously for the direct effects of hazards in the source and the destination country and for time-varying country characteristics absorbed in the MR terms. $\epsilon_{ij,t}$ is an additive error term.

Our model suggests that α_1 is positive such that hazards in the origin induce migration out of affected countries, while α_2 is negative indicating that hazards in potential destinations reduce migration. We will now bring this theoretical prediction to the data.

4. Data

4.1 International migration

We combine two data sets. The Global Migrant Origin Database (Version 4, 2007) provided by the World Bank reports bilateral migration stocks based primarily on the foreign-born concept in intervals of 10 years from 1960 to 2000 for 226 countries. The data set combines census and population register records to construct decennial matrices corresponding to the last five completed census rounds. Data for 2010 are also provided by the World Bank and updates data by Ratha and Shaw (2007) as described in the Migration and Remittances Factbook 2011. The 2010 data set also uses the foreign-born concept and similar sources and methods as the 1960–2000 data.

To calculate bilateral decennial migration rates, we take the difference between contiguous bilateral migrant stocks to approximate migration flows, which we then divide by the non-migrant origin population (following Beine and Parsons 2015). This is constructed as the country's total population [according to World Development Indicators (WDI)] minus the sum of immigrants in that country. In some cases migration stocks shrink over the observed time period which leads to negative values. As the exact reason of the decrease in migration stocks is not clear, we stay in line with the literature and ignore all negative values by setting them to zero, implicitly assuming that migrant stocks decrease due people's deaths.[22]

In our sample, zero bilateral migration flows make up about 65% of observations. To account for these zero migration flows and a potentially heteroskedastic error structure, we estimate a FE PPML approach. Still, we lose observations due to missing data for migration rates, control variables, and natural hazards, preserving 66,673 observations used in the PPML estimation. These preserved observations spread over all three decades (17,556 observations for 1981–1990, 24,806 for 1991–2000, and 24,311 for 2001–2010) and across 162 countries as listed in Appendix B, Table A3. Hence, we expect sufficient variation in our data.[23]

22 The actual reasons for negative differences between subsequent bilateral migrant stocks are related to the underlying issue that migration flows converted from stocks do not factor out stock changes due to mortality, return migration, or migration to a third country (see Beine, Bertoli and Fernández-Huertas Moraga 2016). The data do not allow us to disentangle the true drivers of negative stock differences.

23 The loss of data is commonly known in the literature. For example, Beine and Parsons (2015), the paper closest related to ours, has similar numbers of observations spread over four decades from 1960 to 2000.

Table A1 in Appendix B includes summary statistics for the migration rate. The decennial migration rate ranges between 0% and 50% of the total non-migrant origin population at the beginning of the respective decade. Due to the large number of zero migration flows, the mean migration rate is 0.02%. For a deeper understanding of the dimension of international migration, the table also includes figures for the underlying decennial migration flows, ranging from 0 to 4,705,677 people, with a mean of 1726. The maximum migration flow is observed for migration from Mexico to the USA between 1990 and 2000 and corresponds to a migration rate of 6% of the Mexican non-migrant population at the beginning of 1990. The maximum migration rate of 50% is observed from Brunei to India between 1980 and 1990 and corresponds to a decennial migration flow of 71,089 people.

While temporary international migration may pose a valid mechanism for adapting to transitory natural hazards, it must be emphasized that the decennial World Bank data include such short-term migrants only to a very limited extent. Our results almost exclusively rely on medium- to long-run international migration, which excludes any kind of migration that takes place and is reverted within the 10 years between two census rounds, as these short-term migrants are not captured in the census stocks. The data does not allow identifying the share of temporary vs. long-run migrants. Moreover, the World Bank data relies on official census data; hence, undocumented migrants are not included. Finally, note that a large number of bilateral migrant stocks in the data are estimated rather than observed, such that attenuation due to measurement error may pose an inherent issue.[24]

4.2 Natural hazards

We use natural hazard data from the Ifo GAME database on geological and meteorological events, first introduced by Felbermayr and Gröschl (2014). The database contains physical intensities of earthquakes, volcanic explosions, storms, droughts, floods, and temperature anomalies on a monthly basis from 1979 to 2014 for 232 countries.[25] The data included in Ifo GAME stem from various primary sources and come in two different types of geocoding requiring different treatment: (i) non-gridded hazards (volcanoes, hurricanes, and earthquakes) are aggregated to the country level by directly mapping the data to all countries within a radial geodesic buffer around the exact hazard geolocation[26]; (b) gridded data [temperatures, precipitation, Standardized Precipitation-Evapotranspiration Index (SPEI)] are aggregated to the country level by calculating area-weighted arithmetic means.

24 This implies that presented results only hold for more permanent (long-term) migration, while with this analysis, we cannot say anything about temporary or short-term migration, which still might present a very valid coping strategy in face of transit natural hazards.

25 An earlier version of the Ifo GAME data base ranging from 1979 to 2010, covering 188 countries, and using slightly different mapping procedures is currently available at http://www.cesifo-group.de/ifoHome/research/Departments/International-Trade/Ifo_GAME.html.

26 Not knowing the true spatial extent of natural hazards poses a potential problem. Volcanoes are very local events, but gas plumes can have extensive impact. Also, the true geographic extent of earthquakes and hurricanes is not easy to predict given only their magnitude and location at center. In addition, geological, meteorological and surface characteristics matter. We thus rely on approximations from the literature, as the prediction of the true spatial extent of hazard events lies beyond the scope of this article.

The exact data sources as well as the respective spatio-temporal aggregation procedures and index choices are described in detail below; descriptive statistics are shown in Figure 2.

4.2.1 Earthquakes

We measure a country's earthquake hazard by its maximum magnitude. To obtain this, physical earthquake magnitudes from the Incorporated Research Institutions for Seismology are mapped to each country within 150 km of the respective epicenter. We aggregate to the decennial level by collapsing maximum earthquake magnitudes across all months. The resulting earthquake magnitude is distributed between 0 and 10, with a mean of 5.9 and a standard deviation of 1.9 (compare Figure 2).

4.2.2. Volcanic explosions

A country's volcanic activity is measured by its maximum volcanic explosivity index (VEI). VEI is obtained from the Smithsonian Global Volcanism Program and mapped to each country within 50 km of the respective volcano's geolocation. We aggregate VEI for each country to the decennial level by collapsing VEI to their maximum across all months. Resulting VEIs are distributed between 0 and 6, with a mean of around 0.4 and a standard deviation of 1.1 (compare Figure 2).

4.2.3 Storms

To measure a country's storm hazard, we use the maximum combined wind speed of a country from two data sources. Hurricane wind speeds in knots at the exact locations and paths of hurricane centers come from the International Best Track Archive for Climate Stewardship v03r07, provided by the World Meteorological Organization and the US National Oceanic and Atmospheric Administration. We map hurricane wind speeds to each country within a 100-km range of the respective hurricane eye. Wind speeds of winter or summer storms in knots stem from weather station data of the Global Summary of the Day statistics. This reports wind speeds measured at terrestrial weather stations worldwide by the exact geolocation of the respective station. To obtain a decennial measure for each country, we collapse maximum wind speeds across all months. Resulting combined wind speed is distributed between 16 and 165 knots, with a mean of 78.3 and a standard deviation of 29.8 (compare Figure 2).

4.2.4 Temperature

We measure extreme temperature by the absolute mean temperature difference from the long-run monthly mean. Monthly mean land surface air temperatures in degrees Celsius at $0.5^\circ \times 0.5^\circ$ latitude-longitude grid cell levels come from the Climate Prediction Center of the National Centers for Environmental Prediction. The data combine and interpolate data collected from the Global Historical Climatology Network Version 2 and the Climate Anomaly Monitoring System. Spatially aggregating grid cell data addresses two caveats. First, coordinates of measuring points are located at grid cell centers which means that (i) small countries may not have any measuring points within their geographic boundaries, and (ii) for larger countries, measuring points in border regions may concern only a relatively small aerial fraction. Second, fixed-degree grid cells feature varying metric area along latitudes due to the earth's curvature. Hence, measuring points more remote from the equator affect smaller land area. We apply the following procedure to address both caveats: First, we split each country

Figure 1. An example of 2.5° grid cell aggregation.

i into fractions *frac* by grid cells. Second, we calculate geodesic land area a in km^2 for each fraction in a cell. At any point in time t, we add values of each measuring point to all fractions within its respective cell, as they constitute the best proxy available in their respective grid cell (compare Figure 1). Finally, we aggregate gridded observations to the country level by calculating a weighted mean using each country's geodesic land area within a grid cell as analytic weights using

$$\bar{x}^{*i,t} = \frac{\sum_{frac \in i} a^i_{frac} \cdot x^{i,t}_{frac}}{\sum_{frac \in i} a^i_{frac}} \tag{11}$$

We then calculate the differences between monthly mean temperatures and the long-run (1979–2014) monthly mean for each country. For our decennial data, we collapse temperature differences across all months. To treat heat and cold waves alike, we take the absolute value of the measure (see also Felbermayr and Gröschl 2014). The absolute temperature difference is distributed between 0 and 1.4 degrees Celsius, with a mean of 0.3 and a standard deviation of 0.2 (compare Figure 2).

4.2.5 Precipitation

Excessive precipitation, which might exceed percolation and sewage capacities, is captured by the positive maximum precipitation difference from the long-run monthly mean. We obtain monthly mean precipitation in mm/day at 2.5° × 2.5° latitude-longitude grid cell level from the National Aeronautics and Space Administration Global Monthly Merged Precipitation Analyses of the Global Precipitation Climatology Project Version 2.2, which combines and harmonizes observations from satellites and weather stations (gauges). We aggregate the gridded observations to the country level in the same way as for temperatures (see equation (11)). For each country, we then calculate the differences between monthly mean precipitation and the long-run (1979–2014) monthly mean. For the decennial level, we use maximum precipitation differences across all months. To avoid picking up the effect of potential droughts, we only work with positive maxima. The resulting indicator is distributed between 0.1 and 21.2, with a mean of 4.2 and a standard deviation of 2.9 (compare Figure 2).

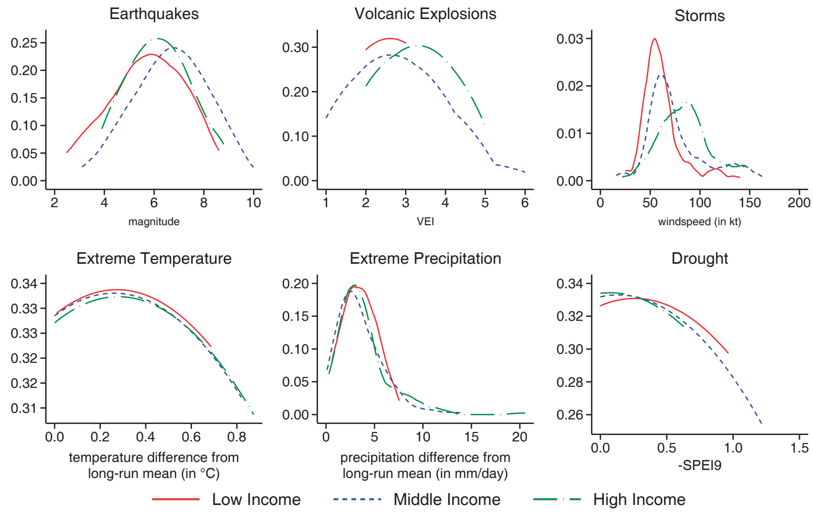

Figure 2. Kernel densities of hazard indicators; zeroes excluded for earthquakes and volcanic explosions.

4.2.6 Droughts

To approximate droughts, we deploy the negative mean of the SPEI computed at a time scale of 9 months.[27] We obtain monthly mean precipitation in mm/day at 0.5° × 0.5° latitude-longitude grid cell level from the Climatic Research Unit of the University of East Anglia (CRU TS v3.23). While this data set is based on weather stations its longer time-scope and the availability of information on evapotranspiration are necessary ingredients to calculate the SPEI. We calculate the climatic water balance (precipitation minus potential evapotranspiration) at grid cell level for each month. The water balance is then standardized for each grid cell by use of a log-logistic distribution function (applying an unbiased Probability Weighted Moments method).[28] The SPEI is standardized with 0 mean and a standard deviation of 1, where negative values indicate a drought. We aggregate the gridded SPEIs to the country level by use of equation (11). To get to the decennial level, we collapse SPEI values to their mean across all months and take only negative values in absolute terms. The resulting SPEI indicator is distributed between 0 and 1.2, with a mean of 0.1 and a standard deviation of 0.2 (compare Figure 2).

4.2.7 Distribution across income groups

When we compare the above indicators across income groups in Figure A1 in the Appendix, we find that earthquakes are more common among middle-income countries with a mean magnitude of 6.5, than in high- or low-income regions. Volcanic explosions

27 The SPEI is specifically designed to quantify and monitor droughts according to their intensity and duration (Vicente-Serrano et al. 2010). It takes the amount of rainfall at given locations as well as the evapotranspiration into account and thus is an advancement of the Standardized Precipitation Index (compare McKee et al. 1993).

28 Data from the current month and of the respective past 9 months are used, giving all months the same weight and taking 1901–2014 as a reference period for obtaining the distribution parameters.

also mostly spread across middle-income countries, while there is very little volcanic activity in low-income countries, but quite some activity in high-income groups with a lower standard deviation but a higher mean of 0.5. Storms have the lowest mean density (61.8 knots) in low-income regions with some spread especially at the higher end (>100 knots). Middle-income countries have a higher mean (75.7) but experience more storms in the upper tail, while high-income countries have the highest mean with 85.4 knots. Contrasting this, temperature differences are quite evenly distributed across income groups, as are differences in excess precipitation where middle-income and especially high-income countries experience a long tail. Droughts measured at absolute negative SPEI levels are more prevalent in low-income countries with a mean of 0.3 but less spread than in middle-income regions (standard deviation of 0.2).

4.2.8 Hazard index

We use a combination of four different disaster indices. The simplest one combines all types of hazard intensity measures into an index variable, $\text{Hazard Index}_{i,t} = \text{Quake}_{i,t} + \text{Volcano}_{i,t} + \text{Storm}_{i,t} + \Delta\ \text{Precipitation}_{i,t} + \text{Drought}_{i,t} + \Delta\ \text{Temperature}_{i,t}$, using an equal weights scheme. We also consider an index weighted by the inverse of the standard deviation of each hazard type within a country (compare Felbermayr and Gröschl 2014). This is guided by the idea of precision weights, such that no one hazard component dominates the movement of the index. Finally, we also take the time dimension into account by weighting each physical intensity with a probability obtained from a normal distribution $f(x) = N(0; 1)$ which we fit over 120 months in a decade.[29] This way, hazard magnitudes are onset weighted at the monthly level, such that events which occur earlier or later within a decade get a smaller weight than events occurring in the middle of a decade when aggregating to the decennial level. The rational for using a bell-shaped onset weighting scheme is that the effect of natural hazards that occurred at the beginning of the decade may already have smoothed out before the next census, whereas events occurring at the very end of a decade might not yet show an effect in the census as it takes some time for people to adjust. This approach is adapted to our framework based on an idea by Noy (2009), who studies the impact of disasters on macroeconomic output over a year and linearly adjusts hazards by onset month to account for their occurrence during the observed year. We again take the simple and the inverse standard deviation weighted index combined with onset weighting.

As the impact of a hazard on the economy might depend on the hazard intensity relative to the size of the economy, we follow the literature (that is, Skidmore and Toya 2002) and scale all respective disaster variables by land area. This is potentially important, because it alleviates biases resulting from spatial aggregation. Larger countries ceteris paribus have a higher chance of being hit by a hazard of a given magnitude. Moreover, the larger a country is the less likely will a natural hazard at a given location within that country have a statistically significant impact on inward or outward migration. Descriptive statistics on the various hazard indices can be found in Table A1 in the Appendix.

29 We shift the distribution such that the first and the last month each correspond to f(−3) and f(3), respectively, and then re-scale such that $max[f(x)] = 1$, ensuring a maximum probability-weight of 1.

4.3 Controls

Data on population size and GDP per capita stem from the World Bank's WDI. Information on civil wars are taken from the Intra-State War Data (v4.1) of the Correlates of War Project. We work with the total number of years involving civil wars within the last 10 years of the reported migration observation. Geographic and cultural linkages—distance, common border, common language, colonial relation—as well as land area in square kilometers are taken from the French Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) Geographic and Bilateral Distance Database (2011). Information on regional trade agreements (RTA) comes from the RTA-Gateway of the World Trade Organization (WTO).[30] Countries' income groups are defined along 2014 World Bank Gross National Income per capita, using the World Bank Atlas Method.

5. Results

This section presents results on the impact of aggregated natural hazards and disaggregated hazard types on medium- to long-run migration patterns. We also look into heterogeneity across income groups and present a sensitivity analysis.

5.1 Baseline results

Table 1 reports our baseline results. All regressions include origin and destination country FE, year dummies, and respective MR terms. Each column uses a different specification of the physical hazard intensity index as described in Section 4. All hazard indicators are divided by the log land area to account for size differences of countries.[31]

Across all four specifications, control variables are consistent in sign, overall magnitude, and level of significance. According to column (1), one additional year of civil war at the origin country implies an increase in the bilateral migration rate by 5.7% over a decade.[32] Conversely, one additional year of civil war at destination leads to a decline in the bilateral inward migration rate by 23% over a decade. Presence of a mutual regional trade agreement, a proxy for regional networks, increases the bilateral migration rate by 31.3%. The controls for cultural proximity are also in line with the gravity literature on migration. If bilateral distance increases by 10 percent, bilateral migration decreases by 7.5%. The presence of a common official language or common colonial history boost bilateral migration by 65.7% or 60%, respectively. Wage differences, proxied by the log ratio of destination over origin GDP per capita, show a positive but not statistically significant effect. Moreover, a 10% increase in the lagged bilateral migrant stock, a proxy for network effects, implies an increase in the bilateral migration rate by 3.6%. The effect is slightly smaller than the estimated 4% by Beine and Parsons (2015) and lower than the 6.5% estimated by Beine et al. (2011), who use different time and country samples.[33]

30 The RTA gateway is accessible via http://rtais.wto.org/UI/PublicMaintainRTAHome.aspx.

31 Note that if we do not scale by log land area, we obtain similar results.

32 $\%\Delta \text{Mig.Rate} = 100 \times [e^{\beta} - 1]$

33 Munshi (2014) points at endogeneity concerns of using the lagged bilateral migration stock as a network variable, since it could, for example, reflect unobserved demand shocks or matching skills available at the origin and needed at the destination. We refrain from using bilateral FE in the preferred specification, since our migration data only covers three decennial waves and thus

Table 1. Baseline results

Dependent variable: Migration rate$_{ij,t}$				
	Basic		Onset weighted	
	Simple (1)	sd weighted (2)	Simple (3)	sd weighted (4)
Hazard Index$_{i,t}$	−0.111	−0.009***	−0.060	0.004***
	(0.09)	(0.00)	(0.11)	(0.00)
Hazard Index$_{j,t}$	0.025	−0.002	0.012	−0.013
	(0.11)	(0.01)	(0.14)	(0.01)
Controls				
ln(GDPp.c.$_{j,t}$/GDPp.c.$_{i,t}$)	0.168	0.206	0.175	0.201
	(0.23)	(0.23)	(0.23)	(0.23)
Civil war$_{i,t}$	0.055**	0.058**	0.042*	0.060**
	(0.03)	(0.03)	(0.03)	(0.03)
Civil war$_{j,t}$	−0.261**	−0.259**	−0.258**	−0.258**
	(0.11)	(0.11)	(0.11)	(0.11)
RTA$_{ij,t}$	0.272**	0.290**	0.291**	0.294**
	(0.12)	(0.12)	(0.12)	(0.12)
ln(Mig.Stock$_{ij,t-1}$+1)	0.357***	0.357***	0.358***	0.357***
	(0.03)	(0.03)	(0.03)	(0.03)
ln(Distance$_{ij}$)	−0.748***	−0.747***	−0.743***	−0.744***
	(0.08)	(0.08)	(0.08)	(0.08)
Contiguity$_{ij}$	0.381**	0.380**	0.371**	0.377**
	(0.16)	(0.16)	(0.16)	(0.16)
Common language $_{ij}$	0.505***	0.505***	0.501***	0.508***
	(0.11)	(0.11)	(0.11)	(0.11)
Colony$_{ij}$	0.470***	0.467***	0.463***	0.471**
	(0.17)	(0.17)	(0.17)	(0.17)
Log−likelihood	−73.980	−74.024	−73.895	−74.013
Observations	66,673	66,673	66,673	66,673

Note: ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Constant, origin, destination, and decade FE and MR terms are included but not reported. Natural hazards are scaled by log land area. Robust standard errors reported in parentheses.

The physical intensity hazard index itself shows mixed results across specifications. In column (1), we use the simple physical intensity hazard index, which sums up the physical intensities across all hazard types. Using this indicator, we do not find any statistically significant evidence for a causal effect of natural hazards on the bilateral migration rate. In column (2), we use the hazard index weighted by its inverse standard deviation to ensure that the entire index is not driven by variation in only one hazard type. Using this indicator, estimates imply a counter-intuitive negative push effect, suggesting that natural hazards at

within-group variation is limited. We refrain from using instrumental variable methods as network effects are not the focus of this article. As a robustness check, we therefore show that the exclusion of lagged migration stocks does not affect our results on the natural hazard variables, see Appendix B, Table A4.

origin have overall led to a decline in the decennial bilateral migration rate.[34] Timing of the migration decision related to natural hazards might play an important role. Hence, hazards happening at the beginning or towards the end of the decade might not induce migration counting into the decennial census rounds. In columns (3) and (4), we thus take the time dimension into account using a bell-shaped onset-weighting scheme as explained in Section 4. Using the simple onset weighted index still does not yield any statistically significant evidence (column 3). However, if we use onset weighting with the hazard index weighted by inverse standard deviations in column (4), we find a positive and statistically significant push effect, suggesting that natural hazards at origin have overall led to an increase in the bilateral migration rate by 1.68% (evaluated at the mean). Pull effects are negative but not statistically significant.

The latter finding implies that the timing of migration decisions combined with natural hazard events plays an important role for the identification of migration responses to natural hazards. We thus take column (4) as our default specification.[35]

5.2 Heterogeneity across hazard types

As a next step, we simultaneously use intensities of all hazard types.[36] Again, all physical intensity measures are weighted by log land area, but we obtain very similar results if not done so.

Table 2 shows the coefficients for each physical intensity type. If basic intensity measures are used, we do not find any statistically significant evidence for causal effects (column (1)). Using onset weighting in column (2) reveals positive push effects of volcanic explosions, suggesting that volcanic events at origin boost the decennial bilateral outward migration rate by 7.9% (evaluated at the mean). We also obtain a counter-intuitive positive pull effect for earthquakes in destinations, suggesting that people migrate more toward earthquake-prone countries. This result may be driven by middle-income countries, which are more prone to earthquakes (compare Figure A1) but are also preferred destinations for migrants from low- and other middle-income countries. The reasoning might be that even though earthquakes destroy a lot of capital, the migrants might still be better off due to reconstruction purposes that might create new jobs (particularly in high- or top-middle-income countries with high insurance and investment rates). We cannot pin down evidence for the effects of other hazard types. Findings on controls (not shown in the Table) are similar with respect to signs, magnitudes, and levels of significance as in our baseline specification in Table 1.

34 As we show in part 5.3 of this section, this effect is driven by high-income origin countries.

35 While onset weighting can only proxy for the timeliness of adjustment, the exact shape of the actual onset response function requires further research, which lies beyond the scope of this article.

36 Using all physical intensities simultaneously might induce multicollinearity into the regression as temperature is also used as a component of potential evapotranspiration in calculating the SPEI. However, if temperature events are omitted from the regression, this does not change our results.

Table 2. Heterogeneity across hazard types

Dependent variable: Migration rate$_{ij,t}$	Basic (1)	Onset weighted (2)
Earthquake$_{i,t}$	0.643	−0.451
	(0.48)	(0.65)
Earthquake$_{j,t}$	0.631	2.434***
	(0.77)	(0.71)
Volcanic explosion$_{i,t}$	2.144	2.452**
	(1.46)	(1.24)
Volcanic explosion$_{j,t}$	1.565	−1.442
	(2.06)	(1.09)
Windspeed$_{i,t}$	−0.120	−0.044
	(0.08)	(0.11)
Windspeed$_{j,t}$	0.038	0.000
	(0.10)	(0.13)
ΔPrecipitation$_{i,t}$	0.235	0.384
	(0.36)	(0.50)
ΔPrecipitation$_{j,t}$	−1.058	−0.797
	(1.05)	(0.76)
ΔTemperature$_{i,t}$	0.120	4.373
	(3.96)	(7.44)
ΔTemperature$_{j,t}$	−2.434	−15.279
	(6.95)	(15.70)
Drought (SPEI)$_{i,t}$	−5.300	2.076
	(3.42)	(6.63)
Drought (SPEI)$_{j,t}$	−1.014	6.467
	(4.94)	(8.97)
Log-likelihood	−73.882	−73.743
Observations	66,673	66,673

Note: ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Constant, origin, destination, and decade FE and MR terms are included but not reported. Natural hazards are scaled by log land area. Robust standard errors reported in parentheses. Controls included as in Table 1.

5.3 Heterogeneity across origin country groups

Migration responses of individuals are likely to differ systematically across countries depending on income characteristics. On the one hand, individuals in poor countries may not migrate internationally after a hazardous event, because they are liquidity constrained (see Cattaneo and Peri 2016). On the other hand, high-income countries usually feature high insurance penetration rates. Thus, individuals from high-income countries may not see the need to migrate if losses from natural hazards are insured. In fact, crop yield destruction can easily be compensated by high-income countries via imports (as they are often financially open), whereas insured damages in built structures and capital assets may even result in a growth-propagating replacement with new, higher quality or more innovative substitutes. This might in turn boost individual's expected earnings and therefore may lead to a decline in migration. In line with this reasoning, we expect not to find evidence for a significant migration response to natural hazards by liquidity-constrained low-income countries, whereas insured high-income countries may either show no or even a negative effect for hazards at origin. Middle-income countries, where individuals have the financial means to migrate but insurance penetration rates are rather low, are thus most likely to migrate internationally in case of natural hazards. Consequently, pooling over all country pairs across all origin income groups might induce aggregation bias into our baseline regression.

Table 3 tests this hypothesis and shows estimates by origin country income groups.[37] Columns (1) and (2) contain the results for low-income origin countries only. In line with the liquidity-constraint hypothesis (see also Beine and Parsons 2017), we find no significant evidence for migration effects of our hazard indices. Columns (3) and (4) contain the results for middle-income origins. Evaluated at the mean, the basic result in column (3) suggests a negative and statistically significant pull effect of hazards in potential destinations of -7.3%; $[100 \times (e^{-0.015 \cdot 5.075} - 1)]$. If we consider the time dimension in column (4), we observe that hazards in the origin increase migration by 1.4% {evaluated at the mean $[100 \times (e^{0.003 \cdot 4.529} - 1)]$ and a negative pull effect at the mean of -11.5% $[100 \times (e^{-0.030 \cdot 4.085} - 1)]$}. Thus, push and pull effects are largely in line with our priors for the group of middle-income-origin countries. Again, timing is important to identify causal effects. Columns (5) and (6) show results for high-income origins. We observe a negative and statistically significant push effect of natural hazards for the basic index in column (5). This finding is in line with the hypothesis that natural hazards might potentially hamper outward migration from high-income countries due to positive income effects resulting from the replacement of insured losses. Moreover, given the absence of evidence for significant push effects for low- and middle-income country groups in columns (1) and (3), we conclude that high-income-origin countries do drive the negative push effects in column (4) of Table 1. If we weight by onset month in column (6), the evidence for this effect again vanishes.

The result that middle-income countries show a positive and statistically significant push effect of natural hazards on bilateral migration is in line with findings on monadic regression by Cattaneo and Peri (2016). Interestingly, our control variables also show heterogeneity across income groups: While there is no evidence that overall wage differences, proxied by relative GDP per capita, play a significant role for the decision to migrate from middle- and high-income countries, they significantly drive migration from low-income countries. A 10% increase in the per capita GDP ratio implies a nearly proportionate increase in the bilateral migration rates from low-income countries by 8–9%. Interestingly, armed conflicts in the destination have a very strong deterring effect on potential migrants from high-income countries (who seem to have a strong preference for safety), a smaller but still significantly positive effect for low-income countries (for whom other motives, like escaping poverty, might be more important), and a negative but non-significant effect for middle-income countries. A similar ranking, albeit with less pronounced differences in magnitude, obtains for RTAs. Contiguity on the other hand plays the strongest role for low-income countries, with more than three times the effect on the migration rate than for middle-income countries. There is no evidence for adjacency to play a role for high-income countries. This finding supports the hypothesis that migrants from poorer countries are on

37 For descriptives on the distributions of natural hazard types across low-, middle- and high-income countries, see Figure A1 in Appendix B.

Table 3. Heterogeneity across origin country income groups

Dependent variable: Migration rate$_{ij,t}$

	Low-income origins		Middle-income origins		High-income origins	
	Basic (1)	Onset weighted (2)	Basic (3)	Onset weighted (4)	Basic (5)	Onset weighted (6)
Hazard Index$_{i,t}$	−0.011	0.039	−0.001	0.003***	−0.010**	−0.037
	(0.03)	(0.08)	(0.02)	(0.00)	(0.00)	(0.04)
Hazard Index$_{j,t}$	0.005	−0.001	−0.015**	−0.030*	−0.001	−0.015
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Controls						
ln(GDPp.c.$_{j,t}$/GDPp.c.$_{i,t}$)	0.895**	0.801*	0.370	0.369	−0.322	−0.540
	(0.45)	(0.45)	(0.23)	(0.23)	(0.42)	(0.41)
Civil war$_{i,t}$	−0.052	−0.050	0.050*	0.043	0.172	0.158
	(0.04)	(0.04)	(0.03)	(0.03)	(0.21)	(0.20)
Civil war$_{j,t}$	−0.179*	−0.177*	−0.019	−0.027	−0.477***	−0.484***
	(0.10)	(0.10)	(0.04)	(0.04)	(0.13)	(0.13)
RTA$_{ij,t}$	0.577**	0.523**	0.173	0.213	0.705***	0.714***
	(0.27)	(0.26)	(0.17)	(0.18)	(0.23)	(0.23)
ln(Mig.Stock$_{ij,t-1}$+1)	0.386***	0.390***	0.372***	0.371***	0.249***	0.247***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
ln(Distance$_{ij}$)	−0.488***	−0.481***	−0.780***	−0.776***	−0.694***	−0.696***
	(0.12)	(0.12)	(0.10)	(0.10)	(0.11)	(0.11)
Contiguity$_{ij}$	1.111***	1.103***	0.521***	0.506***	0.130	0.121
	(0.22)	(0.21)	(0.16)	(0.16)	(0.36)	(0.35)
Common language$_{ij}$	0.240*	0.243*	0.881***	0.876***	0.139	0.141
	(0.14)	(0.15)	(0.14)	(0.14)	(0.29)	(0.29)
Colony$_{ij}$	0.580	0.543	0.313	0.346*	0.709***	0.723***
	(0.39)	(0.38)	(0.21)	(0.21)	(0.25)	(0.25)
Log-likelihood	−8.183	−8.179	−38.895	−38.905	−24.749	−24.759
Observations	11,302	11,302	33,080	33,080	22,291	22,291

Note: ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Constant, origin, destination, and decade FE and MR terms are included but not reported. Natural hazard indicator components are weighted with their inverse standard deviation. Natural hazards are scaled by log land area. Robust standard errors reported in parentheses.

average more financially constrained, as moving to neighboring countries implies lower migration cost. Common language is important for middle-income countries, more than doubling the bilateral migration rate, but there is no evidence that it affects migration for high-income economies. On the other hand, colonial relationships are of major importance for high-income origins, but less so for low- and middle-income economies. Finally, diasporas are equally important for low- and middle-income, but less for high-income countries.

We can conclude that heterogeneity in migration behavior exists across income groups of countries. This leads to aggregation bias if considered jointly and may be responsible for some counterintuitive or absent evidence (effects level out) we have found earlier in this article.

5.4 Sensitivity analysis

Migration might only take place if major events occur that drive people out of their home country, while small-scale events may not exert an effect on international migration. As a first check, we thus re-construct the hazard intensity index using only the top two standard deviations of our hazard type indicators while setting smaller events to zero. This way, our hazard variable captures major events only. Table 4 column (1) shows that this modification does not lead to statistically significant estimates.[38]

As noted earlier, it might take some time for people to react to hazards and to come up with the decision to migrate, particularly across international borders. As a second check, we thus choose an alternative approach. Instead of applying a bell-shaped onset weighting scheme, we exclude all hazards that took place within 2 years before each census from our hazard index. The results are shown in Table 4 column (2). Again, the hazard index does not show evidence for a significant impact on the bilateral migration rate, but might also not consider timing properly.[39]

The frequency rather than the intensity might matter for the migration decision. We change our hazard variable from physical intensities capturing the strength of hazardous events to a count variable capturing the frequency. For each hazard type we count the number of months within a decade whenever an event beyond a specified threshold[40] has occurred, and then sum up over all types, creating the inverse weighted index. Columns (3) and (4) in Table 4 show that the hazard frequency does not imply any evidence for statistically significant push or pull effects, whether we consider timing or not.

Fourth, we deviate from using FE PPML as the preferred estimation technique and use Ordinary Least Squares (OLS) with fixed effects. Estimating FE OLS causes a loss of 43,418 observations for which the dependent variable is zero. Columns (5) and (6) show that hazards do exert a significant effect on migration.[41] One peculiarity of the OLS results is that we obtain significant negative effects for RTAs. This finding occurs in OLS due to the lack of country-pair FE causing omitted variable bias (for an overview of the large body of trade gravity literature on this topic, see Head and Mayer 2014). If bilateral FE are included, RTA effects become insignificant, but in turn the network variable reverses (see Appendix B, Table A5). Since our migration data only cover three decennial waves, the inclusion of bilateral FE is problematic as within-group variation is limited. This problem is aggravated by OLS compared to PPML due to zero migration flows. Hence, we follow Beine and Parsons (2015) by excluding bilateral FE and using direct gravity controls for common country characteristics in all previous and prospective specifications.

38 If we use the simple instead of the sd-weighted index, results do not change.

39 Again, using the simple instead of the sd-weighted index does not change this result.

40 Chosen thresholds are given in Appendix B, Table A2.

41 Using the simple hazard index instead yields positive push and negative pull effects which are statistically significant. However, this finding is not robust, potentially due to heteroskedastic error terms. A White test proposed by Wooldridge (2003, pp. 268–269) for applications with lengthy regressors yields White's special chi-square test statistic of 109.07 and a p-value of 2.1e-24. The Null hypothesis of homoscedasticity is rejected such that estimated variances under OLS are biased. PPML, beyond solving the problem of zero dependent variables, consistently estimates the gravity equation and is robust to measurement error and different patterns of heteroscedasticity (see Santos Silva and Tenreyro 2006; Head and Mayer 2014; Fally 2015). Estimating FE PPML based on the smaller OLS sample does not yield statistically significant hazard estimators.

Table 4. Sensitivity analysis

Dependent variable: Migration rate$_{ij,t}$ (log in OLS)

	Exclude hazards (intensity)		Hazard frequency (count)		OLS (intensity)		Heckman selection (intensity)	
	<Max −2 sd (1)	Census −2 years (2)	Basic (3)	Onset weighted (4)	Basic (5)	Onset weighted (6)	Probit, onset weighted (7)	OLS, onset weighted (8)
Hazard Index$_{i,t}$	−0.334	−0.005	−0.038	−0.013	0.000	−0.000	−0.000	−0.000
	(0.38)	(0.02)	(0.05)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
Hazard Index$_{j,t}$	0.028	0.001	0.018	−0.039	−0.002	−0.006	−0.002***	−0.006
	(0.07)	(0.01)	(0.06)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
Controls								
ln(GDPp.c.$_{j,t}$/GDPp.c.$_{i,t}$)	0.210	0.238	0.216	0.214	0.117**	0.117**	0.008	0.109**
	(0.23)	(0.22)	(0.24)	(0.23)	(0.05)	(0.05)	(0.03)	(0.05)
Civil war$_{i,t}$	0.052**	0.056**	0.055**	0.059**	0.005	0.006	0.006	0.005
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)
Civil war$_{j,t}$	−0.260**	−0.277**	−0.259**	−0.259**	0.015	0.015	−0.022***	0.018*
	(0.12)	(0.11)	(0.11)	(0.11)	(0.01)	(0.01)	(0.00)	(0.01)
RTA$_{ij,t}$	0.290**	0.310**	0.290**	0.279**	−0.066**	−0.064**	0.064***	−0.065**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.03)	(0.03)	(0.02)	(0.03)
ln(Mig.Stock$_{ij,t-1}$+1)	0.358***	0.354***	0.357***	0.357***	0.590***	0.590***	0.033***	0.584***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)
ln(Distance$_{ij}$)	−0.745***	−0.719***	−0.746***	−0.748***	−0.521***	−0.520***	−0.283***	−0.475***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.02)	(0.02)	(0.01)	(0.02)
Contiguity$_{ij}$	0.373**	0.450***	0.379**	0.378**	0.457***	0.458***	0.027	0.454***
	(0.17)	(0.15)	(0.16)	(0.16)	(0.07)	(0.07)	(0.06)	(0.07)
Common language$_{ij}$	0.506***	0.480***	0.504***	0.506***	0.384***	0.383***	0.167***	0.349***

(continued)

Table 4. (continued)

Dependent variable: Migration rate$_{ij,t}$ (log in OLS)

	Exclude hazards (intensity)		Hazard frequency (count)		OLS (intensity)		Heckman selection (intensity)	
	<Max −2 sd	Census −2 years	Basic	Onset weighted	Basic	Onset weighted	Probit, onset weighted	OLS, onset weighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.11)	(0.11)	(0.11)	(0.11)	(0.03)	(0.03)	(0.02)	(0.03)
Colony$_{ij}$	0.469***	0.488***	0.472***	0.467***	0.007	0.009	−0.014	0.011
	(0.17)	(0.17)	(0.17)	(0.17)	(0.09)	(0.09)	(0.07)	(0.09)
Common religion$_{ij}$							0.234***	
							(0.03)	
ρ								−0.239***
								(0.07)
σ								0.352***
								(0.01)
Log-likelihood/R^2	−74.013	−73.122	−74.019	−74.022	0.783	0.783		−68899.91
Observations	66,673	66,048	66,673	66,673	23,255	23,255		65,386

Note: ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Physical intensity indicator components are weighted with their inverse standard deviation. Natural hazards are scaled by log land area. Constant, origin, destination, and decade FE and MR terms are included but not reported. Robust standard errors reported in parentheses.

Finally, we estimate a Heckman selection model to explore potential heterogeneity in the adaptation mechanism at the extensive versus the intensive margin. In absence of a better instrument, we use the Helpman et al. (2008) common religion measure as a selection variable. Our results suggest that natural hazards in the destination country negatively affect the probability to observe a non-zero migration rate between a country pair (column 7), whereas conditional on the probability that bilateral migration takes place, there is no evidence that hazards have any statistically significant push or pull effects (column 8). Thus, we conclude that natural hazards rather tend to affect migration at the extensive margin whereas we do not find evidence for an effect at the intensive margin.[42]

6. Concluding Remarks

This article aims to provide an answer to the question on the impact of natural hazards on international migration. To motivate the empirical strategy, we construct a stylized gravity framework of bilateral migration introducing hazards as random shocks. To test the implications empirically, we deploy a full matrix of international migration available for increments of 10 years from 1980 to 2010 and hazard data based on intensity measures of geological and meteorological events only. We run a conditional FE PPML model to address the issue of zero migration flows and potentially heteroskedastic standard errors. The gravity estimations are augmented by the use of explicit MR terms to control for unobservable time-varying country characteristics.

Our PPML findings show little robust, if at all noisy evidence for push and pull effects of natural hazards on medium- to long-run international relocation. We find evidence that hazard intensity in the origin causes bilateral migration to increase by 1.7% (evaluated at the mean) only if we consider the timing of events with respect to the migration decision using a bell-shaped onset weighting scheme. If timing is neglected or alternative hazard measures are applied, this finding turns out not to be robust. Decomposing natural hazards by type does not show evidence for a clear pattern of events either. Nevertheless, if we distinguish between origin income groups, we find substantial heterogeneity, suggesting that natural hazards have positive push and negative pull effects for middle-income countries. These are neither financially constraint (as low-income countries) nor do they show high insurance penetration rates (as high-income countries). We conclude that examining the effects of natural hazards on migration using a full country sample may lead to aggregation bias.

Finally, we cannot rule out the possibility that the mere aggregation of our 10-year data smooths out a big amount of information, making identification of causal effects problematic. Above all, temporary international relocation, which is a potential mechanism for adapting to transient natural hazards, is not captured by our data. Also, a large number of bilateral migrant stocks is estimated rather than observed, giving rise to attenuation bias as a consequence of measurement error. These are potential key reasons for the absence of causal evidence. Given these migration data restrictions, our outlined findings must therefore be taken with caution.

42 Note that Heckman results are not directly comparable to PPML, which nest the intensive and extensive effects in one estimate, while Heckman separates them.

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Appendix

Details on the Taylor series expansion to obtain tractable MR terms estimated in the empirical specifications. From the theoretical derivations in Section 2, MR terms are given by

$$\tilde{\Gamma}_{i,t} = \left[\sum_j \delta_{j,t} \left(\frac{\theta_{ij,t}}{\tilde{\Gamma}_{j,t}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}, \tag{A.1}$$

$$\tilde{\Gamma}_{j,t} = \left[\sum_i \delta_{i,t} \left(\frac{\theta_{ij,t}}{\tilde{\Gamma}_{i,t}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}, \tag{A.2}$$

where δ is $N_{i,t}/N_t$ or $N_{j,t}/N_t$, respectively.

The first-order Taylor series expansion of any function $f(x_i)$, centered at x, is given by $f(x_i) = f(x) + [f'(x)](x_i - x)$. We follow Baier and Bergstrand (2009) and center around symmetric migration frictions $\theta_{ij,t} = \theta$. We start by dividing both sides of equation (A.1) by a constant $\theta^{1/2}$:

$$\begin{aligned}\tilde{\Gamma}_{i,t}/\theta^{1/2} &= \left[\sum_j \delta_{j,t}\left(\theta_{ij,t}/\theta^{1/2}\right)^{1-\sigma}/\tilde{\Gamma}_{j,t}^{1-\sigma}\right]^{\dfrac{1}{1-\sigma}} \\ &= \left[\sum_j \delta_{j,t}\left(\theta_{ij,t}/\theta\right)^{1-\sigma}/\left(\tilde{\Gamma}_{j,t}/\theta^{1/2}\right)^{1-\sigma}\right]^{\dfrac{1}{1-\sigma}}\end{aligned} \tag{A.3}$$

We define $\hat{\Gamma}_{i,t} = \tilde{\Gamma}_{i,t}/\theta^{1/2}$, $\hat{\theta}_{ij,t} = \theta_{ij,t}/\theta$, and $\hat{\Gamma}_{j,t} = \tilde{\Gamma}_{j,t}/\theta^{1/2}$. Substituting these in the previous equation, we obtain

$$\hat{\Gamma}_{i,t} = \left[\sum_j \delta_{j,t}\left(\hat{\theta}_{ij,t}/\hat{\Gamma}_{j,t}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{A.4}$$

It will later be useful to rewrite equation (A.4) as

$$e^{(1-\sigma)\ln\ \hat{\Gamma}_{i,t}} = \sum_j e^{\ln\ \delta_{j,t}} e^{(\sigma-1)\ln\ \hat{\Gamma}_{j,t}} e^{(1-\sigma)\ln\ \hat{\theta}_{ij,t}}, \tag{A.5}$$

where e is the natural logarithm operator. In a world with symmetric migration costs $\theta_{ij,t} = \theta$, connoting $\hat{\theta}_{ij,t} = 1$, the latter implies

$$\hat{\Gamma}_{i,t}^{1-\sigma} = \sum_j \delta_{j,t}\hat{\Gamma}_{j,t}^{\sigma-1} \tag{A.6}$$

multiplying both sides by $\hat{\Gamma}_{i,t}^{\sigma-1}$ yields

$$1 = \sum_j \delta_{j,t}(\hat{\Gamma}_{i,t}\hat{\Gamma}_{j,t})^{\sigma-1}. \tag{A.7}$$

As noted in Feenstra (2004, p. 158, footnote 11), the solution to this equation is $\hat{\Gamma}_{i,t} = \hat{\Gamma}_{j,t} = 1$. For this reason, under symmetric migration costs $\hat{\theta}_{ij,t} = \hat{\Gamma}_{i,t} = \hat{\Gamma}_{j,t} = 1$ and $\Gamma_{i,t} = \Gamma_{j,t} = \theta^{1/2}$.

A first-order log-linear Taylor series expansion of $\hat{\Gamma}_{i,t}$ from equation (A.5), analog for $\hat{\Gamma}_{j,t}$, centered at $\hat{\theta} = \hat{\Gamma}_{i,t} = \hat{\Gamma}_{j,t} = 1$ yields

$$\ln\ \tilde{\Gamma}_{i,t} = -\sum_j \delta_{j,t}\ln\ \tilde{\Gamma}_{j,t} + \sum_j \delta_{j,t}\ln\ \theta_{ij,t} \tag{A.8}$$

and

$$\ln\ \tilde{\Gamma}_{j,t} = -\sum_i \delta_{i,t}\ln\ \tilde{\Gamma}_{i,t} + \sum_i \delta_{i,t}\ln\ \theta_{ij,t}. \tag{A.9}$$

Using $d[e^{(1-\sigma)\ln\ \hat{x}}]/d[\ln\ \hat{x}] = (1-\sigma)e^{(1-\sigma)\ln\ \hat{x}}$, some mathematical manipulation and assuming symmetry of migration costs, a solution to the above equations is

$$\ln\ \tilde{\Gamma}_{i,t} = \left[\sum_{j}\delta_{j,t}\ln\ \theta_{ij,t} - \frac{1}{2}\sum_{k}\sum_{m}\delta_{k,t}\delta_{m,t}\ln\ \theta_{km,t}\right] \tag{A.10}$$

and

$$\ln\ \tilde{\Gamma}_{j,t} = \left[\sum_{i}\delta_{i,t}\ln\ \theta_{ij,t} - \frac{1}{2}\sum_{k}\sum_{m}\delta_{k,t}\delta_{m,t}\ln\ \theta_{km,t}\right], \tag{A.11}$$

where MRs are normalized by (the square root of) population weighted average migration frictions (the combined shock-cost measure).

In the empirical specification MR terms are calculated as

$$\begin{aligned} \mathrm{MRDIST}_{ij,t} = [(&\sum_{k=1}^{C}\delta_{k,t}(\ln\ \mathrm{Dist}_{ik} + \Phi_{k,t} - \Phi_{i,t})) \\ &+(\sum_{m=1}^{C}\delta_{m,t}(\ln\ \mathrm{Dist}_{mj} + \Phi_{j,t} - \Phi_{m,t})) \\ &-(\sum_{k=1}^{C}\sum_{m=1}^{C}\delta_{k,t}\delta_{m,t}(\ln\ \mathrm{Dist}_{km} + \Phi_{m,t} - \Phi_{k,t}))], \end{aligned} \tag{A.12}$$

$$\begin{aligned} \mathrm{MRADJ}_{ij,t} = [(&\sum_{k=1}^{C}\delta_{k,t}(\mathrm{Adj}_{ik} + \Phi_{k,t} - \Phi_{i,t})) \\ &+(\sum_{m=1}^{C}\delta_{m,t}(\mathrm{Adj}_{mj} + \Phi_{j,t} - \Phi_{m,t})) \\ &-(\sum_{k=1}^{C}\sum_{m=1}^{C}\delta_{k,t}\delta_{m,t}(\mathrm{Adj}_{km} + \Phi_{m,t} - \Phi_{k,t}))], \end{aligned} \tag{A.13}$$

where δ denotes a states' share of population over 'total' world population, $\mathrm{N}_{k,t}/\mathrm{N}_t$ and $\mathrm{N}_{m,t}/\mathrm{N}_t$.

MR terms for RTA, Colony, and Common Language are calculated analogously.

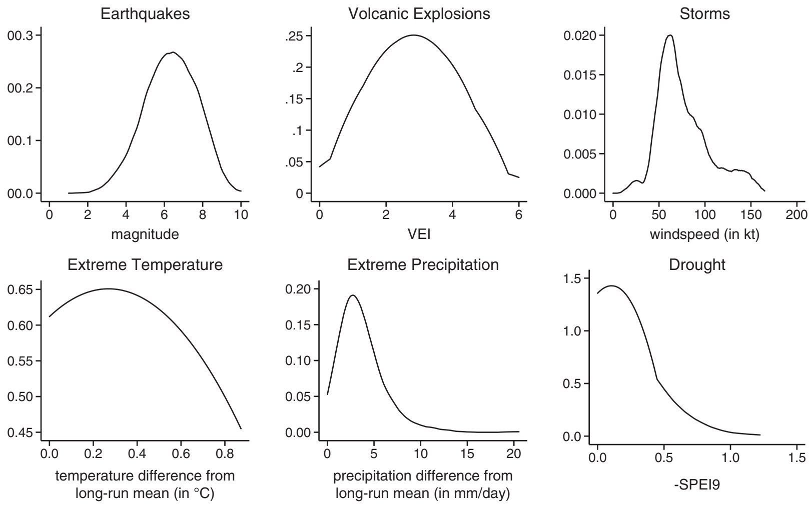

Figure A1. Kernel densities of hazard indicators by country income groups at decennial level; zeroes excluded for earthquakes and volcanic explosions.

Table A1. Summary statistics, PPML, full sample

Variable	Mean	sd	Min	Max
Migration rate$_{ij,t}$	0.0002	0.003	0	0.500
Migration flow$_{ij,t}$	1,726	28,712	0	4,705,677
Aggregate hazard indices				
Hazard Index$_{i,t}$	7.370	2.842	1.616	19.557
Hazard Index$_{j,t}$	7.421	2.855	1.616	19.557
Hazard Index$_{i,t}$, onset weighted	5.777	2.247	0.767	15.522
Hazard Index$_{j,t}$, onset weighted	5.813	2.256	0.767	15.522
Hazard Index$_{i,t}$, sd weighted	5.096	21.526	0	322.040
Hazard Index$_{j,t}$, sd weighted	5.102	22.082	0	322.040
Hazard Index$_{i,t}$, onset weighted, sd weighted	4.156	14.855	0	533.030
Hazard Index$_{j,t}$, onset weighted, sd weighted	4.196	15.113	0	533.030
Hazard Index$_{i,t}$, major	1.873	4.061	0	17.709
Hazard Index$_{j,t}$, major	1.896	4.101	0	17.709
Hazard Index$_{i,t}$, census − 2years	7.130	2.749	1.621	19.305
Hazard Index$_{j,t}$, census − 2years	7.182	2.764	1.621	19.305
Hazard counts$_{i,t}$	14.137	6.144	2.565	33.542
Hazard counts$_{j,t}$	14.152	6.199	2.565	33.542
Hazard counts$_{i,t}$, onset	5.880	2.528	0.710	13.827
Hazard counts$_{j,t}$, onset	5.886	2.550	0.710	13.827
Hazard types (basic)				
Earthquake$_{i,t}$	0.511	0.158	0	0.947
Earthquake$_{j,t}$	0.510	0.160	0	0.947
Volcanic explosion$_{i,t}$	0.042	0.093	0	0.476
Volcanic explosion$_{j,t}$	0.043	0.093	0	0.476
Windspeed$_{i,t}$	6.455	2.641	1.133	17.709
Windspeed$_{j,t}$	6.502	2.649	1.133	17.709

(continued)

Table A1. (continued)

Variable	Mean	sd	Min	Max
ΔPrecipitation$_{i,t}$	0.329	0.278	0.008	2.936
Δ Precipitation$_{j,t}$	0.333	0.282	0.008	2.936
Δ Temperature$_{i,t}$	0.023	0.018	2.1e-05	0.115
Δ Temperature$_{j,t}$	0.023	0.018	2.1e-05	0.115
Drought (SPEI)$_{i,t}$	0.012	0.018	0	0.127
Drought (SPEI)$_{j,t}$	0.012	0.018	0	0.127
Hazard types (onset weighted)				
Earthquake$_{i,t}$	0.418	0.155	0	0.792
Earthquake$_{j,t}$	0.418	0.155	0	0.792
Volcanic explosion$_{i,t}$	0.031	0.072	0	0.311
Volcanic explosion$_{j,t}$	0.0315	0.073	0	0.311
Windspeed$_{i,t}$	5.094	2.127	0.119	13.899
Windspeed$_{j,t}$	5.127	2.135	0.119	13.899
ΔPrecipitation$_{i,t}$	0.218	0.198	0.006	1.404
Δ Precipitation$_{j,t}$	0.221	0.199	0.006	1.404
Δ Temperature$_{i,t}$	0.011	0.008	9.9e-05	0.048
Δ Temperature$_{j,t}$	0.011	0.008	9.9e-05	0.048
Drought (SPEI)$_{i,t}$	0.005	0.009	0	0.072
Drought (SPEI)$_{j,t}$	0.005	0.009	0	0.072
Controls				
ln(GDPp.c.$_{j,t}$/GDPp.c.$_{i,t}$)	0.028	2.187	−6.149	6.149
Civil war$_{i,t}$	0.729	1.947	0	10
Civil war$_{j,t}$	0.721	1.948	0	10
RTA$_{ij,t}$	0.169	0.375	0	1
ln(Mig.Stock$_{ij,t-1}$+1)	2.608	3.084	0	16.053
ln(Distance$_{ij}$)	8.718	0.774	2.349	9.894
Contiguity$_{ij}$	0.021	0.143	0	1
Common language$_{ij}$	0.147	0.354	0	1
Colony$_{ij}$	0.013	0.114	0	1

Note: Total 66,673 observations; all hazard variables are land area weighted.

Table A2. Standard thresholds for hazard count variables

Count indicator	Intensity measure	Bound	Minimum event type
Earthquakes	Maximum magnitude	≥4	Felt shaking of the earth with light damage caused to buildings and structures
Storms	Maximum sustained wind speed	≥64 knots	Some damage to buildings and trees, extensive damage to power lines and poles(Cat. 1 on Saffir-Simpson Hurricane Scale)
Volcanoes	Maximum VEI	≥1	Light eruption with ejecta volume >10,000 m^3
Extreme precipitation	Positive difference of monthly mean precipitation from monthly long-run mean	≥1.5 mm/day	Excess-rain anomaly
Extreme temperatures	Absolute difference of monthly mean temperature from monthly long-run mean	≥1.5 °C	Temperature anomaly
Droughts	Mean Standardized Precipitation Evapotranspiration Index (SPEI)	≤0	Mild drought (Vicente-Serrano et al 2010)

Table A3. Countries in PPML specification

	Case numbers			Case numbers	
Country	Origin	Destination	Country	Origin	Destination
Afghanistan	151	0	Kuwait	307	318
Albania	439	450	Kyrgyzstan	439	450
Algeria	440	289	Lao People's Democratic Republic	439	450
Angola	439	450	Latvia	307	318
Argentina	439	450	Lebanon	440	289
Armenia	307	318	Lesotho	439	450
Australia	439	450	Liberia	439	450
Austria	439	450	Libya	307	318
Azerbaijan	307	318	Lithuania	307	318
Bahamas	439	450	Luxembourg	439	450
Bahrain	439	450	Madagascar	439	450
Bangladesh	439	450	Malawi	439	450
Belarus	307	318	Malaysia	439	450
Belgium	439	450	Mali	439	450
Belize	439	450	Mauritania	439	450
Benin	439	450	Mauritius	439	450
Bhutan	150	161	Mexico	439	450
Bolivia (Plurinational State of)	439	450	Mongolia	439	450
Bosnia and Herzegovina	307	318	Morocco	440	289

(continued)

Table A3. (continued)

Country	Case numbers		Country	Case numbers	
	Origin	Destination		Origin	Destination
Botswana	440	289	Mozambique	439	450
Brazil	439	450	Namibia	439	450
Brunei Darussalam	439	450	Nepal	439	450
Bulgaria	439	450	Netherlands	439	450
Burkina Faso	439	450	New Zealand	439	450
Burundi	439	450	Nicaragua	439	450
Cambodia	307	318	Niger	439	450
Cameroon	439	450	Nigeria	439	450
Canada	439	450	Norway	439	450
Central African Republic	439	450	Oman	439	450
Chad	439	450	Pakistan	440	289
Chile	439	450	Panama	439	450
China	440	289	Papua New Guinea	439	450
China, Hong Kong Special Administrati.	439	450	Paraguay	439	450
Colombia	439	450	Peru	439	450
Congo	439	450	Philippines	439	450
Costa Rica	439	450	Poland	307	318
Croatia	307	318	Portugal	439	450
Cuba	439	450	Puerto Rico	439	450
Cyprus	439	450	Qatar	150	161
Czech Republic	307	318	Republic of Korea	439	450
Côte d'Ivoire	439	450	Republic of Moldova	439	450
Democratic Republic of the Congo	440	289	Romania	307	318
Denmark	439	450	Russian Federation	439	450
Djibouti	307	318	Rwanda	439	450
Dominican Republic	439	450	Saudi Arabia	439	450
Ecuador	439	450	Senegal	439	450
Egypt	439	450	Sierra Leone	439	450
El Salvador	439	450	Singapore	439	450
Equatorial Guinea	307	318	Slovakia	307	318
Eritrea	308	157	Slovenia	307	318
Estonia	307	318	Solomon Islands	307	318
Ethiopia	439	450	South Africa	439	450
Fiji	439	450	Spain	439	450
Finland	439	450	Sri Lanka	439	450
France	439	450	Sudan	439	450
Gabon	439	450	Suriname	439	450
Gambia	439	450	Swaziland	439	450
Georgia	439	450	Sweden	439	450
Germany	439	450	Switzerland	439	450
Ghana	440	289	Tajikistan	439	450
Greece	439	450	Thailand	439	450
Guatemala	439	450	The former Yugoslav Republic of Maced.	307	318

(continued)

Table A3. (continued)

Country	Case numbers		Country	Case numbers	
	Origin	Destination		Origin	Destination
Guinea	439	450	Togo	439	450
Guinea-Bissau	439	450	Trinidad and Tobago	439	450
Guyana	439	450	Tunisia	439	450
Haiti	307	318	Turkey	439	450
Honduras	439	450	Turkmenistan	439	450
Hungary	307	318	Uganda	439	450
Iceland	439	450	Ukraine	439	450
India	439	450	United Arab Emirates	150	161
Indonesia	439	450	United Kingdom of Great Britain and N.	439	450
Iran (Islamic Republic of)	439	450	United Republic of Tanzania	439	450
Iraq	439	450	United States of America	439	450
Ireland	439	450	Uruguay	439	450
Israel	439	450	Uzbekistan	439	450
Italy	439	450	Vanuatu	439	450
Jamaica	439	450	Venezuela (Bolivarian Republic of)	439	450
Japan	439	450	Viet Nam	440	289
Jordan	439	450	Yemen	307	318
Kazakhstan	307	318	Zambia	439	450
Kenya	439	450	Zimbabwe	439	450

Note: Case numbers extracted from post-estimation sample tabulation.

Table A4. Baseline results, not controlling for migrant networks

Dependent variable: Migration rate$_{ij,t}$

	Basic		Onset weighted	
	Simple (1)	sd weighted (2)	Simple (3)	sd weighted (4)
Hazard Index$_{i,t}$	−0.112	−0.010***	−0.061	0.004***
	(0.09)	(0.00)	(0.11)	(0.00)
Hazard Index$_{j,t}$	0.018	−0.001	0.001	−0.008
	(0.10)	(0.01)	(0.14)	(0.01)
Controls				
ln(GDPp.c.$_{j,t}$/GDPp.c.$_{i,t}$)	0.239	0.282	0.240	0.271
	(0.22)	(0.22)	(0.22)	(0.22)
Civil war$_{i,t}$	0.037	0.039	0.025	0.042
	(0.03)	(0.03)	(0.03)	(0.03)
Civil war$_{j,t}$	−0.203**	−0.200**	−0.198**	−0.199**
	(0.08)	(0.08)	(0.08)	(0.08)
RTA$_{ij,t}$	0.617***	0.629***	0.634***	0.632***
	(0.12)	(0.12)	(0.12)	(0.12)
ln(Distance$_{ij}$)	−1.309***	−1.311***	−1.309***	−1.309***
	(0.08)	(0.08)	(0.08)	(0.08)
Contiguity$_{ij}$	0.903***	0.901***	0.897***	0.900***
	(0.18)	(0.18)	(0.18)	(0.18)
Common Language$_{ij}$	1.017***	1.016***	1.015***	1.019***
	(0.16)	(0.16)	(0.16)	(0.16)
Colony$_{ij}$	1.434***	1.436***	1.435***	1.438***
	(0.20)	(0.20)	(0.20)	(0.20)
Log-likelihood	−76.644	−76.685	−76.577	−76.675
Observations	66673	66673	66673	66673

Note: ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Constant, origin, destination, and decade FE and MR terms are included but not reported. Natural hazards are scaled by log land area. Robust standard errors reported in parentheses.

Table A5. OLS, full sample, 1980–2010, bilateral FE

Dependent variable: Migration rate$_{ij,t}$	Basic		Onset weightd	
	Simple (1)	sd weighted (2)	Simple (3)	sd weighted (4)
Hazard Index$_{i,t}$	0.059**	−0.062	0.070*	0.106
	(0.03)	(0.08)	(0.04)	(0.08)
Hazard Index$_{j,t}$	−0.174***	−0.196**	−0.070*	0.269***
	(0.03)	(0.08)	(0.04)	(0.09)
Controls				
ln(GDPp.c.$_{j,t}$/GDPp.c.$_{i,t}$)	0.371***	0.398***	0.419***	0.415***
	(0.06)	(0.06)	(0.06)	(0.06)
Civil war$_{i,t}$	0.011	0.010	0.008	0.012
	(0.01)	(0.01)	(0.01)	(0.01)
Civil war$_{j,t}$	0.027***	0.026***	0.032***	0.033***
	(0.01)	(0.01)	(0.01)	(0.01)
RTA$_{ij,t}$	−0.052	−0.049	−0.050	−0.043
	(0.06)	(0.06)	(0.06)	(0.06)
ln(Mig.Stock$_{ij,t-1}$+1)	−0.114***	−0.121***	−0.122***	−0.125***
	(0.01)	(0.01)	(0.01)	(0.01)
R^2 (within)	0.079	0.071	0.071	0.071
Observations	23,255	23,255	23,255	23,255

Note: ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Constant, bilateral and decade FE, and MR terms are included but not reported. Robust standard errors reported in parentheses.

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Out-migration from Coastal Areas in Ghana and Indonesia—the Role of Environmental Factors

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Abstract

Projections of climatic and environmental changes have generated a growing effort to assess their implications for human migration. Because migration is always a multi-causal phenomenon, this study aims to disentangle the impact of environmental factors from other migration-inducing factors to shed some light on the complex relationship between the environment and migration. Thus, we conducted quantitative microlevel studies in low-lying communities in two high-mobility countries—Ghana and Indonesia—that are particularly exposed to coastal hazards like erosion, land subsidence, storm surges and an increasing sea level, and are prone to flooding on a regular basis. Different measures of environmental threats were collected, ranging from individual perceptions over the household's distance to the coast to expert opinions. We analyzed the relationships using logistic regressions and controlled for contextual factors on multiple levels. No statistically significant direct impacts of slow-onset environmental events on migration decisions could be detected. Perceptions of storms, a clearly sudden-onset event, however, were found to be significantly linked to out-migration decisions in Ghana. These findings support the hypothesis that environmental factors are generally not a primary cause of migration, and their effects are rather context specific—especially for slow-onset changes. (JEL codes: R23, O15, Q54.)

Key words: mobility, environment, microeconomics

1. Introduction

Scientists expect that increases in global temperatures will lead to sea-level rise and greater weather variability which could result in droughts, increased rainfalls, and intensified extreme coastal events (IPCC 2007). These projections have generated a growing effort to assess the impact of climate change, including its implications for human migration. However, 'the science of climate change is complex enough, even before considering its impact on societies' (Brown 2008, p. 8). Consequently, global estimates of future migration caused by climate and environmental change vary extremely. One of the most famous estimations resulted in around 200 million ‘environmental refugees’ until the year 2050, 162 million of them due to sea-level rise in Asia and Africa (Myers 2002). Other scholars have produced even higher estimates. The Christian aid report, for example, predicted that 1 billion people will be forced to leave their home in the same period (Christian Aid 2007). These estimates, however, have been heavily criticized by other scholars who reject this deterministic view of climate change being the primary and direct cause of out-migration. Instead, migration is recognized as a complex phenomenon which is ‘always the result of a multi-causal relationship between environmental, political, economic, social, and cultural dimensions’ (Piguet 2010, p. 517). As these dimensions are closely intertwined, it makes not much sense to consider any of the migration determining factors in isolation.

Despite this high level of interest, quantitative micro-level studies accounting for this multi-causal relationship are still underrepresented (Gray and Bilsborrow 2013). Therefore, this study aims to contribute to the existing literature by using a quantitative multilevel model where several migration-determining factors are simultaneously considered to isolate the net effect of the environment. Since low-lying regions in Asia and Africa are considered especially vulnerable, data have been collected in two coastal regions in Indonesia and Ghana which experience floods and erosion on a regular basis. Economic, social, and cultural conditions vary considerably between both regions which helps to understand in how far migratory responses to environmental threats are context specific.

Empirically, this study improves on existing works in several ways. First of all, a micro-level survey was conducted in two different developing countries, which enables the analysis of the relationship between the environment and out-migration in a quantitative and comparative way. Second, very different environmental variables ranging from perceptions over expert opinions to more objective measures have been collected. While most quantitative studies have so far focused on sudden changes in the environment, this study especially looks at rather gradual changes and slow-onset events. Third, both people who stayed and people who moved were included which is important for a better understanding of migration decisions. Additionally, instead of relying on information from a proxy respondent who answers on behalf of the migrant, migrants were personally interviewed. This procedure enables the inclusion of individual perceptions and preferences.

While this study is able to explain migration decisions well with the help of contextual factors on community, household, and individual level, no direct link between the main environmental factors—floods and erosion—and out-migration could be detected. However, there is evidence of a positive effect of storm perceptions on individual migration decisions in Ghana which lead to the hypothesis that long-term, gradual changes do not tend to increase the likelihood of out-migration directly, while sudden-onset events might do. Additionally, there is weak evidence that the effect of environmental degradation on migration depends on other migration-facilitating factors such as networks in Indonesia and the number of children in Ghana.

2. Migration and the Environment

Despite substantial and ongoing progress in migration theories, the environment was not incorporated explicitly for most of the time (Black et al. 2011).[1]

1 At the same time, also research on environmental change has completely ignored the role of migration (Black et al. 2011).

The idea that human migration patterns may respond to the environment, however, is not new. A large body of literature indicates that prehistoric settlements were strongly linked to changes in the climate (McLeman and Smit 2006). Examples of climatic influences on human settlement patterns can also be found in the more recent past. The Great Plains in Oklahoma, as for example, experienced a high level of in-migration during the 1920s which coincided with a period of favorable agricultural conditions. During the 1930s, however, droughts and dust storms made hundred thousands of Americans leave this 'Dust Bowl' (McLeman 2006). Later on, Hurricane Mitch struck Central America leading to wide-scale migration movements in 1998 and Hurricane Katrina resulted in around 2 million displaced people in 2005 (McLeman and Hunter 2010).

Yet only 30 years ago, the term 'environmental refugee' came into regular use (El-Hinnawi 1985) and in the early 1990s the international community slowly began to recognize the potential implications of environmental change on human migration. The Intergovernmental Panel on Climate Change (IPCC) warned that the greatest single impact of climate change could be on human migration (IPCC 1990). From that moment the subject became increasingly polarized and Suhrke (1993, 1994) identified two main groups: 'Maximalists' claimed that the environment is the primary and direct cause of forced migration, whereas 'minimalists' suggested that the relationship is more complex and, thus, the environment only a contextual factor. In the course of this debate, Myers (1993, 1997, 2002) became the most prominent and widely cited author within the maximalist school. In his various studies he estimated the current number of environmental refugees at 25 million and predicted the number to rise up to 200 million until the year 2050.[2] Black (2001), supported by Castles (2002), disagreed with such scenarios and questioned the assumption of the environment being the primary cause of migration. It would not only be problematic to assume that people move directly because of the environment—as this assumption neglects the essential role of humans in dealing with those changes—but also that everyone who leaves a region experiencing environmental change is actually leaving due to that environment (Black 2001). Today, the field has generally moved beyond these polarized debates and most social scientists emphasize multilevel migration drivers and the importance of contexts (Morrissey 2009).

Yet, environment–migration theories still do not lead to a consistent prediction in which direction environmental changes will impact on out-migration and how large this impact might be relative to other migration-inducing factors. Adverse environmental factors are mostly seen as stressors, push factors, or local disamenities which decrease individuals' happiness and incomes and which encourage them to move to places with better environments (Hunter 2005; Gray 2009). Other theories emphasize that migration decisions are rarely an individual choice but rather made by households (Stark 1991). Thus, it is assumed that when environmental changes lead to the loss of assets or income, households may decide to send out migrants to receive remittances and replace lost assets. While this would be a direct response to the effects of environmental events, sending out migrants may also serve as an ex-ante strategy whenever environmental effects are expected in the future. Since

2 Foresight (2011) shows that also most other estimates of the number of environmental migrants base on Norman Myers' (1993, 2002) methodology or estimates (so for example the numbers of Christian Aid (2007), Stern (2007) and Friends of The Earth (2007). Piguet (2010) calls these numbers 'nothing but the rule of the thumb' (p.517) and the IPCC (2007) labels them as 'at best, guesswork' (p. 365).

migrants' earnings are mostly uncorrelated with environmental threats in the home community, the out-migration of one or more household members can act as an insurance against future environmental damage by diversifying the household's income sources (Stark and Bloom 1985). In case of severe events, however, migration of whole households might be necessary and unavoidable to seek shelter in a different area (Gray and Bilsborrow 2013).

Nevertheless, there is agreement that migration is generally costly and thus cannot be considered a default response to environmental stressors. As long as the costs of dealing with environmental events are lower than the costs of migrating, individuals are expected to stay in their home community—coping with and adapting to the adverse environmental changes. Similarly, environmental shocks and degradation might make out-migration even less likely because it requires forms of capital, whereas affected populations often experience a decrease in the very capital required for a migratory move (Foresight 2011).

Since environment–migration theories do not lead to clear predictions regarding the direction and relative importance of environmental factors on out-migration decisions, it was called for more detailed case studies and analytical attempts to further assess the impact of environmental degradation. Consequently, in the past two decades the literature on environmental change and migration grew extensively; most of the studies suggesting that the environment 'can' lead to migration (Henry et al. 2004; Laczko and Aghazarm 2009; Kniveton et al. 2011). Highly vulnerable households of dry areas in Ethiopia were found to send migrants to urban areas during times of famine (Ezra and Kiros 2000). Results from another study indicated that in dry periods male migration is increasing, while female migration decreases (Gray and Müller 2012). In drought-prone areas of Burkina Faso individuals engaged in rural–rural migration to areas with better agricultural outcomes and reduced their international migration (Henry et al. 2003). Gray and Bilsborrow (2013), on the other hand, found that dry periods in Ecuador decreased internal moves but increased international migration. Halliday (2006) found increased international mobility with loss of harvest for wealthy households but overall decreased migration following an earthquake in El Salvador. These and other papers illustrate how diverse findings regarding the environment–migration nexus can be.

Despite the already extensive literature, there is still room for further research addressing the shortcomings of existing work. First, existing research mostly focuses on one specific environmental threat and cannot make statements about differences across different environmental factors in the same region. The most investigated environmental threat is drought or rainfall, while other environmental events and their impacts get rather neglected (Jónsson 2010). This study adds by focusing on different coastal events. Second, the majority of micro-level field studies have used qualitative methods. Although these studies offer valuable insights into people's migratory responses toward environmental change, they cannot successfully isolate environmental aspects from other migration-inducing factors (Piguet 2010). Therefore, quantitative micro-level research methods are used which are still largely underrepresented (see Moriniere 2009).[3]

3 Moriniere (2009) reviewed the environment–migration literature, consisting of 321 publications and found only two articles in which the researchers used quantitative multivariate methods to examine the effect of environmental factors on out-migration. Laczko and Aghazarm (2009) argue that in fact there have been few more quantitative papers. Nevertheless, they criticize that most of those few studies use rainfall data to investigate the link. The few studies which have focused on other environmental factors are criticized for having clear measurement problems by only using very subjective environmental variables (Ezra and Kiros 2001).

Furthermore, since sudden and extreme environmental events have received much more attention (Gray 2011), this study will especially focus on rather gradual and long-term changes. While both types of environmental stressors have the potential to impact on out-migration decisions, long-term changes are often not regarded as severe enough to cause the relocation of whole households. Households experiencing long-term changes are rather expected to send out individual household members to diversify and supplement their income sources and to adapt to those changes over time, since they are generally easier to anticipate than sudden-onset events (Koubi et al. 2016). Thus, long-term gradual environmental changes are expected to have an overall smaller impact on individual out-migration decisions than sudden-onset events. This study tests this hypothesis and adds to the literature by interviewing both migrants and non-migrants in two coastal regions.

3. Methods

As mentioned above, quantitative research methods were used to isolate environmental degradation from other migration-inducing factors. To do so, micro-level[4] data for both migrants and non-migrants who originally came from the same region were required. This data requirement ensures that the context is similar for every respondent. Thus, a retrospective survey was conducted in two developing countries.

3.1 Research sites

Even though many countries in the world face environmental problems, low-lying coastal communities are considered, especially, vulnerable because they are particularly exposed to environmental hazards like coastal erosion, tidal waves, storm surges and an increasing sea level, and thus at the risk of experiencing floods.

However, coastal regions are not only particularly exposed to environmental hazards; they are also associated with a large and rapidly growing human population. Currently, low-lying coastal regions are home to 10% of the world population, while nearly half of the world population lives within 150 km from the coast (Foresight 2011). Two coastal regions, characterized by ongoing erosion and regularly occurring floods, and a longstanding tradition in regional migration, were selected: Keta district in southeastern Ghana and Semarang in Indonesia. A comparative case study approach was chosen, since several studies have shown that this approach is especially useful to pinpoint the impact of site-specific factors on the respective outcomes.

3.1.1 Keta, Ghana

Keta municipality is located in rural southeastern Ghana, and has a population of about 100,000 inhabitants. It was chosen, since it has been the site of acute coastal erosion since about 1907 (Akyeampong 2001). By independence, more than half of Keta was robbed by the sea. This ongoing erosion process is caused by increased storm intensity, soft geology, and low-lying topography but is also influenced by anthropogenic activities like illegal sand

4 The International Organization for Migration emphasizes in its report 'Migration, Environment and Climate Change: Assessing the evidence' that now 'collecting data on households in rural areas is fundamentally important, since households are the major decision makers about [...] migration' (Laczko and Aghazarm 2009, p. 175).

mining or the building of the Akosombo dam on the Volta River in 1964 which decreased the sediment flow to the coast (Boateng 2012). In the end of the twentieth century, annual recession rates ranged from 2 m/year in the northeast to 8 m/year in the southwest (Nairn 2001). Land became extremely scarce and the distance between the sea and the Keta Lagoon is often not exceeding 3 miles. At various sections, especially affected by the environmental change, the lagoon and the sea are within 15–30 m of each other, only separated by a thin tongue of sand. These erosion processes and the concomitant retreating shoreline have direct effects on some coastal households which have to deal with tidal inundation and the threat of losing their house. While erosion and tidal floods are generally seen as rather slow and foreseeable processes, storm surges hit the coastline with destructive and unpredictable power.

3.1.2 Semarang, Indonesia

Semarang, the provincial capital of Central Java, has around 1.6 million inhabitants[5] and is, thus, essentially bigger than Keta. It is a coastal urban area at the Northern coast of Java, located between Jakarta and Surabaya, the two major cities of Indonesia. During colonial times, Semarang has emerged as a successful and important port, and is still seen as an important regional center and port today (Knaap 2015).

Very similar to Keta, coastal communities of Semarang are exposed to massive coastal changes which threaten the development of the area. Substantial land subsidence due to excessive groundwater extractions and extensive construction works causes coastal communities to sink with a rate of 2 up to 10 cm per year. This subsidence in combination with high tides is often resulting in tidal flood inundation which poses a major threat to infrastructure and settlements of urban coastal communities (Marfai and King 2008). Not only is the majority of industry located in these communities but also has a large part of the population of Semarang settled there. Consequently, many people have been experiencing the threat of tidal inundation with different depth of seawater flooding (Marfai et al. 2008). Even though communities are sinking at an alarming rate, subsidence and erosion are rather slow-onset changes, and inundation is regularly experienced by households at risk. Therefore, the great majority of affected households responds to the threats by elevating their houses and raising the floors every 5–10 years if they can afford it. So far, there is no prospect of an end of these environmentally adverse conditions (Harwitasari and van Ast 2009).

3.2 Sampling

The two coastal regions—Keta in Ghana and Semarang in Indonesia—were purposefully chosen because of their changing coast. In each of the regions, several communities were also purposefully selected due to their exposure to coastal changes. This non-random selection of communities ensures that the sample contains both affected and non-affected communities and, thus, that there is sufficient variation in the variables of interest.[6] Once each

5 Dispendukcapil.semarangkota.go.id (2016). Available at: http://dispendukcapil.semarangkota.go.id/statistik/jumlah-penduduk-kota-semarang/2016-04-17 [accessed 31 May 2016].

6 Even though communities share the same regional coastline, not every community is affected by coastal changes. In Ghana, few communities are protected by a sea defense and therefore even experiencing accretion instead of erosion. In Indonesia, some communities are located well above the sea level not facing the previously mentioned threats.

community was chosen, households got randomly selected to avoid sampling bias. In Semarang, high-resolution satellite pictures and randomly generated GPS points were used to select households. In Keta, which is substantially smaller and less densely populated, households got carefully chosen at regular intervals. Once the households were selected, a household survey was the main method to gather data. After household characteristics were obtained by interviewing the household head, the enumerator randomly selected and interviewed a household member above the age of 18 years. Since this study does not want to focus solely on migration intentions or the individual's willingness to migrate but on actual migration, one randomly chosen migrant of the household was additionally interviewed—in case there was any. This sampling strategy has the disadvantage that by definition it does not include households which have moved as a whole. If households which move as a whole are systematically different from households which stay and only send out a migrant, this sampling strategy is likely to produce a sampling bias. However, this study focuses especially on rather gradual and long-term changes which are often not regarded as severe enough to induce the inevitable relocation of whole households. Only very few houses become completely uninhabitable due to coastal changes in Keta and Semarang. Households experiencing long-term changes are therefore expected to be left by individual household members (Koubi et al. 2016). Those migrants, however, are part of this study's sample. Furthermore, the migrant sample is found to be quite diverse: only 42% of sampled migrants from Keta and 35.4% of migrants from Semarang had actually moved unaccompanied. The rest moved mainly together with their spouses and children but also with parents and siblings—leaving behind only parts of the generally quite large and intergenerational households which have been especially found in the Ghanaian study area. Even though the error caused by the omission of whole households is thus expected to be rather small, one should keep the sampling strategy in mind when interpreting the results. The great advantage of this sampling approach, however, is that environmental migration can be investigated even when high-quality census data are not available. Therefore, this generally applicable approach is very helpful for studying migration decisions in many different contexts.

4. Data and Analysis

In line with the Foresight Report (2011), migration is understood as a movement from one place to another for a period of 3 months or more. This study does not focus on international migration only but also considers everyone a migrant who moves within her country—to another region, district, or community. Not only did first informal interviews reveal that only very few people from Semarang actually leave Indonesia, studies have also shown that the majority of environmental migrants move internally (Obokata et al. 2014). While it is common in the literature to get information about the migrant from a proxy respondent like the household head, migrants in this study have been contacted and interviewed by phone. Thereby, it was able to avoid proxy errors and to include very individual perception, preferences, and opinion questions. Since no panel data were available, migrants were asked to provide information about certain characteristics like age, education, and perceptions for the time when they left to avoid reverse causality problems. This also enables the comparison of non-migrants and migrants before their out-migration. Additionally, migrants were only included when they had left within the past 10 years to reduce recall bias.

Table 1. Destination of migrants

	% of migrants, Indonesia	% of migrants, Ghana
Within Semarang/Keta	30.68	6.98
Within region[7]	38.95	20.93
Within country to capital	26.32	65.12
	11.46	36.78
International	4.05	6.98

Ultimately, in Indonesia, 240 households got interviewed out of which 105 households (43.75%) listed at least one migrant in the past 10 years. In Ghana, 190 households participated in the survey out of which 101 (53.16%) had at least one migrant. As Table 1 shows, the great majority of migrants in the sample moved internally: only 4% of Indonesian migrants and only 7% of Ghanaian migrants actually left the country. In Indonesia, nearly a third of movements happened within Semarang, while in Ghana only 7% of migrants moved within Keta.

This finding is not very surprising, since Semarang is essentially bigger and economically stronger than Keta. That might also be the reason why most Indonesian migrants stay within the region (Central Java), whereas Ghanaian migrants tend to leave the region (Volta region), mostly to move to the Greater Accra region. Flow maps (see Figures 1 and 2) further illustrate the range of destinations of migrants.

The other variable of main interest, environmental threats, was measured in three different ways. First, in line with other papers about the environment–migration link, this research uses perceptions because they are considered central for how people respond to environmental threats and because they can differ substantially between individuals from the same household (Mortreux and Barnett 2009, Koubi et al. 2016). Respondents were asked about their perceptions of flood and erosion in both study areas. Since subsidence poses an additional environmental threat in Indonesia, it was included in the Indonesian questionnaire. The same applies to storms for the Ghanaian case which is the only clearly sudden-onset environmental event. Respondents were asked to indicate on a scale from 1 to 10 how much they have been affected by those environmental threats within the past 5 years.

Nevertheless, individuals' perceptions might be biased or incomplete, and it is frequently argued that studies should focus more on objective measures (Laczko and Aghazarm 2009). Therefore, the household's distance to the coast is used as a proxy for its exposure to coastal changes. On top of these measures on individual and household level, the sampled communities have been categorized according to their recent exposure to floods (Indonesia) and shoreline erosion (Ghana). This classification of communities into different hazard categories is based on the knowledge of experts.

A first look at the environmental variables shows that perceptions are in line and highly correlated with the more objective measures (see Table 2). As expected, individuals from households living further away from the coast perceived to be less affected by erosion, floods, and subsidence. Additionally, those who perceive to be highly affected by environmental threats are significantly more likely to live in high-hazard communities.

To get a first impression of the general reasons for moving, at the beginning of the interview and thus before mentioning the focus on environmental factors, migrants were asked why they had moved away from their community. Migrants could openly name up to three

7 To be more precise: Volta Region in Ghana, and Central Java in Indonesia.

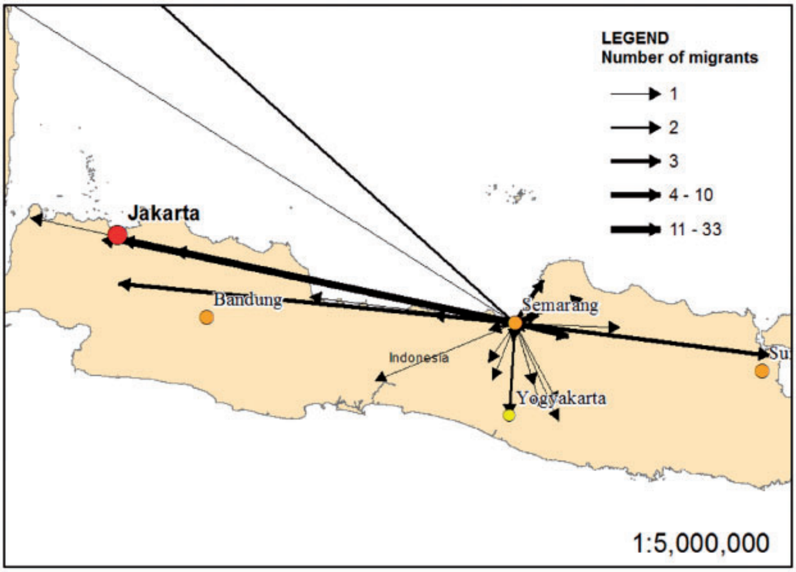

Figure 1. Flow map, migrants from Semarang, Indonesia.

Source: Author's illustration.

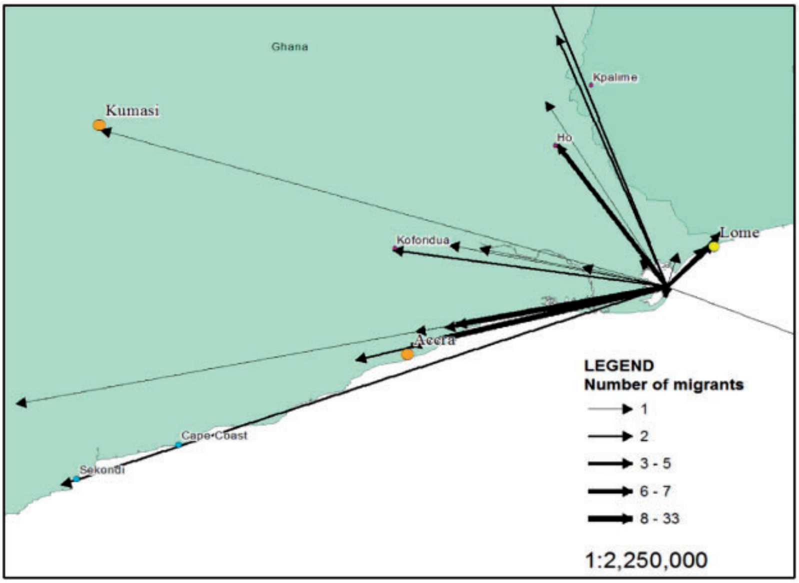

Figure 2. Flow map, migrants from Keta, Ghana.

Source: Author's illustration.

main reasons, which have been sorted into five different categories. Ultimately, 9% of the Indonesian and 3% of the Ghanaian migrants mentioned floods or other environmental threats as a reason (see Figure 3).

Table 2. Correlation of environmental variables

Indonesia/ Ghana	Individual level: perceptions			Household level	Community level
	Flood	Erosion	Subsidence/storm	Distance	Hazard
Flood	1.00				
Erosion	**0.1764***/ 0.7070*****	1.00			
Subsidence/Storm	**0.4323***/ 0.5917*****	**0.3466***/ 0.4890*****	1.00		
Distance	**−0.3909***/ −0.1578*****	**−0.0428***/ −0.1935*****	**−0.3909***/** −0.0724	1.00	
Hazard	0.0278/ **0.3094*****	**0.1172**/ 0.4089*****	**0.2426***/ 0.1972*****	**0.2595***/ 0.4319*****	1.00

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

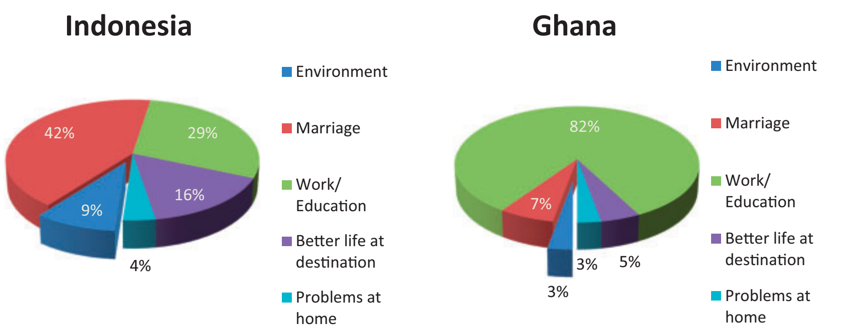

Figure 3. Reasons for migration, multiple answers per migrant.

Source: Author's illustration.

Even though self-reported reasons give a first impression of the relevance of the environment in individual migration decisions, Van der Geest (2011, p. 3) acknowledges that, 'the underlying causes of migration [...] will not be mentioned by respondents who are asked about their personal motivation to migrate'. Often people use rather standardized answers in explaining migration (Jónsson 2010) or reinterpret the reality after their migration experience (Henry 2006). Therefore, additional quantitative regression analyses are used to answer this question.

Since the dependent variable is a dummy reflecting the individual's decision to migrate or to stay, binary logistic regressions were used to analyze the data.

Thus, the model for testing the relationship between environmental threats and the decision to migrate is

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha + \beta \text{ environment}_i + \gamma X_i + u_i, \tag{1}$$

where π_i is the probability of out-migration of individual i. The factor 'environment' corresponds to one of the variables which measure the exposure of individual i to environmental change. X stands for a set of control variables which represent important factors mentioned in economic migration theories. U stands for the residuals.

The set of control variables includes variables on community, household, and individual level, since it is assumed that migration responses are the result of a complex combination of multiple factors that shape the decision of individuals. The selection of these variables was guided by previous studies and common theories regarding migration decisions. Thus, at the community level, control variables include the community's population density as well as its percentage of employed inhabitants. In addition, the percentage of the population without an own toilet is included as a wealth proxy.

At the household level, control variables include a dummy for female-headed households and household size which are expected to impact positively on the propensity to migrate, as well as the number of children in the household and the ownership status, which are expected to be negatively correlated with migration decisions.[8] Another important variable for testing the New Economics of Labor Migration theory is the relative household income, since Stark and Bloom (1985) emphasize that households engage in income comparisons and may migrate due to their relative deprivation within the community. Households with low relative incomes can be expected to have a stronger incentive to migrate or to send out a migrant.

To acknowledge the network theory, a control variable indicating an individual's network was added. According to the theory, most common individual characteristics like sex, age, marital and employment status, education, and previous migration experience have been added. Younger, single males who have a good education but do not have a job at the current place and who have already migrated once or more before are expected to have a higher likelihood to migrate. Since it is assumed that individual preferences matter, individual's risk aversion and impatience get included as well. Both types of preferences are expected to be negatively correlated with migration decisions which bear uncertainties and risks and can be seen as an investment which just brings benefits in the future. Together these controls account for the most important migration drivers found in previous studies.

A further definition and summary statistics of the variables used in this article are provided in Tables 3 and 4.

Since independence of observations cannot be assumed and individuals from one household are expected to be more similar, all models get adjusted for clustering at the household level. Furthermore, it is accounted for the fact that there is only information for one migrant (non-migrant) per household, regardless of the total number of migrants (non-migrants) by weighting the observations based on the inverse of the probability of selection. The model is then estimated separately for the two study regions.

4.1 Indonesia

The results for Indonesia are presented in Table 5. Overall, the results of the control variables are consistent with previous studies. At the community level, it is found that the community's percentage of people with employment has a strong and significant impact on the

8 The number of children in the household is expected to be negatively correlated with the decision to migrate, since parents and other household members are needed to help with raising the children. The household size, however, is seen as an indicator for household-level labor abundance and expected to be positively correlated with migration propensities (Ackah and Medvedev 2010).

Table 3. Definition of variables

Community level	
Logarithm population density	Logarithm of the community's population density per square kilometer
Employment ratio	Percentage of population employed
Toilet	Percentage of population having no toilet or using public toilet
Hazard	Indonesia: Community's flood risk based on flood data of past 5 years, data from Indonesia National Agency for Disaster Management (BNPB), 2015
	Ghana: Community's erosion/flood risk based on average shoreline erosion within past 10 years, data for five communities from Center for Tropical Marine Research Bremen (ZMT), 2015
	With 1=low, 2=low-medium, 3=medium, 4=medium-high, 5=high
Household (HH) level	
Female-headed HH[a]	=1 if household head is female, =0 otherwise
Number of children in HH[a]	Number of children of the age less than or equal to 16 years living in household
Household size[a]	Total number of household members
Relative HH income[a]	Household income as reported by HH relative to average community income
Distance to coast[a]	Household's linear distance to coast in kilometers
Individual level	
Migrant status	=1 if migrant, =0 otherwise
Ownership[a]	=1 if house is owned by respondent or spouse, =0 otherwise
Network[a]	Index between 0 and 5, based on how many of the following questions could be answered with 'yes': 1(2): Do you have immediate family members (other family members or friends) living abroad? 3(4): Do you have immediate family members (other family members or friends) living in another province of Indonesia? 5: Do you have family members or friends living in another community in Semarang (Keta)?
Unemployed[a]	=1 if respondent reported to be unemployed when asked about occupation, =0 otherwise
Sex[a]	=1 if female, =0 otherwise
Age[a]	Age of respondent in years
Age^{2a}	Age squared
Marital status[a]	=1 if married, =0 otherwise
Education[a]	Years of education
Migration experience[a]	=1 if has lived somewhere else between age 18 years and now, =0 otherwise
Risk aversion	'In general, I am very willing to take risks', Likert scale from 1= Agree strongly to 5= Disagree strongly
Impatience	'I am a patient person'. Likert scale from 1= Agree strongly to 5= Disagree strongly
Flood[a] Subsidence[a]/storm[a] Erosion[a]	'In your opinion, how much have environmental events affected you within the last 5 years? Please indicate your opinion regarding the following events on a scale from 0 to 10, where 0 stands for 'not affected at all' and 10 for 'extremely affected'.
Aggregated Environmental change index[a]	Sum of individual's perception on flood, subsidence/storm, erosion

[a]If migrant: at the time of migration, if non-migrant: at the time of interview.

Table 4. Summary statistics for Indonesian sample (Ghanaian sample in brackets)

Variable	Number of Observations	Mean	Standard deviation	Minimum	Maximum
Community level					
Logarithm of the population density	309	8.76	1.09	5.30	9.87
Employment ratio	309	0.55	0.038	0.50	0.61
Toilet	309	0.12	0.08	0.01	0.31
Hazard	309 (174)	2.94 (2.65)	0.80 (1.15)	2 (1)	4
Household (HH) level					
Female-headed HH	309 (277)	0.15 (0.44)	0.36 (0.49)	0	1
Number of children in HH	309 (277)	0.73 (0.98)	1.03 (1.33)	0	6 (8)
Household size	309 (277)	4.60 (5.82)	1.99 (2.81)	1	13 (15)
Relative HH income	309 (277)	1 (1)	0.67 (0.91)	0.06 (0.03)	6.94 (5.06)
Distance to coast	309 (277)	2.67 (2.10)	1.49 (2.37)	0	8.64 (7.38)
Individual level					
Migrant status	309 (277)	0.31 (0.31)	0.46 (0.46)	0	1
Ownership	309 (277)	0.53 (0.10)	0.49 (0.30)	0	1
Network	309 (277)	1.95 (3.93)	1.17 (0.96)	0	5
Unemployed	309 (277)	0.35 (0.37)	0.48 (0.48)	0	1
Sex	309 (277)	0.57 (0.53)	0.49 (0.49)	0	1
Age	309 (277)	36.63 (9.94)	14.45 (4.81)	18	86 (88)
Age^2	309 (277)	1550.37 (1709.83)	1261.41 (1527.56)	324	7396 (7744)
Marital status	309 (277)	0.69 (0.42)	0.46 (0.49)	0	1
Education	309 (277)	11.13 (9.94)	3.64 (4.81)	0	18 (20)
Migration experience	308 (277)	0.30 (0.69)	0.45 (0.46)	0	1
Risk aversion	308 (277)	2.29 (2.77)	0.77 (1.33)	1	5
Impatience	308 (277)	2.35 (1.87)	0.83 (0.98)	1	5
Perception, flood	309 (277)	5.69 (5.24)	3.67 (3.67)	1	10
Perception, erosion	301 (277)	1.39 (4.20)	1.40 (3.56)	1	10
Perception, subsidence	302	3.09	3.33	1	10
Perception, storms	(277)	(4.00)	(3.54)	1	10
Aggregated Environmental change index	300 (277)	10.03 (13.23)	6.47 (9.22)	3	30

individual migration decision. The better the employment situation in a community, the less likely are people to leave this community.

On the household level, only one variable, namely, the number of children younger than 17 years of age, turns out to be significant. As expected, a higher number of younger children reduces the probability to migrate.[9] However, there seems to be a very important role of networks. Individuals, who have more friends and family members living in another district or abroad and thus have a better network which helps facilitating migration, are more likely to move. At the individual level, there is a negative and highly significant correlation

9 Also other household-level variables like individual or household income in absolute terms do never turn out significant when included. It is not included here due to its correlation with relative household income.

Table 5. Regression results Indonesia

	(1) Migrant status	(2) Migrant status	(3) Migrant status	(4) Migrant status	(5) Migrant status
Logarithm population density	−0.094	−0.143 (0.23)	−0.086	0.091	0.045
	(0.20)		(0.19)	(0.21)	(0.23)
Employment ratio	**−12.008****	**−11.922****	**−12.200****	**−11.736****	**−14.721****
	(5.01)	**(5.13)**	**(5.06)**	**(5.06)**	**(5.83)**
Toilet type	−0.077	−0.577	−0.756	−3.060	2.007
	(2.46)	(2.29)	(2.28)	(2.73)	(3.02)
Female-headed Household (HH) (=1)	0.133	0.062	0.134	0.146	0.149
	(0.45)	(0.48)	(0.48)	(0.49)	(0.47)
Number of children in HH	**−0.435****	**−0.580****	**−0.525****	**−0.411****	**−0.430****
	(0.21)	**(0.24)**	**(0.23)**	**(0.21)**	**(0.21)**
Household size	0.119	0.113	0.136	0.137	0.127
	(0.10)	(0.11)	(0.11)	(0.11)	(0.10)
Ownership	−0.559	−0.532	−0.529	−0.564	−0.614
	(0.40)	(0.42)	(0.42)	(0.42)	(0.41)
Relative HH income	0.143	0.261	0.184	0.118	0.159
	(0.30)	(0.31)	(0.30)	(0.32)	(0.31)
Network	**0.485*****	**0.500*****	**0.488*****	**0.485*****	**0.502*****
	(0.17)	**(0.18)**	**(0.17)**	**(0.17)**	**(0.17)**
Unemployed (=1)	**−1.396*****	**−1.229*****	**−1.311*****	**−1.576*****	**−1.511*****
	(0.43)	**(0.43)**	**(0.44)**	**(0.44)**	**(0.44)**
Sex (female =1)	−0.198	−0.257	−0.172	−0.098	−0.124
	(0.40)	(0.41)	(0.41)	(0.41)	(0.41)
Age	**1.008*****	**1.014*****	**0.969*****	**1.021*****	**1.020*****
	(0.25)	**(0.26)**	**(0.26)**	**(0.26)**	**(0.26)**
Age^2	**−0.020*****	**−0.020*****	**−0.020*****	**−0.021*****	**−0.020*****
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
Married (=1)	**0.531****	**0.504****	**0.542****	**0.578****	**0.585****
	(0.25)	**(0.25)**	**(0.25)**	**(0.25)**	**(0.26)**
Education	−0.035	−0.055	−0.028	−0.033	−0.036
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Migration experience (=1)	−0.010	−0.007	−0.093	0.090	−0.026
	(0.43)	(0.45)	(0.47)	(0.42)	(0.45)
Risk aversion	**−0.526****	**−0.482***	**−0.562***	**−0.586****	**−0.549****
	(0.26)	**(0.28)**	**(0.28)**	**(0.28)**	**(0.27)**
Impatience	**−0.740*****	**−0.629****	**−0.670****	**−0.749*****	**−0.751*****
	(0.24)	**(0.30)**	**(0.28)**	**(0.24)**	**(0.24)**
Flood	−0.034				
	(0.05)				
Subsidence		−0.083			
		(0.08)			
Erosion			−0.143		
			(0.16)		
Distance to coast				**−0.262***	
				(0.13)	

(continued)

Table 5. Continued

	(1) Migrant status	(2) Migrant status	(3) Migrant status	(4) Migrant status	(5) Migrant status
Hazard					−0.449
					(0.41)
Constant	−0.254	−0.105	0.059	−1.119	−3.065
	(4.92)	(5.61)	(5.19)	(4.76)	(5.31)
Community fixed effects	No	No	No	No	No
BIC	550.211	533.145	536.327	544.351	549.187
AIC	475.674	459.069	462.319	469.814	474.650
Pseudo R^2	0.534	0.543	0.537	0.541	0.535
Percent correctly classified[10]	83.71%	83.61%	84.00%	85.34%	85.02%
Percent reduction in error	48.10%	47.78%	49.03%	53.29%	52.28%
N	307	300	299	307	307

Note: The dependent variable is migrant status. Robust standard errors in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

between being unemployed and out-migration. Moreover, age is found to have a very significant effect on the migration propensity, with a peak at the age of 25 years. Married individuals and individuals who are rather risk-loving or patient are also more likely to migrate. While non-married people would be expected to be more likely to move, this finding is easy to explain in the Indonesian context. As seen before, marriage was named as the main reason for moving. In Semarang it is common to wait until after the wedding with moving together. This results in many just married individuals who leave their community to move to their spouse. The effect of the stated preferences, however, is exactly as anticipated: rather risk-loving as well as rather patient people are more likely to migrate.

Taking a look at the variables of main interest, there is no significant correlation between the individual's perceptions of flood, subsidence, and erosion, and her out-migration decision. Also the hazard categorization of communities cannot be linked to individual migration decisions. The household's distance to the coast, however, which serves as a more objective measure of exposure to coastal events has a significant impact on migration behavior. Individuals living in households closer to the coast have a higher probability to leave the community than people living further away. This finding serves as a first indicator that the environment actually has a direct effect on migration. However, the coefficient is only significant at the 10% level and does not survive further robustness tests (see Section 5.3).

To evaluate the accuracy and the goodness-of-fit of the models, the AIC and BIC as well as McFadden pseudo R^2 are included which do very well.[11] Additionally, the percentage of correctly classified cases, which is a commonly used goodness-of-fit measure and assesses how well the predictions fit the observed outcome, and the percent reduction in error are

10 Classification of models calculated without p-weights.

11 The pseudo R^2 cannot be interpreted as the common ordinary Least Squares R^2, but nevertheless, higher values of R^2 indicate a better model fit.

included.[12] Even though, the environmental variables do not add much to the goodness of fit, the models are able to predict around 85% of the outcome correctly.

4.2 Ghana

The results for Ghana are presented in Table 6. Unfortunately, no official data on community level were available which reduces the set of control variables to household- and individual-level factors. Nevertheless, to account for differences in communities, community fixed effects are included. Overall, the models support common findings. Like in Indonesia, there is a weak link between the number of children in a household and out-migration. Additionally, migrants are significantly more likely to move away from bigger households as well as from relatively deprived households—just as expected. This is supporting the hypothesis that households with a lower relative income send out a migrant to diversify risks and to generate income somewhere else. Networks which turned out to be imperative in Indonesia are not found to explain migration decisions in Ghana which is probably due to the fact that nearly everyone in Ghana has friends or family in other parts or even outside of the country—making it less crucial for own migration decisions. At the individual level, younger persons[13] are more likely to move, whereas the marital status does not seem to play a role in the Ghanaian context. Furthermore, there is weak evidence in three of the five specifications that men are more likely to leave than women. Individual unemployment, as well as the level of education, is positively correlated with the decision to migrate, as expected, and significant at the 1% level. Risk aversion and time preference do also play a role again. These findings can be strongly supported by open-ended interviews conducted in those communities. Keta is an economically rather weak and rural region not offering many jobs, especially for well-educated people. Thus, individuals who are not able to find work and better educated people who have better chances to find a job somewhere else often take their chance in urban areas like Accra, Tema, or Lomé.

Coming again to the variables of interest, no correlation between individual perceptions of flood or erosion, the household's distance to coast or the community's level of hazard, and migration decisions can be found. However, the coefficient of storm perceptions is found to be significant at the 5% level and meaningful in size. When looking at predicted probabilities, individuals, who perceived to be highly affected by storms, are 11% more likely to leave the community than their less affected neighbors.

12 In specification (1), 83.71% of cases get correctly predicted. This may seem impressive; however, it does not tell anything about the proportion of correctly classified cases beyond the number that would be correctly guessed by choosing the most frequent outcome. Since 212 of 308 respondents are non-migrants, just by chance 68.61% of outcomes would be predicted correctly. Thus, White (2013) recommends using this information and calculating the proportional reduction in error, which is reported in Table 5 as well, and which shows that specification (1) reduces the error by 48.10%.

13 Please note that age is not included as a quadratic term in the Ghanaian case because no non-linearity could be detected. Tests show that the inclusion of age^2 would not improve the goodness-of-fit of the model.

Table 6. Regression results Ghana

	(1) Migrant status	(2) Migrant status	(3) Migrant status	(4) Migrant status	(5) Migrant status
Female-headed Household (HH) (=1)	0.263	0.320	0.231	0.311	0.770*
	(0.33)	(0.31)	(0.33)	(0.32)	(0.41)
Number of children in HH	−0.210*	−0.212*	−0.177	−0.212*	−0.329*
	(0.12)	(0.12)	(0.12)	(0.12)	(0.19)
Household size	0.314***	0.317***	0.276***	0.314***	0.364***
	(0.09)	(0.09)	(0.08)	(0.09)	(0.12)
Ownership	−1.429	−1.282	−1.385	−1.353	(Dropped)[14]
	(0.96)	(0.97)	(0.89)	(0.97)	
Relative HH income	−0.329*	−0.347**	−0.339*	−0.339*	−0.118*
	(0.18)	(0.18)	(0.17)	(0.17)	(0.06)
Network	0.137	0.116	0.155	0.119	0.496*
	(0.20)	(0.20)	(0.21)	(0.20)	(0.28)
Unemployed (=1)	0.984***	0.964***	0.985***	0.983***	1.342***
	(0.36)	(0.36)	(0.37)	(0.36)	_(0.47)
Sex (female = 1)	−0.583	−0.648*	−0.475	−0.615*	−1.196***
	(0.35)	(0.35)	(0.37)	(0.35)	(0.46)
Age	−0.056***	−0.058***	−0.055***	−0.057***	−0.022
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Married (=1)	−0.236	−0.235	−0.267	−0.232	−0.373
	(0.21)	(0.21)	(0.21)	(0.20)	(0.23)
Education	0.399***	0.391***	0.405***	0.393***	0.341**
	(0.15)	(0.15)	(0.15)	(0.14)	(0.17)
Migration experience (=1)	0.934**	0.931**	0.920**	0.935***	0.923*
	(0.41)	(0.41)	(0.41)	(0.41)	(0.50)
Risk aversion	−0.439***	−0.434***	−0.468***	−0.437***	−0.570***
	(0.16)	(0.16)	(0.17)	(0.16)	(0.20)
Impatience	−0.318*	−0.318*	−0.289**	−0.323*	−0.535**
	(0.17)	(0.17)	(0.17)	(0.17)	(0.21)
Flood	0.027				
	(0.05)				
Erosion		−0.027			
		(0.06)			
Storm			0.130**		
			(0.06)		
Distance to coast					

(continued)

4.3 Robustness checks

Environmental events like flooding, erosion, subsidence, or storms are clearly exogenous to the individual's decision to migrate which avoids the problem of reverse causality. Additionally, also the control variables are exogenous to migration, since they refer to the time just before the migration and are therefore not influenced by the migration itself. Only

14 Dropped since sample does not contain migrants who owned a house.

Table 6. Continued

	(1) Migrant status	(2) Migrant status	(3) Migrant status	(4) Migrant status	(5) Migrant status
				−0.007	
				(0.48)	
Hazard					−0.037
					(0.25)
Constant	−0.840	−0.437	−1.139	−0.531	−1.215
	(1.64)	(1.63)	(1.64)	(3.25)	(1.86)
Community fixed effects	Yes	Yes	Yes	Yes	Yes
BIC	646.543	646.619	639.499	647.136	399.020
AIC	566.815	566.891	559.770	567.407	346.956
Pseudo R^2	0.362	0.362	0.371	0.361	0.339
Percent correctly classified[15]	82.31%	81.59%	83.05%	81.59%	78.48%
Percent reduction in error	43.75%	41.46%	46.10%	41.46%	37.28%
N	277	277	277	277	174[16]

Note: The dependent variable is migrant status. Robust standard errors in parenthesis.
*p < 0.1; **p < 0.05; ***p < 0.01.

the control variables risk aversion and patience were measured after the migration took place.[17] Thus, they might have changed due to positive or negative feedback of the migration experience.[18] Even though the focus is on the effects of environmental factors, which are clearly not influenced by individual migration decisions and therefore exogenous, it has to be ensured that the estimates for the environmental factors are not biased. Additionally, multicollinearity of covariates could also reduce the efficiency of the estimates (see also correlation matrix (Table 7)). Thus, several robustness checks get performed (see Tables 8 and 9). In different specifications it is tested whether the inclusion or exclusion of community fixed effects, the omission of clusters at the household level, or a reduced set of control variables impact on the effect of environmental factors on migration. Since Clarke (2005) argues that including control variables at all may already increase the bias, an additional specification without any controls is also estimated. It is found that results are robust to these changes, and only the anyhow weak coefficient of the Indonesian households' distance to the coast loses its significance in the majority of robustness tests. An additional robustness test checks whether an analysis at household level provides new insights, since members within one household are expected to be exposed to the same environmental changes.[19] However, perceptions of the

15 Classification of models calculated without p-weights.

16 Less observations since hazard data are not available for every community.

17 While it is easy for a migrant to recall how many children or what kind of occupation she had at the time of migration, it is difficult or confusing to recall how willing she was to take risks or how patient she was at that time.

18 Nevertheless, studies suggest that preferences are rather stable over time and not affected by major life events like migration (Andersen et al. 2008; Conroy 2009)

19 However, perceptions of respondents from the same household might still differ due to different personal experiences, different coping mentalities, and/ or different recalling of scope and intensity of the event.

Table 7. Correlation matrix of covariates

Indonesia/ Ghana	Logarithmic population	Employment status	Toilet	Female-headed Household (HH)	Number of children in HH	Household size	Ownership	Relative HH income	Networks	Sex	Age	Marital status	Education	Unemployed	Migration experience	Risk aversion	Patience
Logarithm population	1.00																
Employment	−0.324***	1.00															
Toilet	0.436***	0.241***	1.00														
Female headed	0.077	−0.099*	0.030	1.00													
Number of children	−0.129**	0.073	−0.018	−0.028/ 0.025**	1.00												
Household size	−0.054	0.041	0.096*	−0.122**/ −0.016	0.322***/ 0.699***	1.00											
Ownership	−0.109*	−0.017	−0.087	0.007/ −0.18***	0.062/ 0.048	−0.20***/ −0.031	1.00										
Relative HH income	−0.000	0.000	0.000	−0.103**/ −0.18***	−0.06/ −0.011	0.113**/ 0.111*	−0.001/ 0.044	1.00									
Networks	0.064	−0.246***	−0.033	−0.059/ 0.074	−0.18***/ 0.015	−0.038/ −0.096	0.008/ 0.088	0.133**/ 0.032	1.00								
Sex	0.066	0.044	0.121**	0.133**/ 0.274***	0.002/ 0.003	0.002/ 0.037	−0.001/ 0.003	−0.086/ −0.170***	−0.044/ −0.026	1.00							
Age	0.019	−0.188***	−0.142**	0.049/ 0.000	0.008/ −0.032	−0.008/ −0.110*	0.434***/ 0.339***	−0.101*/ −0.157***	0.052/ −0.003	0.016/ 0.088	1.00						
Marital status	−0.069	0.012	−0.052	0.237***/ −0.267***	0.352***/ 0.111**	0.352***/ −0.003	0.201***/ 0.191***	0.024/ −0.174***	0.052/ −0.014	−0.004/ 0.071	0.186***/ 0.225***	1.00					
Education	0.066	−0.142**	−0.110*	−0.062/ −0.109*	−0.144**/ −0.072	−0.144**/ −0.034	−0.116**/ −0.146**	0.288***/ 0.235***	0.186***/ 0.112*	−0.082/ −0.285***	−0.27***/ −0.314***	0.076/ −0.094	1.00				
Unemployed	0.077	0.012	0.028	0.020/ 0.167***	0.019/ −0.094	0.019/ −0.024	0.119**/ −0.010	−0.069/ 0.018	−0.046/ −0.105*	0.087/ −0.010	0.166***/ −0.153**	−0.081/ −0.325***	−0.099*/ −0.18***	1.00			
Migration experience	−0.001	−0.181***	−0.138**	−0.010/ −0.05	0.072/ 0.063	0.072/ 0.012	0.045/ 0.065	0.11*/ 0.101*	0.16***/ 0.122*	−0.121**/ −0.022	0.166***/ 0.184***	0.056/ 0.087	0.22***/ 0.063	−0.014/ −0.094	1.00		
Risk aversion	0.055	−0.065	−0.047	0.076/ −0.003	−0.056/ 0.089	−0.056/ 0.095	−0.017/ 0.130**	−0.041/ −0.119**	−0.061/ −0.146**	0.176***/ 0.139**	0.137**/ 0.219***	−0.015/ 0.092	−0.102*/ −0.19***	0.126**/ −0.032	−0.081/ −0.078	1.00	
Patience	−0.019	0.041	−0.020	0.004/ 0.209***	−0.011/ −0.175***	−0.011/ −0.111*	0.000/ −0.042	0.001/ −0.058	−0.042/ 0.013	0.041/ 0.077	−0.112*/ −0.146**	0.051/ −0.076	0.088/ 0.003	−0.015/ 0.098	0.022/ 0.003	0.035/ −0.086	1.00

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table 8. Robustness checks, Indonesia

	(1) Community fixed effects	(2) No clustering	(3) Reduced set of controls	(5) Exclusion of controls	(6) Household level[a]	(7) Aggregated index
Alternative specification 1						
Flood	−0.020	−0.034	−0.035	0.022	0.010	–
	(0.06)	(0.05)	(0.04)	(0.03)	(0.07)	
Alternative specification 2						
Erosion	−0.104	−0.143	0.016	0.058	−0.533	–
	(0.20)	(0.16)	(0.13)	(0.09)	(0.45)	
Alternative specification 3						
Subsidence	−0.129	−0.083	−0.080	−0.049	−0.095	–
	(0.10)	(0.08)	(0.06)	(0.05)	(0.07)	
Alternative specification 4						
Distance to coast	−0.333	**−0.262***	−0.014	0.052	0.007	–
	(0.38)	**(0.15)**	(0.10)	(0.06)	(0.11)	
Alternative specification 5						
Hazard	−0.542	−0.449	0.089	0.105	−0.144	–
	(0.43)	(0.45)	(0.18)	(0.12)	(0.37)	
Alternative specification 6						
Aggregated Environmental change index	–	–	–	–	–	−0.042
						(0.04)
Control variables	Yes	Yes	Age, age^2, unemployed, sex	No	Yes	Yes
Community dummies	Yes	No	No	No	No	No

Note: The dependent variable is migrant status. Robust standard errors in parenthesis.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
[a]The dependent variable is migrant household (=1 if migrant in household, =0 if otherwise), individual characteristics and perceptions of environmental events included for household head.

household head, the household's distance to the coast, and the community's hazard categorization do not help to explain whether a household has a migrant. Only the household head's perception of storms is highly significant, supporting the findings on individual level. Another robustness test addresses the question whether individuals are only found to migrate when experiencing more than one adverse environmental condition simultaneously. Therefore, we sum up the different perception measures to have one aggregated index. However, this index does not turn out to be significant.

Furthermore, it is tested whether the effect of environmental factors is the same for different distances. Thus, a multinomial logit regression is used to estimate the impact of environmental factors on the probability of moves within the region or moves out of the region (relative to staying). Still, no robust significant effect can be detected in the Indonesian case study. However, it reveals that the perception of storms is only significant for rather long-distance internal moves, while it has no effect on moves within the region of origin (see Tables 10 and 11).

Table 9. Robustness checks, Ghana

	(1) No community fixed effects	(2) No clustering	(3) Reduced set of controls	(5) Exclusion of controls	(6) Household level[a]	(7) Aggregated index
Alternative specification 1						
Flood	0.049	0.027	−0.015	−0.10	0.039	–
	(0.05)	(0.05)	(0.04)	(0.03)	(0.07)	
Alternative specification 2						
Erosion	0.009	−0.027	−0.034	−0.032	0.076	–
	(0.05)	(0.06)	(0.04)	(0.03)	(0.07)	
Alternative specification 3						
Storms	**0.142****	**0.130***	**0.089***	**0.066****	**0.168*****	**–**
	(0.06)	**(0.07)**	**(0.05)**	**(0.03)**	**(0.06)**	
Alternative specification 4						
Distance to coast	−0.015	−0.007	0.009	0.036	−0.435	–
	(0.06)	(0.61)	(0.04)	(0.03)	(0.46)	
Alternative specification 5						
Hazard	−0.189	−0.449	−0.080	−0.059	−0.424	–
	(0.15)	(0.45)	(0.12)	(0.08)	(0.28)	
Alternative specification 6						
Aggregated Environmental change index	–	–	–	–	–	−0.025 (0.02)
Control variables	Yes	Yes	Age, unemployed, sex	No	Yes	Yes
Community dummies	No	Yes	No	No	Yes	Yes

Note: The dependent variable is migrant status. Robust standard errors in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
[a]The dependent variable is migrant household =1 if migrant in household, =0 if otherwise), individual characteristics and perceptions of environmental events included for household head.

4.4 Interaction effects

Since environmental factors were found to play a limited direct role, an additional set of exploratory models tested whether the effect of the environment depends on other factors and, thus, whether the environment might only lead to migration in certain contexts. However, only few potential interactions could be detected.

In the Indonesian case two conditional effects could be found. First, the community's level of hazard has a negative impact on out-migration for male respondents, while no effect can be found for female respondents (see Figure 4).[20] Second, a highly significant interaction between distance to coast and networks was found. The marginal effect of the distance to the coast decreases with the improvement of networks, i.e. living closer to the coast increases the probability of out-migration for individuals with better networks, while it has no effect on individuals with no or small networks (see Figure 5).

In Ghana it is found that the effect of individual storm perceptions does also depend on the number of children in the household. The marginal effect of storms on out-migration

20 Marginal effect of hazard for male respondents is − 0.115, while the one for female is around 0.02.

Table 10. Multinomial logit: different distances, Indonesia

	Migration distance	(1) Migrant status	(2) Migrant status	(3) Migrant status	(4) Migrant status	(5) Migrant status
Flood	In region	−0.047				
		(0.05)				
	Out of region	−0.06				
		(0.05)				
Erosion	In region		−0.022			
			(0.19)			
	Out of region		−0.058			
			(0.17)			
Subsidence	In region			−0.085		
				(0.08)		
	Out of region			−0.016		
				(0.05)		
Distance to coast	In region				−0.233	
					(0.20)	
	Out of region				−0.155	
					(0.14)	
Hazard	In region					−0.455
						(0.44)
	Out of region					0.244
						(0.26)
Full set of control variables		Yes	Yes	Yes	Yes	Yes
BIC		1042.398	1022.666	1029.510	1029.673	1044.676
AIC		893.324	874.648	881.359	880.599	895.602
Pseudo R^2		0.415	0.417	0.414	0.424	0.414
N		307	299	300	309	309

Note: The dependent variable is migrant status. Robust standard errors in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

increases with every additional child in the household. While it is 0 for someone from a childless household and, thus, has no effect on the individual's out-migration decision, it increases to 0.078 for someone from a household with eight children. Same relation can be found for the number of household members, since this indicator is highly correlated with the number of children in the household (see Figures 6 and 7). These results indicate that there might be a conditional effect of the environment on migration. However, these few interactive effects seem to be very context-specific and could only be found for one of the environmental variables in one of the study regions. Nevertheless, these results could also be seen as an indicator for future in-depth research.

4.5 Environmentally induced economic migration?

Even though no robust, generalizable impact of environmental characteristics on migration decisions could be detected, the environment could still impact indirectly. Afifi (2011)

Table 11. Multinomial logit: different distances, Ghana

	Migration distance	(1) Migrant status	(2) Migrant status	(3) Migrant status	(4) Migrant status	(5) Migrant status
Flood	In region	−0.046				
		(0.05)				
	Out of region	−0.428				
		(0.32)				
Erosion	In region		−0.093			
			(0.06)			
	Out of region		−0.044			
			(0.05)			
Storm	In region			0.025		
				(0.07)		
	Out of region			**0.093****		
				(0.04)		
Distance to coast	In region				−0.085	
					(0.10)	
	Out of region				0.051	
					(0.05)	
Hazard	In region					−0.060
						(0.20)
	Out of region					−0.098
						(0.13)
Full set of control variables		Yes	Yes	Yes	Yes	Yes
BIC		1069.779	1061.697	1064.327	1066.106	696.739
AIC		910.322	902.240	904.870	906.649	583.013
Pseudo R^2		0.326	0.333	0.331	0.329	0.345
N		277	277	277	277	174

Note: The dependent variable is migrant status. Robust standard errors in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

therefore introduces the term ‘environmentally induced economic migration’ and argues that ‘the economic factor can act as the mechanism through which environmental degradation leads to migration’ (p. 100). It is assumed that environmental conditions impact on economic outcomes like food security, income, and employment—especially in rural developing countries. Using Sobel–Goodman tests, it is tested whether economic conditions like personal income or unemployment status act as a mediator of the relationship between environmental change and out-migration. These tests estimate the effect of the environmental variables on migration and on the economic factors, unemployment, and income, as well as their effects on migration and test whether there is a potential indirect link.

In the Indonesian case, these tests cannot detect any significant indirect effect. Only one significant link between an environmental variable and an economic outcome (path *a* in Figure 8) was found: respondents affected by erosion are earning significantly more than those less affected by erosion processes. While this link might not be causal, it does also not translate into out-migration (path *b*). However, this absence of indirect effects is not very

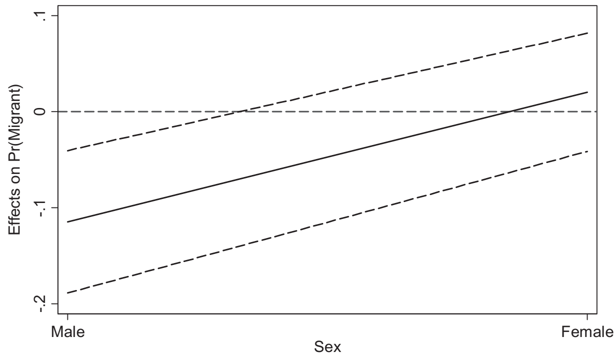

Figure 4. Marginal effect of hazard on probability of migrating by sex of respondent, Indonesia.

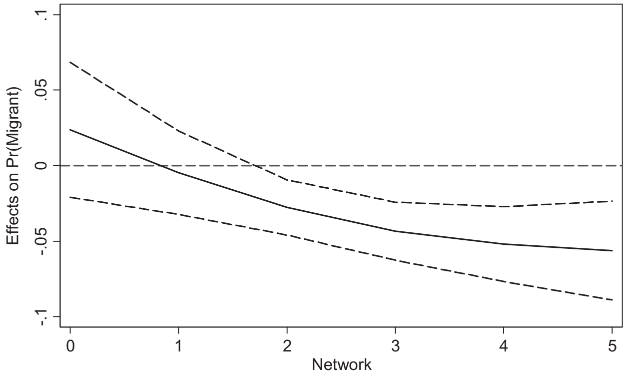

Figure 5. Marginal effect of distance to coast on probability of migrating by network of respondent, Indonesia.

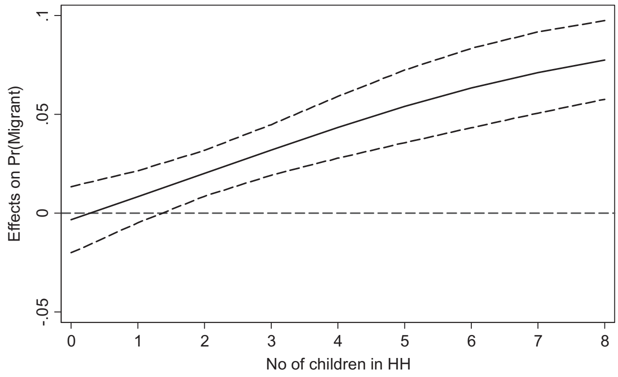

Figure 6. Marginal effect of storm perception on probability of migrating by number of children, Ghana.

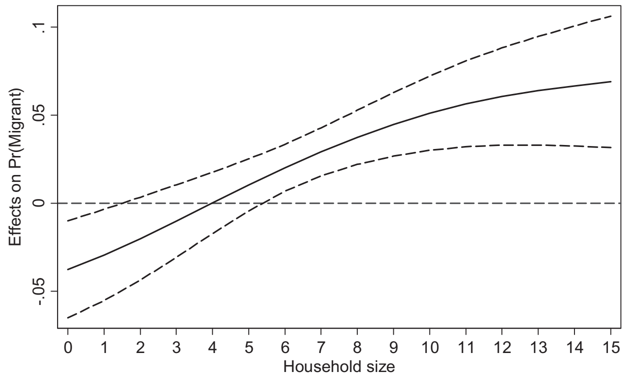

Figure 7. Marginal effect of storm perception on probability of migrating by number of household members, Ghana.

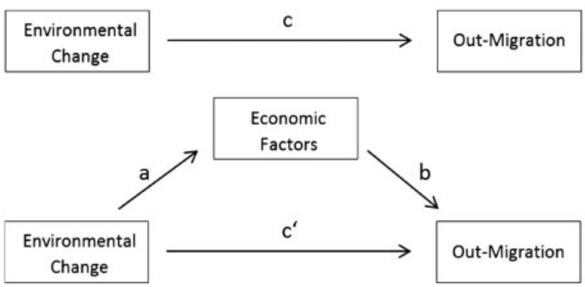

Figure 8. Indirect effect of environmental change on migration through economic factors.

Source: Author's representation, based on Preacher and Hayes (2008).

surprising, since Semarang is a thriving industrialized city with many factories, a big harbor, and good work opportunities, especially in the coastal areas.

Nevertheless, also in the more rural and economically weaker region in Ghana, the Sobel–Goodman test cannot detect any indirect effect of coastal changes on out-migration.[21] Again only one significant link between environmental change and economic factors was found: respondents living further away from the coast earn more than those closer to the coast. One explanation for this might be that richer households can afford property which is further inland and thus less threatened by coastal changes. But just as in the Indonesia case, this link does not translate into a significant correlation to out-migration and no indirect effects can be found. This might be due to the very special case of gradual coastal changes. In contrast to agricultural output depending on rainfall or soil quality, or

21 P-value of indirect effect of the environment through unemployment status: 0.096. We are aware that these p-values are only accurate estimates of the true p-values if the sample size is big enough (and thus the term a*b is normally distributed). Since it is difficult to test whether the sample is big enough, we re-estimate the indirect effects by using bootstrapping which does not rely on distributional assumptions (Preacher and Hayes 2008). Ultimately, the p-value decreases to 0.104 which leads to the conclusion that there is no indirect effect.

fish catch depending on the health of ecosystems, economic activities of respondents in this study do not depend much on experienced coastal degradation. Thus, it is not very unexpected that no indirect effect of the environment can be found in these case studies.

5. Discussion

Various scholars as well as public institutions have suggested that environmental change could result in the migration of millions of people, especially in coastal areas. Migration on such a massive scale would be a challenge for both sending and receiving regions—as current debates about migration flows in Europe show. However, empirical evidence for such environmentally induced migration is mixed. This study sought to contribute to the discussion by using a multilevel model where individual-, household-, and community-level factors are all simultaneously considered to isolate the net effect of slow- and sudden-onset environmental factors.

Due to the lack of available high-quality census data, both migrants and non-migrants of households located in the two coastal study regions have been interviewed directly. When interpreting the following results, it should be kept in mind that this approach does not include households which have moved as a whole. In summary, it can be stated that the data explain individual migration behavior of the sampled respondents quite well. In both regions, age and the employment status of the respondent were found to be especially important which emphasizes the influence of individual characteristics. But also other variables like risk aversion, patience, and the number of children in the household in general; networks, the community's employment situation, and marital status in Indonesia; and migration experience, education, household size, and relative household income in Ghana help in explaining who migrates and who stays, and support different economic migration theories.

Taken together, no generalizable direct link between the main coastal events and outmigration could be detected. Only one region-specific environmental event—perceptions of storms in Ghana—turned out to have a robust and direct impact on the respondents' decision to migrate. This result indicates that the more an individual perceives herself as affected by storms, the higher is the probability of out-migration. Further tests showed that this finding holds only for moves out of the region. This finding is not very surprising, since storms, unlike erosion, do not only affect particular sections of the shoreline. Looking at the nature of the included environmental events, it has to be noted again that most of them can be considered as rather long-term in nature with a limited geographical scope. Both regions experience severe erosion processes; nevertheless, erosion is still a rather gradual and predictable process. The same can be said about subsidence in Semarang which can be clearly anticipated by affected households, since rates of yearly subsidence do not change much.[22] Also the floods experienced in both regions are mostly tidal floods and not severe sudden-onset flooding. Respondents perceive them as less severe, since streets and houses are regularly inundated for a shorter period of time without threatening health or lives.

22 The observed erosion in Ghana and subsidence in Indonesia are occurring at very fast rates (several centimeters per year) compared to erosion or subsidence somewhere else. Nevertheless, compared to all potential environmental events, these are very gradual and well-known processes which can be anticipated by inhabitants long before.

Inhabitants of both regions are used to floods and see them as part of daily life.[23] Erosion and subsidence have also been experienced for several decades already with the result that their impacts are not new for respondents in those regions. Furthermore, the great majority of people in Semarang adapts to constant subsidence and the concomitant inundation threats by lifting houses, floors and valuables, building drainages, and similar. Even though less adaptation strategies at the household level have been observed in Keta, mostly because the eroding coastline cannot efficiently be stopped by single households, households whose house got eaten by the sea tend to rebuild their houses in the neighborhood—sometimes knowing that the newly built house will also only last for several years before the coastline has also reached the new houses. Altogether, the costs associated with coping with and adapting to those slow-onset environmental changes might be lower than those associated with migration, which include, for example transport, psychic and social costs, and uncertainties about economic success of the migration.

Looking at the only statistically significant environmental event, storms[24], however, it can be stated that they hit the communities unexpectedly and with greater power, destroying buildings, roofs, and boats, making it difficult for fishermen to fish. Storms are only a problem in Ghana and, thus, there is no comparable sudden-onset measure for the Indonesian case study. Nevertheless, it is very likely that the effect of environmental events strongly depends on the nature of these events. Long-term, gradual changes like sea-level rise, erosion, and land subsidence were not found to increase the likelihood of out-migration, while sudden environmental events could be more likely to induce migration. Overall, however, no convincing evidence for a general direct impact of environmental change on migration decisions could be found.

Regardless of the nature of the environmental event, its effect on out-migration might still be either moderated or mediated. In Indonesia the effects of two of the environmental events get moderated by the gender and network of respondents. There is no effect of the community's level of hazard on out-migration of women, while a higher hazard is found to lead to less out-migration of men. This finding indicates that the likelihood of male out-migration is smaller in communities with high hazards than in those with lower. When further looking at high-hazard communities, it is found that a significantly higher proportion of the population is employed than in low-hazard communities. Thus, the reduced out-migration of men who are the main breadwinner in Indonesian households might not be due to the hazard itself, but to the increased employment opportunities. This effect might not be found for the female subpopulation because of different gender roles. Additionally, people living closer to the coast are more likely to leave if they have good networks, which emphasizes the crucial effect of networks, especially for the more vulnerable coastal population. In Ghana, the number of children seems to act as a moderating factor on the effect of storm perceptions on migration decisions. While someone's migration decision is not affected by storm perceptions if she is from a childless household, someone from a child-rich household will be more likely to move when affected by storms. This could be attributed to the fact that storms might seem less dangerous for households which are not responsible for

23 'We are fishermen, we are used to water. I just walk through' (Respondent in community Kedzi (Keta, Ghana), when asked about flood problems, 5 October 2015)

24 Please note that by 'storm' Ghanaians understand strong winds in combination with heavy tidal waves, whereas flood can be understood as any form of inundation, regardless of the cause (often rain or tidal floods inundate the streets).

children. Childless households might be better able to cope with the immediate consequences of storms. While the effects of environmental change on out-migration might be moderated and context-dependent in some cases, no mediating economic factors have been found which is not much surprising, since economic activities of the respondents do not depend much on the considered coastal changes and, thus, cannot be compared to environmental changes like droughts in agricultural regions.

6. Conclusion

The results of this study have relevant implications for environment–migration theories, for future research in this field and for policies in the two study regions. Regarding environment–migration theories, the study's findings indicate that there is no generalizable direct effect of environmental change on out-migration—especially when looking at slow-onset coastal changes. This finding highlights the importance of contexts in environment–migration relationships and suggests that, if the past can be used to predict future scenarios, then predictions of large-scale displacements are most likely exaggerated.

With regard to research methods, this study improves common methods by directly interviewing people who left regions affected by coastal hazards to get personal views on perception and preferences. It also extends the number of studies which have used quantitative multilevel methods to estimate the influence of environmental change on individual migration (Henry et al. 2004; Gray 2011). This approach aims at providing a generalizable methodology in a field 'where sophisticated empirical applications have lagged significantly behind the high level of interest by academics and policy makers' (Gray 2011). However, more differentiated analyses are needed to test whether there are differences in the impact of sudden-onset and more gradual environmental events. A high-quality longitudinal data set, preferably collected through quantitative panel studies, which include also households which move as a whole, would additionally help to get a clearer picture of the environment–migration nexus. Furthermore, greater comparability in measurement of the variables of interest would be desirable to compare case studies from a wider range of contexts and, thus, make stronger generalizations. McLeman (2013) even calls for the integration of environmental data and common standards into official censuses, since most environmentally induced migration is likely to occur internally. Such an implementation could improve further research on the environment–migration nexus and allow for further theoretical, methodological, and empirical improvements.

Finally, these findings have implications for policies in both study countries. Some evidence suggests that networks in Semarang moderate the effect of environmental change, leading to the conclusion that improving information and institutional support in affected areas might help those who are willing to leave but do not have helpful network ties. Improving economic situations or offering alternative livelihoods to those affected might benefit vulnerable child-rich households without resulting in rural depopulation. However, evidence for these moderating or mediating factors is weak to non-existent, and overall findings indicate that most of the people prefer not to migrate when facing longer-term gradual environmental problems, but to use other forms of adaptation and rather migrate due to more individual or economic reasons. Therefore, it is critical that policies get implemented which do not only take into account that migration 'might' occur as consequence of coastal changes but which promote adaptation to environmental change and increase the resilience of coastal populations. Thus, aid could be more targeted to areas affected by environmental changes to promote adaptation on individual and community level.

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Climate Variability and Inter-State Migration in India

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Abstract

We match climate data to migration data from the 1991 and 2001 Indian Censuses to investigate the impact of climate variability on internal migration. The article makes four contributions to the existing literature on macro-level migration flows. First, use of census data allows us to test and compare the effect on migration of climatic factors prior to migration. Second, we introduce relevant meteorological indicators of climate variability, to measure the frequency, duration, and magnitude of drought and excess precipitation based on the Standardized Precipitation Index. Third, we estimate the total effect (direct and indirect effects) of climate variability on bilateral migration rates. Fourth, we examine three possible channels through which climate variability might induce migration: average income, agriculture, and urbanization. The estimation results show that drought frequency in the origin state increases inter-state migration in India. This effect is stronger in agricultural states, and in such states the magnitude of drought also increases inter-state migration significantly. Drought frequency has the strongest effect on rural–rural inter-state migration. (JEL codes: O15, Q54).

Key words: climate variability, drought, excess precipitation, India, internal migration, PPML, SPI

1. Introduction

Negative effects linked to climate variability are becoming ever more apparent. It is causing both increased numbers of natural disasters resulting in huge economic and human losses, and long-term consequences on the economy and on population distribution. The most recent Intergovernmental Panel on Climate Change (IPCC) assessment report discusses the different ways that climate may affect migration, although expected flows are difficult to quantify (IPCC, 2014). The detailed studies in a report commissioned by the UK government (Government Office for Science, 2011) show that environmental change will affect migration in the present and in the future but that its influence will be evident principally in its economic, social, and political effects. Climate variability can have particular direct effects, such as degraded health, increased mortality risk, capital destruction and disruption to socioeconomic activities, and also indirect effects—on the environment and the economy—through price and wage adjustments in the market, which directly or indirectly induce migration. The objective of this article is to test the hypothesis that climate variability acts as a push factor that increases internal migration in India.

We match bilateral migration data from the 1991 and 2001 Indian Census with state-level climate data. We estimate bilateral migration rates to control for important existing migration determinants in origin and destination states, and account for zero flows using a Poisson pseudo-maximum likelihood (PPML) estimator. The article makes four contributions to the existing literature on macro-level migration flows. First, the advantage of the current study is that it uses the 1-year migration definition from the Indian Census which enables an exact timing of climatic factors prior to migration and the observed migration flow which in turn allows us to rule out simultaneity. Existing studies rely on average migration flows over 5- or 10-year periods linked to average climate anomalies over the same 5- or 10-year periods. We compare estimations based on 10-year averaged migration flows on 10-year average climate variability with estimations based on a 1-year migration flow and climate variability before migration. Second, we introduce relevant meteorological indicators of climate variability based on the Standardized Precipitation Index (SPI). The SPI measures anomalies in rainfall compared to the long-run average defined from 1901 up to the year of the census. The advantage provided by the SPI versus other measures used in the literature is that it allows comparability across states, and the possibility to measure not only the magnitude but also the frequency and duration of droughts and excess precipitation. Third, unlike most existing studies, we estimate the total effect of climate variability on bilateral migration rates, addressing possible over-controlling bias by excluding income and other migration determinants dependent on climate from the estimations of the total effect of climate variability. Fourth, we examine separately three possible channels through which climate variability might induce migration: total income, agriculture, and urbanization.

The estimation results show that drought frequency has a significant impact on inter-state bilateral migration rates when controlling for migration costs, origin-state characteristics, and destination-state pull factors. Each additional month of drought in the origin state during the 5 years preceding the year of migration increases the bilateral migration rate by 1.5% averaged over all states, and by 1.7% for agricultural states. In the case of agricultural states in particular, the magnitude of the drought also has an effect. The results are robust to controlling for the area of irrigated land in the state, and the inclusion of controls for all time-invariant bilateral fixed effects. The relative effect of climate variability is quite small compared to the effect of migration costs measured by the barriers to inter-state migration. When exploring several potential channels for the indirect effect of climate variability on bilateral inter-state migration rates in India, we find evidence that part of the mechanism works through total income and agricultural income. Inter-state migration is driven not just by agricultural income but by total income in the destination state compared to the origin state. Controlling for the urbanization rate in the state of origin does not change the effect of drought frequency on bilateral inter-state migration rates, and we conclude that the effect does not work via urbanization in the case of Indian inter-state migration. A novelty of our study compared to the literature is that we analyze actual migration flows across rural and urban areas at the inter-state level, and thus can test the effect of climate variability on these flows as well as on state aggregate urbanization rates. Decomposition of total inter-state migration into rural–rural and rural–urban migration shows that the effect of drought frequency is the strongest on rural–rural inter-state migration rates.

We find also that a higher number of months with excess precipitation lower bilateral inter-state migration, which is contrary to the expected ex ante effect if excess precipitation measures flood events. This means that either floods need to be represented by different measures than excess precipitation or the migration response is different after floods. Following additional tests with alternative flood indicators, we argue that the results indicate that excess precipitation or floods matter less than droughts for explaining permanent inter-state migration in India.

The article contributes to a growing literature that analyzes the link between migration and climate variability. The idea that negative environmental conditions increase international migration was proposed in the 'environmental refugees' literature (Myers, 1997) but was re-interpreted and moderated by Piguet (2010) and Gemenne (2011) among others. Several studies use detailed microeconomic data to analyze the factors linking migration to climatic conditions. For example, in a large household study of Bangladesh, Gray and Mueller (2012) found that floods had no significant impact on migration but that weather-related crop failures increased migration. In another study that relates counts of natural disasters to permanent migration inferred from the Indonesian Family Life Surveys data, Bohra-Mishra et al. (2014) find no significant impact of natural disasters other than landslides on internal migration of entire households but find a significant and large effect of temperature and a significant but smaller effect of rainfall. This stream of the literature, which is reviewed in Lilleor and Van den Broeck (2011), shows how individual household factors contribute to vulnerability and explains what makes some households migrate and others not. However, it is difficult to generalize the findings from these studies to other countries.

Macroeconomic studies on international migration flows, such as Reuveny and Moore (2009), Beine and Parsons (2015), Coniglio and Pesce (2015), Cattaneo and Peri (2016), and Cai et al. (2016), test for the effects on cross-border flows. Reuveny and Moore (2009) show that both weather-related natural disasters and climate anomalies may (directly) induce increased migration into the Organisation for Economic Cooperation and Development (OECD) countries. In a comprehensive study of international migration over the period 1960–2000, Beine and Parsons (2015) find no effect of either temperature or rainfall deviations on international bilateral migration flows, including south-south migration which is an important difference compared to OECD migration data. Coniglio and Pesce (2015) test additional definitions of weather variables and find evidence of a positive effect of rainfall inter-annual variability on out-migration to OECD countries. These different findings are due in part to the use of different data sets: Beine and Parsons (2015) use migration flows calculated from migration stock data at 10-year intervals from 1960 to 2000, while Coniglio and Pesce (2015) and Cai et al. (2016) use annual data over a shorter time span (1990–2001 and 1980–2010). Cattaneo and Peri (2016) analyze the heterogeneous response in relation to income levels. Using the same data as Beine and Parsons (2015), they find that higher temperatures increase out-migration in middle-income countries, whereas in poor countries higher temperatures reduce out-migration.

The current article adds to a recent strand of work analyzing climatic factors and migration that relies on the most comprehensive data on migration flows at a country level, that is census data. Few studies use census data to study climatic factors and internal migration in large countries, and those that do focus mainly on the USA (Boustan et al. 2012; Feng et al. 2012).[1] Feng et al. (2012) study the indirect effect of temperature-induced crop shocks on out-migration from the US corn belt states, while Boustan et al. (2012) show that floods and tornadoes had a significant effect on gross migration flows in the USA in the 1920s and 1930s. Our study is the first to use census data to analyze bilateral internal migration rates in a large developing economy such as India.

We focus on internal (inter-state) migration in India where migration induced by climate variability is more likely to occur within national borders due to migration costs and legal barriers (Marchiori et al. 2012; Beine and Parsons 2015). Also, low-income and lower-middle-income countries are more vulnerable to climate variability than high-income countries (Stern 2007; Government Office for Science 2011) due to their ability to adapt and their geographical location. To account fully for all possible factors influencing migration, we need to study bilateral flows which prohibit use of the more detailed district-level data in the Indian Census, which record the destinations but not the origins of migrants. We contribute to the migration literature which typically uses gravity-type models that incorporate socioeconomic but not environmental factors (Karemera et al. 2000; Mayda 2010; Van Lottum and Marks 2010; see in particular Özden and Sewadeh 2010, for India).

The only other studies of migration and climate in India analyze either cross-section household-level data from the National Sample Survey (NSS), as in Kumar and Viswanathan (2013), or use census data to apply Feng et al.'s (2012) method to study migration induced by agricultural shocks (Viswanathan and Kumar 2015). The state-level analysis in Viswanathan and Kumar (2015) shows that weather-induced shocks to agricultural income induce out-migration for employment reasons. The objective of our analysis is to measure the total effect (direct and indirect effects) on internal migration. Also, our study uses complete census data (31 of the 32 states according to the 1991 state borders) for 1991 and 2001, while Viswanathan and Kumar (2015) analyze data for 15 major states over the period 1981–2001. In addition, they analyze out-migration rates at state level and in-migration rates at district level, while we analyze bilateral migration rates.

The remainder of the article is organized as follows. Section 2 presents the context and statistics for climate variability and inter-state migration in India. Sections 3 and 4 describe the empirical estimation strategy and the data. Section 5 presents the empirical results, and Section 6 concludes.

2. Inter-State Migration and Climate Variability in India

Analyzing inter-state migration in India is particularly appropriate for a study of internal migration because of the heterogeneity among states in relation, especially to demography and climate. Measured by the Environmental Vulnerability Index,[2] India is considered extremely vulnerable because of both its climate and its population density. India has a large range of climatic regions from tropical in the South to temperate and alpine in the Himalayan North. The main natural disasters in India are drought, flood, and tropical cyclones, measured by the number of people affected (Attri and Tyagi, 2010). In the present analysis, we focus on droughts and excess precipitation. India is the second most populous country in the world with 1210 million inhabitants in 2011 which represents 17.5% of the

1 Mastrorillo et al. (2016) analyze South Africa.

2 Index developed by the South Pacific Applied Geoscience Commission (SOPAC) and the United Nations Environment Program (UNEP).

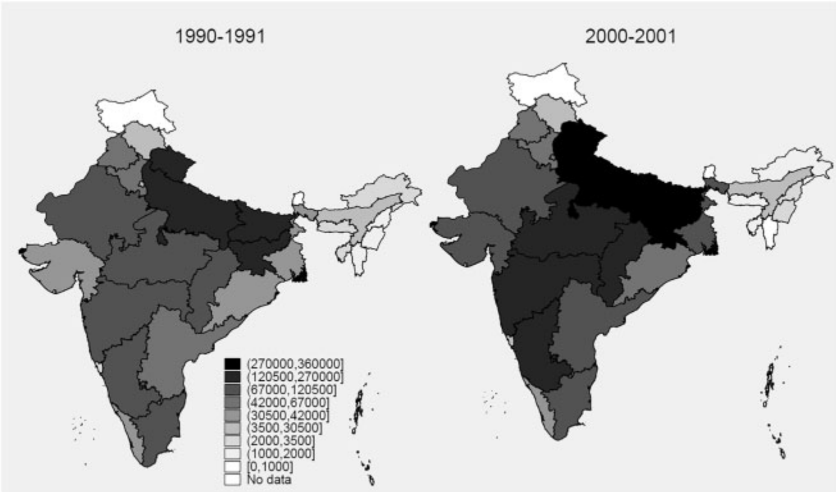

Figure 1. Maps of Indian inter-state out-migration in 1991 and 2001, by state.

Note: Migrants are defined as individuals declaring the last place of residence in year $t-1$ as being different from the place of residence in year t declared in the census.

Source: Authors' calculations based on 1991 and 2001 Indian Census, D2-Series.

world population on only 2.4% of the world surface area, and a population growth between 2001 and 2011 of 17.6%. Its population is mainly rural—69% in 2011 or 833.5 million people (Census of India 2011). Population densities differ widely among states ranging from 17 to 11,297 persons/ km^2 in 2011 (Arunachal Pradesh and Delhi, respectively). In 1991, 26.7% of the total population was internal migrants including 11.8% inter-state migrants. In 2001, these figures increased to 30.1% (310 million persons) and 13.4%. International migration is only 3.8% in India, according to the 64th round of the NSS conducted in 2007–2008 (Czaika 2011). These statistics suggest potential influence of climate variability on internal migration.

Figure 1 shows the number of out-migrants by state in 1990–1991 and 2000–2001. It confirms Özden and Sewadeh's (2010) finding of the major northwestern migration corridors based on data from the 55th round of the NSS in 1999–2000. The states with the highest numbers of inter-state out-migrants are the northern states Uttar Pradesh and Bihar, the central state Madhya Pradesh, and the southwestern states Maharashtra and Karnataka (darker shades).

Figure 2 shows the average SPI for the 5 years preceding the migration flows (1986–1990 and 1996–2000) for illustrative purposes. It ranges from -1 to $+1$, which represents moderate deviations. The lighter shades indicate negative values, and thus a precipitation deficit compared to the long-run mean; the darker shades indicate excess precipitation. Comparison of Figures 1 and 2 shows that before 1991 the major out-migration states all had negative SPI values on average. In the southwestern states of Karnataka and Maharashtra, the average SPI returned to around zero in 2001, while in Bihar (in the North) the average SPI became more negative.

In the econometric analysis, one of the main measures of climate variability that we will use is the frequency of months when the SPI was at least 1 standard deviation above or

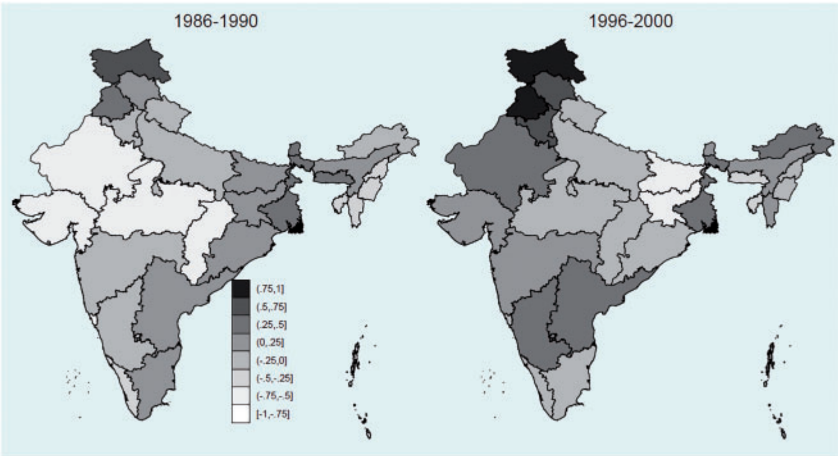

Figure 2. Maps of Indian average SPI by state, 1991 and 2001.

Source: Authors' calculations based on the CRU TS3.21 data.

below its long-run mean. Figure 3 shows the variability in the measure between the two censuses. It shows the number of months with one standard deviation or more of either low precipitation ('drought') or excess precipitation ('flood') in the 5 years preceding the censuses in 1991 and 2001. The first thing to note is that the months with drought by state varied widely between 1991 and 2001, but there is less variation over time in the number of months with excess precipitation by state. The decade 1981–1990 was a dry period in India (Attri and Tyagi 2010). Overall, several of the states recorded no occurrences of drought or excess precipitation at all in the 5 years preceding 2001. The states with a high number of months with low precipitation in the 5 years preceding 1991 are Kerala and Madhya Pradesh and several small states and island states, and in 2001 they are Bihar, Tripura, and Nagaland. The states with the most months of excess precipitation in the 5 years preceding 1991 are Himachal Pradesh, Haryana, Meghalaya, Punjab, Chandigarh, and Andhra Pradesh, and in the 5 years preceding 2001 are Haryana, Jammu and Kashmir, Rajasthan, Himachal Pradesh, and Punjab.

Comparison of the frequency of drought and excess precipitation frequencies with the migration data shows that the four states with the highest out-migration in the years studied (Uttar Pradesh, Bihar, Madhya Pradesh, and Maharashtra) all experienced drought episodes, and especially the major out-migration states of Bihar and Madhya Pradesh. These states all experienced less than 12 months of excess precipitation in the 5 years preceding the 1991 census, and no periods of excess precipitation in the 5 years preceding the 2001 census.

3. Empirical Specification and Method

3.1 Theoretical framework and econometric specification

We base the econometric specification on a random utility model (as in Beine et al. 2011; and Beine and Parsons 2015), where people can choose to stay in their state of residence or

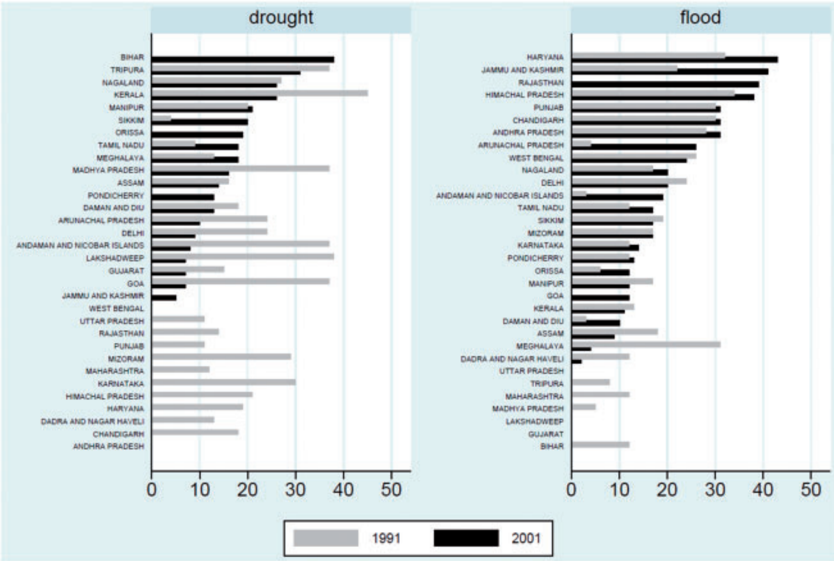

Figure 3. Frequency of low precipitation ('drought') and excess precipitation ('flood') by state, 1991 and 2001.

Note: Frequency of low and excess precipitation is defined as the number of months when the standardized precipitation index (SPI) was at least 1 standard deviation below/above its long-run mean.

Source: Authors' calculations based on the CRU TS3.21 data.

to migrate to another state to maximize their utility. The model specifies the determinants of bilateral migration and controls for factors 'pushing' and 'pulling' migration:[3]

$$\ln \frac{m_{ij,t}}{m_{ii,t}} = \ln \frac{w_{j,t}}{w_{i,t}} + S_{j,t} - S_{i,t} - C_{ij,t}, \tag{1}$$

where $m_{ij,t}$ is the bilateral migration rate from state i to state j during year $t{-}1$ to t, and $m_{ii,t}$ is the stock of the initial population staying in state i during year $t{-}1$ to t. The determinants are the log of the ratio of the per capita income in the destination state ($w_{j,t}$) and the per capita income in the origin state ($w_{i,t}$), the destination state characteristics ($S_{j,t}$), the origin-state characteristics ($S_{i,t}$), and the cost of migration from state i to state j at time t ($C_{ij,t}$).

Since income is endogenous to climate (Dell et al. 2009; Burke et al. 2015), we do not include it in our base estimation. Instead, we follow Dell et al. (2014) and exclude the income ratio, since it would bias the measure of the total effect of climate variability on migration, given that climate is a determinant of income. This results in the following econometric specification:

$$\ln \frac{m_{ij,t}}{pop_{ii,t}} = \alpha_0 + \alpha_1 \sum_{t-5}^{t} clim_{i,t} + \alpha_2 \ln(SC_{i,t} + 1) + \alpha_3 \ln(ST_{i,t} + 1) + \\ \alpha_4 M_{ij,t-5} + \alpha_5 d_{ij} + \alpha_6 b_{ij} + \alpha_7 l_{ij} + \gamma_i + \delta_{j,t} + \epsilon_{ij,t} \tag{2}$$

3 For details of the model, see Beine and Parsons (2015).

The principal variables of interest are those for climate variability ($clim_{i,t}$). We hypothesize that precipitation variation is a push factor in migration. This applies to the case of developing countries, where poor people move not as a result of comparing origin and destination climatic factors but to escape drought or floods which affect their well-being. Accordingly, our variability and adverse weather events variables apply only to the origin state. We define drought and excess precipitation events, based on the SPI, and differentiate between frequency, magnitude, and duration of events during the 5 years preceding migration.

Origin-state characteristics, $S_{i,t}$, include time-varying and time-invariant factors. We include scheduled castes (SCs) and scheduled tribes (STs) rates as a percentage of the total population in the state of origin. In India in 2001, 16.2% of the population belonged to a SC known as 'the untouchables', and 8.2% belonged to STs. Most work on Indian migration takes account of these two factors to examine the role of social factors in the migration decision (Bhattacharya 2002; Mitra and Murayama 2008). The Hindu varna system classifies Indian society into groups based on caste, ethnicity, and religion. This classification is reflected in the labor force participation (Dubey et al. 2006). Iversen et al. (2014) show that SCs do better in villages where they are the majority, which may make them less likely to move.[4] Indeed, Bhattacharya (2002) finds that SC incidence in rural areas is associated with lower out-migration rates, whereas the percentage of STs has no statistically significant effect. Hnatkovska and Lahiri (2015), using the NSS over the period 1983–2008, show that migrants are less likely to be members of backward castes as measured by the proportion of SC/ST. This also goes in line with Munshi and Rosenzweig (2016) who argue that one of the main reasons for India's low urbanization rate is the benefit of caste-based insurance networks in the rural origin villages.

We include time-invariant origin-state fixed effects (FEs) (γ_i) to capture the vulnerability of the geographic zone, in particular mountains, low-level coastal areas, and arid lands. This dummy controls also for the states affected by the 1958 Armed Forces (Special Powers) Act. This Act gives special powers to the armed forces (military and air forces) in so-called 'disturbed' areas of Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, and Tripura. These states have experienced violence which may have induced migration. Migration varies also depending on the employment opportunities in the destination state's labor market, and the education opportunities. These time-varying characteristics of the destination state ($S_{j,t}$) are captured by destination-time fixed effects ($\delta_{j,t}$) including any potential climate pull effect.

The costs of migration ($C_{ij,t}$) are represented by migration networks ($M_{ij,t-5}$), distance (d_{ij}), and dummy variables for common border (b_{ij}) and language (l_{ij}) between states.[5] Migrant networks are time-variant and affect migration by reducing information and assimilation costs, among others. The networks are measured as the stock of past migrants

4 If they migrate, they are more likely to choose destinations where there are members of their own subcaste. Since we do not have data on subcastes (jati), we cannot construct an appropriate measure of caste networks. However, we can control for the lower probability of migration of SCs and STs by the rate of SC/ST in the origin state.

5 Distance, common border, and common language are frequently used in bilateral migration analyses to measure the monetary and nonmonetary costs of migration (Bodvarsson and Van den Berg, 2009). Migrant networks are also important determinants of migration (Munshi, 2003; Beine et al., 2011).

from the same state i residing in the state j, as a percentage of the total population in state j, at time $t-5$. We define the network at $t-5$ to avoid simultaneity of the migration flows, present in the network definition, with the dependent variable and the climatic variables. All control variables are defined in detail in Supplementary Appendix A.

The expected signs on the variables representing the costs of migration are: $\alpha_4 > 0$, $\alpha_5 < 0$, $\alpha_6 > 0$, and $\alpha_7 > 0$. Migrant networks are expected to have a positive effect on bilateral migration rates. The relation between migration and distance is negative and proxies for migration travel costs. A common border and a common language reduce the cost of migration and proxy for cultural similarities between states. As argued above, all else being equal, the rate of SCs should imply lower migration, and we expect $\alpha_2 < 0$. We would expect a similar effect for STs, although STs live in states with more events of violence which could increase out-migration. Ex ante, the coefficient of α_3 could be positive or negative.

For the variables representing climate variability, we expect a positive sign ($\alpha_1 > 0$) for the drought measures which should act to push migration. The sign of excess precipitation is uncertain ex ante because excess precipitation could be a proxy for climatological floods and then $\alpha_1 > 0$. However, flood events depend also on the topology of the land and the geography (rivers; coast) as well as precipitation. Excess precipitation can be associated to better quality of land and growing conditions, and hence, one might expect $\alpha_1 < 0$ for excess precipitation that is at a lower level than extreme precipitation.

3.2 Estimation method and econometric issues

We start by discussing to what extent a causal interpretation of the results of Equation (2) can be inferred. We use exogenous weather data to construct the climate variability variables. This should reduce several potential sources of violation of the zero conditional mean assumption. However, three important econometric issues arise from Equation (2). First, we do not include the income ratio of Model (1) in Equation (2). Angrist and Pischke (2009) discuss the implications of using inappropriate controls, that is controls that are also outcome variables (Section 3.2.3). They explain why it is better to exclude such variables, even if they are correlated with the independent and the dependent variables. If the objective is to measure the causal effect of climate variability on migration, adding income to the regression introduces a bad control and biases the coefficient of climate variability. Indeed, according to Dell et al. (2009) and Burke et al. (2015), among others, income is endogenous to climate.[6] Good control variables for our research question are variables that were fixed at the moment of the climate variability event. If we include income, what we are measuring is the effect of the climate variability for a given income, which will result in selection bias. We thus measure the total effect of climate variability, holding other origin-state characteristics invariant in time, and destination state characteristics and cost of migration fixed. Controlling for origin-state characteristics is important, since they may be highly correlated to climate and migration. Nevertheless, potential omitted variables bias can still arise if the correlated climate variables are not included. We take this into account in the robustness checks performed in Section 5.3.

6 As expected, we find also that the income ratio is significantly affected by the climatic factors (see Supplementary Appendix Table SD3).

Second, in relation to the functional form, the specification in Equation (2) is based on a semi-log form. This represents a problem for those state pairs with zero migration flows, since dropping these observations from the data set could generate selection bias. In the Indian sample, these types of state pairs represent 10% of total observations. One way to avoid sample selection problems arising from excluding observations with zero migration is to add 1 to each bilateral migration rate observation. Nevertheless, the problem remains that the log-linear specification will cause the ordinary least squares (OLS) estimation of elasticities to be inconsistent in the presence of heteroskedasticity in the error term ($u_{ij,t}$).[7] Santos Silva and Tenreyro (2006) suggest using a PPML estimator with robust standard errors to produce consistent estimates in a nonlinear model. The assumption of equality between the standard deviation and the mean of the dependent variable that is characteristic of the standard Poisson maximum likelihood estimator is no longer necessary in the PPML method. Therefore, we rely on the results from using the PPML estimator.

Finally, multilateral resistance has been identified as a potential source of bias in the application of gravity models (Anderson 2011). It implies that the bilateral migration rate would depend not only on the comparison between the origin and the destination state characteristics but also on the opportunities in all the alternative destinations. The estimating equation is derived based on the assumption that the error terms are distributed according to an extreme value type-1 distribution, which effectively means an assumption of independence from irrelevant alternatives for migration. If this assumption does not hold and there is a need to account for multilateral resistance, Feenstra (2002) suggests that the inclusion of time-varying fixed effects for destination states yields consistent estimates in the presence of multilateral resistance. Bertoli and Fernández-Huertas Moraga (2013) suggest using Pesaran's common correlated effects estimator, which requires a long time span of data. However, this is impossible in our case because our data are based on only two census rounds. Instead, we control for possible multilateral resistance through the inclusion of destination state and time fixed effects.

Given the above discussion, we argue that what we measure in the reduced-form Equation (2) is the total effect of climate variability on bilateral migration, although the underlying mechanism through which climate affects migration is not present in the equation.

4. Data and Measures of Climate Variability

4.1 Definition of migration

A migrant in the Indian Census is defined as an individual with the intent of staying permanently, and a stay in the destination state for at least 6 months; it is a measure of permanent rather than temporary migration. The census identifies migration flows according to the current place of residence (destination state) and the place of residence of provenance (origin state), and includes different durations of stay. We use the 1-year duration to retain a strict separation between the timing of climate variability and migration, and to minimize the measurement error linked to subsequent moves. Our dependent variable is the gross

7 The Breusch–Pagan/Cook–Weisberg test of heteroskedasticity in an OLS regression leads to a test statistic of 368.53 and a p-value of 0. Thus, the null hypothesis of homoskedasticity is rejected.

migration flow $m_{ij,t}$ from state i to state j between year $t-1$ and year t, divided by the population that did not move in the same period, and multiplied by 100,000 to allow for scaling. Supplementary Appendix Table SA2 shows that the average bilateral migration rate is around 8 per 100,000 individuals—which might seem small—but the variable measures the bilateral rate for a unique origin-destination pair in single year, for example 8 of 100,000 individuals migrated from Assam to West Bengal between 1990 and 1991, which is almost 1800 individuals.[8] We have 930 such combinations. It is important also to note that the dispersion is large (standard deviation almost four times the mean) and that the bilateral migration rate can take values from 0 and to 455 migrants per 100,000 individuals.

4.2 Climate variability: the SPI

Rainfall is the main factor in vulnerability to water availability. Scarcity of water has negative consequences for food availability and human health, and can be the cause of diseases and population displacements (IPCC 2014). In urban areas, the consequences of scarce water supply include difficulty to cover the drinking water requirements in terms of both quantity and quality. In rural areas, output and quality of crops are also affected. The agricultural sector in India is particularly vulnerable to water availability (O'Brien et al. 2004). To test the hypothesis that climate variability acts as a push factor in internal migration, we compute normalized measures of low precipitation and excess precipitation using the Climatic Research Unit (CRU) TS3.21 data set from the University of East Anglia.

The data allow us to calculate the SPI, a frequently used standardized measure of drought developed by McKee et al. (1993). First, a gamma distribution is fitted to the long-run precipitation data (from 1901 to 2001). This then is transformed into a standard normal distribution with zero mean and variance of 1, which gives the SPI. Conceptually, the SPI represents a z-score, or the number of standard deviations of an event above or below the long-run mean. The SPI allows us to determine drought or excess precipitation during a given period in a given location.

The main advantages of the SPI are that it takes account of the spatial and temporal deviations, and measures the start, length, and intensity of a drought or a period of excess precipitation, rather than only the absolute value of precipitation and temperature. It provides a measure with a fixed mean and variance, allowing comparison of the SPIs for different locations. Although the SPI was developed to measure drought, it has been suggested that it is also a good indicator of flood (see for instance Seiler et al. 2002). However, floods can be of different types (e.g. storm surges; flash floods; river floods), and can depend not just on the quantity of rainfall but also on the soil type of flood banks and the topology of the landscape.

The raw data are district-level data; to aggregate them to state level requires calculation of the SPIs of every state. Supplementary Appendix B provides a principal component analysis to test this procedure. We create three variables based on the SPI to measure the frequency, duration, and magnitude of drought and excess precipitation:

1. *Frequency*: We define a binary variable (by state) that takes the value 1 if there was moderate or severe drought/excess precipitation recorded in a month in that state, and

8 In 1990, 22,408,756 individuals did not move from West Bengal.

0 otherwise.[9] The frequency measure is the number of months with drought/excess precipitation in the origin state during the 5 years preceding migration, to account for persistence in the effects of drought/excess precipitation.[10] These measures count the total months of either severe or moderate drought/excess precipitation; extreme events are not common in state-level data. Aggregation at state level removes district-level extreme events and can lead to less precise results. More frequent drought/excess precipitation may increase expectations of future similar events, and thus higher frequency should encourage migration.

2. *Maximal duration*: To capture the impact of a long period of drought or excess precipitation, we compute the maximal duration in number of months of such an event during the 5 years preceding migration. Long duration of drought or excess precipitation in a given period is more likely to have a strong negative impact on livelihoods and hence encourage migration to seek better economic conditions.
3. *Magnitude*: This variable is defined as the sum of the absolute values of the SPI for drought or excess precipitation in the 5 years preceding migration. Severe or extreme drought/excess precipitation can affect people by destroying their crops or capital, and having negative effects on health all of which encourage or force migration.

Duration and magnitude are widely used measures of climate variability and two main dimensions of drought or excess precipitation (Zargar et al. 2011). Also, these measures are strictly exogenous and not influenced by economic activity at the time-scale considered here. We constructed and tested additional measures to account for interaction effects such as a long and severe drought; these were never significant and are not included here.

4.3 Other migration determinants

Since climatic factors are not the only determinants of migration, we control also for the most important social and economic drivers by estimating bilateral migration rates as a function of distance, common border, common language, bilateral migrant networks, the rate of SCs and STs in the origin state, and a set of fixed effects. Climate-dependent explanatory variables, such as income and agricultural income per capita, irrigation, and urbanization rates, are discussed in Section 5.1.3, where we explore channels of the indirect effect of climate variability on inter-state migration. Supplementary Appendix A describes the measures, data sources, and descriptive statistics.

5. Results

We start by presenting the OLS estimates of Equation (2) with bilateral fixed effects instead of distance, common border, and common language, to capture all potential time-invariant factors that may affect bilateral migration. The estimation results in Table 1 indicate that

9 See definition of moderate and severe drought/excess precipitation in Supplementary Appendix Table SA1.

10 In an analysis of the impact of drought on rural wages in Brazil, Mueller and Osgood (2009) identify a 5-year persistence effect from drought. Barrios et al. (2006) and Strobl and Valfort (2013) also use a lag of 5 years for the impact of natural disasters and climate variables. Estimations in Supplementary Appendix Table SD6 show the results with different lags.

Table 1. Inter-state migration and drought with bilateral fixed effects in an OLS model

	(1)	(2)	(3)
$\ln SC_{it}$	−7.220	−0.530	−5.197
	(12.675)	(12.612)	(12.657)
$\ln ST_{it}$	−2.023	−0.515	−1.689
	(8.778)	(8.865)	(8.847)
Network_rate$_{ijt}$	0.198	0.222	0.224
	(0.175)	(0.176)	(0.173)
Drought frequency$_{it}$	0.017**		
	(0.007)		
Longest drought dur$_{it}$		0.013*	
		(0.007)	
Drought magnitude$_{it}$			0.008
			(0.005)
Origin-state FE	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes
Bilateral FE	Yes	Yes	Yes
N	1860	1860	1860
R^2	0.828	0.828	0.827

Note: The dependent variable is ln(bilateral migration rate + 1) from state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$.

one additional month of drought increases the bilateral migration rate by 1.7% at the 5% level of significance (Column (1)). The longest drought duration (Column (2)) is weakly significant (10% level). Drought magnitude (Column (3)) and the other covariates are not significant, and the coefficient estimates may be inconsistent in the presence of heteroskedasticity (Section 3.2). To illustrate the effect of using the PPML estimator, we compare the results using OLS and PPML (Supplementary Appendix Table SD1). In general, the results vary much between the two estimators. In the full sample (Columns (1) and (3)), the effect of drought frequency goes from 1.7% with OLS to 1.5% with the PPML estimator and with a decrease in significance. Since PPML gives consistent estimates, we present all the following results with the PPML estimator, accounting for zero observations, unless otherwise stated. All the estimations include origin-state fixed effects and destination-time fixed effects, but not bilateral fixed effects, since adding too many explanatory variables creates convergence problems when using the PPML estimator.

Climate variability can have both a direct (amenity effect) and an indirect effect on internal migration. Section 5.1 analyzes the total effect of climate variability in terms of drought, and Section 5.1.2 presents the different migration responses. Section 5.1.3 discusses the potential channels underlying the results. Section 5.2 presents the results from the measures of excess precipitation, and Section 5.3 presents some robustness tests using alternative measures of climate variability and a different econometric specification. In Section 5.4 we calculate the magnitude of the migration flows induced by drought variability over the period studied.

5.1 Drought and migration

Table 2 presents the main estimation results of Equation (2) for the drought measures. The different measures are introduced separately in the estimations because of their correlation (see Supplementary Appendix Table SA3).

The results show that the proxies for the costs of migration are the most important factors in internal migration in terms of value and statistical significance. Bilateral migration rates between contiguous states are 2.4 times higher than for states with no common border. States with a common language have 50% higher bilateral migration rates.[11] Geographical distance is also statistically significant with a 1% larger distance decreasing the bilateral migration rate by 0.7%. A 1 percentage point increase in the migrant network rate increases the bilateral migration rate by 6.4%, which is in line with the findings in the literature on migrant networks (Beine et al. 2011). The SC and ST rates in the origin state are not significant.

Among the three drought measures tested, the duration of the longest drought is rejected as a push factor for migration. The results indicate that an additional month of drought during the 5 years preceding migration increases the bilateral migration rate by 1.5% (Column (1)) and that an additional 1-unit increase (which is very high) in absolute magnitude in the SPI increases the migration rate by 0.8% (Column (3)). The statistical significance of drought frequency is higher than that of the magnitude of droughts: 5.1 and 10.0%, respectively.

5.1.1 The timing of climatic factors and migration

One of the advantages of our study is the fact that our data allow us to measure climate variability before the migration decision. This contrasts with other work, especially on international migration, where data constrain the analysis to use average climate variability and average migration over the same 5- or 10-year periods. To compare our results with the method used in the literature, we use similar measures of climate variability, that is temperature and rainfall deviations in absolute value from their long-run mean, and anomalies defined as in Marchiori et al. (2012).[12] We also separate positive and negative anomalies to measure excess or deficit temperature and precipitation.

Table 3 presents the difference in results using contemporaneous climate variability compared to climate variability averaged over a longer time span. The dependent variable in Columns (1)–(4) is the average bilateral migration rate between 1982 and 1991 for the 1991 census, and between 1992 and 2001 for the 2001 census. The climate variability measures are defined as temperature and precipitation anomalies and deviations averaged over the same 10-year periods. The dependent variable in Columns (5)–(8) is our 1-year bilateral migration rate, with the climate variability measured in the 5 years preceding migration.

Columns (1) and (5) present the results with positive temperature and negative precipitation anomalies. Columns (2) and (6) present the results with negative temperature and positive precipitation anomalies. Columns (3) and (7), and Columns (4) and (8) present the results with the corresponding measures of temperature and precipitation deviations,

11 The marginal effects of the dummy variables are calculated as $(e^{b_i} - 1)$, where b_i is the estimated coefficient of the variable.

12 The definition is provided in Supplementary Appendix A.

Table 2. Inter-state migration and drought: total effect

	(1)	(2)	(3)
ln distance$_{ij}$	−0.658***	−0.658***	−0.658***
	(0.080)	(0.080)	(0.080)
Border$_{ij}$	1.226***	1.221***	1.222***
	(0.150)	(0.150)	(0.149)
Language$_{ij}$	0.377**	0.376**	0.376**
	(0.160)	(0.161)	(0.162)
$\ln SC_{it}$	−9.682	−1.710	−4.360
	(18.386)	(18.476)	(18.472)
$\ln ST_{it}$	1.540	2.616	1.756
	(6.352)	(6.261)	(6.288)
Network_rate$_{ijt}$	0.064**	0.064**	0.064**
	(0.020)	(0.020)	(0.020)
Drought frequency$_{it}$	0.015*		
	(0.008)		
Longest drought dur$_{it}$		0.010	
		(0.007)	
Drought magnitude$_{it}$			0.008*
			(0.005)
Origin-state FE	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes
N	1860	1860	1860
R^2	0.698	0.695	0.694

Note: The dependent variable is the bilateral migration rate from state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses.
$^*p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

respectively. The results show that for the 10-year averaged migration measure, only positive deviations in precipitation have a weakly significant effect on migration rates, and this effect is negative. Comparing this to the measures of climate variability during the 5 years before the 1-year migration flow, we find that negative precipitation anomalies have a positive impact on the bilateral migration rate (Column (5)) similar to our drought measure, and that positive precipitation anomalies (Column (6)) decrease the bilateral migration rate. This indicates that excess precipitation in this sense is favorable and not equivalent to flood. Qualitatively similar results are obtained using the deviations measures. These results support the improvement in the estimations from measuring the effect with appropriate timing of the climate variability measures and migration resulting from use of census data with a 1-year duration of migration.

5.1.2 Heterogeneous effects

In this section, we show the different migratory responses to drought depending on the level of agricultural activity in the state, irrigation, gender, and origin and destination of migration flows.

Table 3. Inter-state migration and climate anomalies: 10-year average comparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Migration rate 10-year average				Migration rate 1-year flow			
ln distance$_{ij}$	−0.716***	−0.714***	−0.716***	−0.716***	−0.657***	−0.658***	−0.657***	−0.657***
	(0.074)	(0.074)	(0.074)	(0.074)	(0.079)	(0.080)	(0.080)	(0.080)
Border$_{ij}$	1.424***	1.420***	1.422***	1.420***	1.222***	1.223***	1.222***	1.223***
	(0.148)	(0.148)	(0.149)	(0.148)	(0.149)	(0.148)	(0.149)	(0.148)
Language$_{ij}$	−0.013	−0.009	−0.011	−0.010	0.384**	0.390**	0.384**	0.387**
	(0.147)	(0.146)	(0.146)	(0.147)	(0.161)	(0.159)	(0.161)	(0.160)
ln SC_{it}	−2.050	−8.376	−0.990	−4.761	−3.382	−16.151	−3.411	−8.526
	(15.672)	(16.172)	(15.759)	(15.658)	(18.444)	(18.713)	(18.347)	(18.247)
ln ST_{it}	9.887	10.658	9.902	10.298	1.540	2.304	1.820	2.114
	(6.730)	(6.681)	(6.778)	(6.759)	(6.217)	(6.168)	(6.256)	(6.242)
network_rate$_{ijt}$	0.067***	0.065**	0.067***	0.064**	0.064**	0.063**	0.064**	0.062**
	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)	(0.021)
Precipitation (−) anomaly$_{it}$	1.611				2.545**			
	(1.131)				(1.022)			
Temperature (+) anomaly$_{it}$	−3.264				−2.227			
	(2.446)				(2.351)			
Precipitation (+) anomaly$_{it}$		−0.621				−1.104**		
		(0.420)				(0.392)		

(continued)

Table 3. (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Migration rate 10-year average				Migration rate 1-year flow			
Temperature (−) anomaly$_{it}$		0.136				−0.657		
		(0.991)				(0.882)		
Precipitation (−) deviation$_{it}$			0.005				0.006**	
			(0.003)				(0.003)	
Temperature (+) deviation$_{it}$			−0.475				−0.136	
			(0.763)				(0.738)	
Precipitation (+) deviation$_{it}$				−0.002*				−0.003**
				(0.001)				(0.001)
Temperature (−) deviation$_{it}$				−0.050				−0.076
				(0.624)				(0.490)
Origin-state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1860	1860	1860	1860	1860	1860	1860	1860
R^2	0.761	0.759	0.760	0.760	0.696	0.698	0.694	0.697

Note: The dependent variable is the bilateral migration rate from state i to state j. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses.
*p<0.10, **p<0.05, ***p<0.01.

Table 4. Inter-state migration and drought in agricultural states

	(1)	(2)	(3)
ln distance$_{ij}$	−0.729***	−0.730***	−0.729***
	(0.077)	(0.076)	(0.076)
Border$_{ij}$	1.099***	1.099***	1.101***
	(0.116)	(0.116)	(0.116)
Language$_{ij}$	0.037	0.033	0.036
	(0.130)	(0.131)	(0.130)
ln SC_{it}	3.103	2.188	3.898
	(14.632)	(15.082)	(14.490)
ln ST_{it}	10.785	9.450	9.055
	(10.529)	(10.777)	(10.496)
Network_rate$_{ijt}$	0.081***	0.081***	0.081***
	(0.019)	(0.019)	(0.019)
drought freq$_{it}$ $(AgrSt)$	0.017**		
	(0.007)		
longest drought dur$_{it}$ $(AgrSt)$		0.003	
		(0.006)	
drought magnitude$_{it}$ $(AgrSt)$			0.012**
			(0.005)
Origin-state FE	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes
N	1560	1560	1560
R^2	0.672	0.668	0.672

Note: The dependent variable is the bilateral migration rate from state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses.
$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

5.1.2.1 Extent of agriculture in the state economy. To test for a heterogeneous effect in agricultural states, we introduce an interaction term with an agricultural dummy variable that takes the value 1 if the agricultural Net State Domestic Product (NSDP) exceeds the median value among the states (Table 4 Columns (1)–(3)).[13] The sample size is smaller for these estimations, since agricultural NSDP data are not available for four union territories and one state (Chandigarh, Dadra and Nagar Haveli, Daman and Diu, Lakshadweep, and Mizoram). In these estimations, common language no longer affects the bilateral migration rate, and the effect of network is higher. The effect of drought frequency is stronger and more significant in agricultural states, with each additional month of drought inducing an increase in the bilateral migration rate of 1.7% if the origin state is agricultural. In agricultural states of origin, 1 additional unit increase in the magnitude of drought (measured by the SPI in absolute magnitude) implies a 1.2% increase in the average bilateral migration rate. In agricultural states, the two effects are significant at the 5% level.

13 The 13 states with an agricultural NSDP per capita higher than the median are Arunachal Pradesh, Assam, Bihar, Haryana, Himachal Pradesh, Madhya Pradesh, Orissa, Punjab, Rajasthan, Sikkim, Tripura, Uttar Pradesh, and Andaman and Nicobar Islands.

5.1.2.2 Irrigation as an adaptation measure. Other adaptations than migration can limit the impact of climate variability (Barnett and Webber 2010; Mendelsohn 2012). In agriculture, farmers can adapt to shortfalls in precipitation or to increased variability in precipitation by changing to more resistant crops, or by investing in irrigation infrastructure (O'Brien et al. 2004). Here, the analysis is at the macro level, and we cannot control for drought-resistant crops. Although irrigation is likely to be dependent on climatic factors on its own, we control for irrigation capacity as one of the most common adaptation measures against drought. Taraz (2015) finds that Indian farmers adjust their irrigation investment according to monsoon rainfall variability, but that its efficacy in reducing the losses in agricultural profits is limited. To test the effect of irrigation, we use the ratio of net irrigated land in total cultivated land in the origin state. Supplementary Appendix Table SD2 shows the net effect of drought frequency including the net irrigation rate and the interaction terms. The interaction terms between the drought measures and irrigation have the expected negative sign but are never significant (Columns (4)–(6)). Since irrigation is correlated to climate (see Supplementary Appendix Table SA3) and not on its own a determinant of migration, because of multicollinearity, its inclusion will only reduce the precision of the estimated coefficient of drought. We observe that the significance and magnitude of the coefficients of drought are attenuated if the net irrigation measure is included (Columns (1)–(3)). Nevertheless, the effect of drought frequency maintains its sign and order of magnitude, which confirms the robustness of its effect.

5.1.2.3 Male and female migration rates. The Indian Census asks individuals to indicate the reason for migration from a list of work/employment, business, education, marriage, moved after birth, moved with household, and others. Supplementary Appendix Table SC2 shows that the family moving is the main reason for migration among women (41% of women in 1991 and 48% of women in 2001), and employment is the main reason for men (42% of men in 1991 and 54% of men in 2001). To further test the relationship between climate variability and internal migration in India, we run separate estimations on male and female migration rates. Table 5 reports the results for male migration (Columns (1)–(3)) and female migration (Columns (4)–(6)). In the case of male migration, all the determinants have similar size and significance as in the main estimations of total migration rates in Table 2. Most importantly, drought frequency, duration, and magnitude have the same marginal effect, but drought frequency has a higher level of significance. In the case of female migration, the results are similar to the main estimations of total inter-state migration but show a lower significance.

5.1.2.4 Different flows according to source and destination. So far, we have studied total inter-state migration flows. However, the analysis of the precipitation data in Supplementary Appendix B shows that aggregation at state level masks important variability among districts. Detailed modeling of rural–urban migration flows at district level would add to our understanding of the relation between climate variability and migration; however, the census data do not allow this, since origin districts are not recorded. Nevertheless, it is possible within inter-state migration flows to distinguish whether the origin and destination are rural or urban. Note that in India, rural–rural migration is more frequent than rural–urban migration, as shown in Supplementary Appendix Table SC3. We use the information on inter-state migration flows between areas characterized as rural or

Table 5. Inter-state male and female migration and drought

	(1) Male	(2) Male	(3) Male	(4) Female	(5) Female	(6) Female
ln distance$_{ij}$	−0.683***	−0.683***	−0.683***	−0.624***	−0.624***	−0.624***
	(0.084)	(0.083)	(0.083)	(0.081)	(0.080)	(0.081)
Border$_{ij}$	1.099***	1.094***	1.095***	1.394***	1.390***	1.391***
	(0.152)	(0.152)	(0.152)	(0.151)	(0.150)	(0.151)
Language$_{ij}$	0.465**	0.465**	0.464**	0.257	0.254	0.255
	(0.164)	(0.165)	(0.166)	(0.161)	(0.162)	(0.162)
ln SC_{it}	−11.628	−3.782	−6.731	−6.068	1.947	−0.271
	(19.364)	(19.607)	(19.574)	(17.341)	(17.071)	(17.102)
ln ST_{it}	1.091	2.145	1.254	2.500	3.584	2.780
	(6.459)	(6.412)	(6.437)	(6.609)	(6.476)	(6.503)
Network_rate$_{ijt}$	0.061**	0.061**	0.061**	0.068***	0.068***	0.068***
	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)
Drought frequency$_{it}$	0.015**			0.015*		
	(0.007)			(0.009)		
Longest drought dur$_{it}$		0.010			0.009	
		(0.006)			(0.007)	
Drought magnitude$_{it}$			0.008*			0.007
			(0.005)			(0.005)
Origin-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1860	1860	1860	1860	1860	1860
R^2	0.673	0.669	0.668	0.723	0.722	0.721

Note: The dependent variable is the bilateral migration rate from state i to state j between year $t-1$ and state t, separately for male and female migrants. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$.

urban to analyze the patterns of migration in more detail. The results are reported in Table 6. The dependent variable is the bilateral migration rate from one part of a state to one part of another state (e.g. from a rural to an urban area); we therefore exclude the independent variables for the entire state (e.g. SC or ST rates in the origin state, and bilateral migrant networks). We test separately for an effect on total rural out-migration to another state (rural and urban destinations together), rural–urban migration, and rural bilateral migration (rural origin and rural destination involving different states).[14]

Analysis of these three patterns of bilateral migration confirms the hypothesis of drought frequency as a push factor in migration. The results in Table 6 Column (1) show that drought frequency has a higher impact on total rural out-migration than on total inter-state migration: its average effect increases from 1.5 to 2%. Table 6 Column (2) shows that drought frequency has a positive and significant impact on rural–urban migration, but that

14 We show the results on drought frequency, since it has the strongest effect on bilateral migration. The other measures—drought duration and magnitude—are not significant at this disaggregated level.

Table 6. Rural out-migration and drought frequency

Migration pattern	(1) Rural–total	(2) Rural–urban	(3) Rural–rural
ln distance$_{ij}$	−0.702***	−0.663***	−0.740***
	(0.096)	(0.089)	(0.114)
Border$_{ij}$	1.263***	1.201***	1.341***
	(0.175)	(0.187)	(0.202)
Language$_{ij}$	0.444**	0.712***	0.215
	(0.190)	(0.192)	(0.201)
Drought frequency$_{it}$	0.020**	0.017*	0.025**
	(0.010)	(0.009)	(0.011)
Origin-state FE	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes
N	1860	1860	1860
R^2	0.815	0.813	0.751

Note: The dependent variable is the bilateral migration rate from zones in state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$.

the effect is smaller than the effect on total rural out-migration. Column (3) shows that the effect of drought frequency is the largest on the rural–rural bilateral migration flows at 2.5%. Analysis of the separate inter-state migration flows according to rural out-migration supports the robustness of our main estimations using total inter-state migration flows presented in Table 2, and suggests that an important part of the impact of climate variability on migration is its impact on rural areas.

5.1.3 Climate variability and migration: What are the channels?

We have estimated the total (both direct and indirect) effect of drought on internal migration in India. The indirect effects could work through the effects of climate variability on average income (Beine and Parsons 2015), agricultural income or yield (Feng et al. 2012; Viswanathan and Kumar 2015), urbanization (Barrios et al. 2006), and conflict (Wischnath and Buhaug 2014).[15] This section explores the contribution made by three potential channels to explaining the effect of drought frequency on bilateral inter-state migration rates.

5.1.3.1 Income channel. Table 7 presents the same estimations as in Table 2 Columns (1)–(3), but in Columns (2)–(4) adds the ratio of NSDP per capita between the destination and origin states. NSDP per capita in the destination state is a proxy for the average income expected by migrants. Column (1) presents the estimation with the income per capita ratio and without the variables for climate variability. In all the estimations, the income ratio is positive and significant, implying that migrants migrate to states where the expected income is higher than in the origin state. The income ratio elasticity ranges from 0.6 to 0.9. If

15 We performed estimations for the conflict channel using data on homicide rates from the Indian Ministry of Home Affairs, National Crime Records Bureau, but found no effect.

Table 7. Inter-state migration and drought: total income and agricultural channel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln \frac{y_{j,t}}{y_{i,t}}$	0.877**	0.675*	0.795**	0.756*				
	(0.398)	(0.371)	(0.391)	(0.393)				
$\ln \frac{y\_agr_{j,t}}{y\_agr_{i,t}}$					0.178	0.203	0.181	0.201
					(0.233)	(0.233)	(0.235)	(0.237)
ln distance$_{ij}$	−0.658***	−0.658***	−0.658***	−0.658***	−0.693***	−0.693***	−0.693***	−0.692***
	(0.080)	(0.081)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)
Border$_{ij}$	1.224***	1.228***	1.225***	1.225***	1.127***	1.129***	1.127***	1.129***
	(0.149)	(0.149)	(0.149)	(0.149)	(0.124)	(0.124)	(0.124)	(0.124)
Language$_{ij}$	0.379**	0.379**	0.378**	0.378**	0.120	0.121	0.120	0.121
	(0.161)	(0.159)	(0.160)	(0.160)	(0.136)	(0.133)	(0.135)	(0.133)
$\ln SC_{it}$	−0.454	−5.010	2.189	−0.267	7.271	4.182	8.005	5.102
	(18.318)	(18.423)	(18.591)	(18.461)	(15.111)	(14.848)	(15.509)	(14.812)
$\ln ST_{it}$	6.998	5.439	6.986	6.125	10.297	15.682	11.344	11.902
	(6.685)	(6.822)	(6.727)	(6.783)	(10.549)	(10.225)	(10.589)	(10.565)
network_rate$_{ijt}$	0.064**	0.064**	0.063**	0.063**	0.082**	0.082**	0.082**	0.081**
	(0.021)	(0.020)	(0.020)	(0.020)	(0.026)	(0.025)	(0.026)	(0.026)
Drought frequency$_{it}$		0.013*				0.008*		
		(0.007)				(0.005)		
Longest drought dur$_{it}$			0.008				0.002	
			(0.007)				(0.005)	
Drought magnitude$_{it}$				0.005				0.005
				(0.005)				(0.004)
Origin-state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1860	1860	1860	1860	1300	1300	1300	1300
R^2	0.694	0.699	0.697	0.696	0.672	0.677	0.673	0.677

Note: The dependent variable is the bilateral migration rate from state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses.

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

the income channel captures all the effects of climate variability, the coefficients of the climate variability should be nonsignificant in Columns (2)–(4). If we compare Columns (1) and (2), we observe that the significance and magnitude of both average income ratio and drought frequency decrease in Column (2). This change in significance is observed also for drought magnitude (Column (4)). These results suggest that part of the effect of climate variability on migration goes through income. In particular, drought magnitude is captured entirely by the indirect effect on income, but in the case of drought frequency, there is also a direct effect which is smaller—1.3%—and significant only at the 9.3% level.

These effects are explained by the direct impact of drought frequency on income. Columns (1)–(3) in Supplementary Appendix Table SD3 present the estimations of the income ratio on drought. The three drought variables (frequency, duration, and magnitude) have a positive and statistically significant impact on the income ratio. More frequent, longer and severe droughts in the origin state increase the difference in incomes between the destination and the origin states and thus might encourage migration indirectly. Given that all the variables for drought in the origin state have a highly significant impact on the income ratio, we should exclude income ratio from the estimations of bilateral migration rates as in Table 2, to avoid bad control.

5.1.3.2 Agricultural channel. The effects of climate change on agricultural yields in India have been documented extensively (Guiteras 2009; Krishnamurthy 2012). Table 7 Columns (5)–(8) present the results for the agricultural channel. The analysis is similar to the analysis of average income per capita; we include the ratio of per capita agricultural income in the destination state to per capita agricultural income in the origin state.[16] The results show that the *agricultural* income ratio is not significant for determining bilateral migration rates (Column (5)) which depend on *total* per capita income in the destination versus the origin states. Both pull factors of nonagricultural employment and push factors of decreasing agricultural income are at work. When controlling for the ratio of agricultural income between the destination and origin states, the effect of another month of drought decreases to 0.8% (significant at the 8.5% level only) indicating that the effect of climate variability in the origin state is largely mediated by agricultural income. Supplementary Appendix Table SD3 Columns (4)–(6) show that agricultural income in the origin state is significantly and negatively affected by all three drought measures. The results in Tables 7 and Supplementary Appendix Table SD3 confirm that part of the effect of climate variability on migration in India goes through the agricultural channel.

To analyze this channel further, we compare our results with the ones obtained in Viswanathan and Kumar (2015) on inter-state out-migration and agricultural income. They find an elasticity of out-migration with respect to agricultural income of −0.775. The comparison is not straightforward, since Viswanathan and Kumar (2015) (i) analyzes 15 major states;[17] (ii) uses out-migration rates only at state level; (iii) controls for temperature

16 The sample size is smaller for these estimations, since data on agricultural NSDP are not available for four union territories and one state. Using a ratio decreases the sample size further, from 1560 to 1300, because of missing values in either the origin or destination states which might explain why the agricultural income ratio is not significant in these estimations.

17 The 15 major states analyzed by Viswanathan and Kumar (2015) are Andhra Pradesh, Bihar, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal.

and rainfall in absolute levels, and include no other control variables except fixed effects in the origin state; and (iv) takes account only of rural out-migration for male migrants declaring work as the reason for migration. For our sample of states for which we have agricultural NSDP data ($n = 1560$), and using only rural out-migration flows as in Viswanathan and Kumar (2015), the estimations presented in Supplementary Appendix Table SD4 give an elasticity of -0.105 without controlling for fixed effects (Column (3)), and an elasticity of -0.075 that is not significant when controlling for origin-state and destination-time fixed effects and for temperature and precipitation anomalies (Column (4)). We ran other estimations that were as similar as possible to the state-level estimations in Viswanathan and Kumar (2015) to allow for a comparison with the results for elasticity of migration with respect to agricultural income. Supplementary Appendix Table SD4 Columns (1) and (2) present the estimations of the bilateral migration rates using the migration between the same 15 states ($n = 420$); the estimated elasticity is -0.2 with fixed effects, and is not significant. The estimated elasticities with respect to agricultural income on bilateral migration rates we obtained are smaller than the estimated elasticity in Viswanathan and Kumar (2015).

5.1.3.3 Urbanization channel. It is possible that the impact of climate variability on migration is due mainly to rural–urban migration, and thus urbanization. To study this channel, we control for the urbanization rate in the state of origin to proxy for alternative opportunities to inter-state migration. Following drought, a more urbanized origin state should offer more alternative nonagricultural employment probabilities than a less urbanized origin state. Table 8 shows no significant effect of the urbanization rate in the state of origin on the bilateral migration rate. Moreover, the effects of drought frequency and magnitude remain the same as in Table 2. Thus, we find no evidence of an urbanization channel affecting inter-state migration in India.

This does not mean that climate variability has no effect on the urbanization rate in the origin state. Supplementary Appendix Table SD5 Columns (1)–(3) show a positive and significant effect of drought frequency, duration, and magnitude on the urbanization rate. These results are in line with the findings in Barrios et al. (2006) for Sub-Saharan Africa. For example, an additional month of drought is associated with an increase of 0.2% in the urban population rate. However, the potential channel of the effect of climate variability passing through urbanization can be rejected, since a direct effect of drought frequency and magnitude remains in the estimations of bilateral migration rates, even when controlling for urbanization.

The results discussed above show that drought has a significant effect on urbanization in the origin state, but that the effects of drought on migration work through income, and mainly through the agricultural sector.

5.2 Excess precipitation and migration

Table 9 presents the estimations in Tables 2 and 4 using measures for excess precipitation instead of drought. The marginal effects of the frequency, duration, and magnitude of excess precipitation are negative with a level of statistical significance for frequency and magnitude of 5.5 and 7.3%, respectively. In agricultural states, the impact of the duration of an episode of excess precipitation is strongly significant, and reduces bilateral migration rates

Table 8. Inter-state migration and drought: urbanization channel

	(1)	(2)	(3)	(4)
ln urban_rate$_{it}$	−0.263	−0.386	−0.258	−0.413
	(0.535)	(0.523)	(0.529)	(0.536)
ln distance$_{ij}$	−0.657***	−0.657***	−0.657***	−0.657***
	(0.080)	(0.081)	(0.080)	(0.081)
Border$_{ij}$	1.219***	1.227***	1.221***	1.223***
	(0.149)	(0.150)	(0.150)	(0.150)
Language$_{ij}$	0.377**	0.378**	0.376**	0.376**
	(0.163)	(0.160)	(0.162)	(0.162)
ln SC_{it}	−5.088	−8.924	−1.110	−3.211
	(18.343)	(18.486)	(18.580)	(18.653)
ln ST_{it}	−0.026	−1.499	0.598	−1.512
	(6.737)	(7.016)	(6.822)	(6.887)
Network_rate$_{ijt}$	0.064**	0.064**	0.064**	0.064**
	(0.020)	(0.020)	(0.020)	(0.020)
Drought frequency$_{it}$		0.015**		
		(0.008)		
Longest drought dur$_{it}$			0.010	
			(0.007)	
Drought magnitude$_{it}$				0.009*
				(0.005)
Origin-state FE	Yes	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes	Yes
N	1860	1860	1860	1860
R^2	0.691	0.698	0.695	0.694

Note: The dependent variable is the bilateral migration rate from state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses.
*$p<0.10$, **$p<0.05$, ***$p<0.01$.

from these states by 1.5%.[18] The negative impact of excess precipitation can be explained by several factors. First, the measures we use are based on the SPI which is a reliable indicator of drought but a less direct measure of flood, since it captures only climatological floods and not other factors, such as topology and hydrology. Guiteras et al. (2015) compare precipitation data with remote-sensing data on actual flooding in Bangladesh and argue that precipitation data are a weak proxy for floods. We address this concern in Section 5.3.1, where we test alternative flood measures. Second, evidence from other countries, notably Bangladesh (Gray and Mueller, 2012), shows that floods do not always induce migration. Drought can be characterized as a long-run process that does not always induce an immediate response, but when it does may lead to permanent migration. In contrast, flooding is a rapid onset phenomenon which may lead only to short-distance displacement (Barnett and

18 The frequency of excess precipitation retains its negative sign also for rural out-migration. As in the case of drought, the effect is stronger on rural–rural migration but is nonsignificant for rural–urban migration (estimations not shown here, but available on request).

Table 9. Inter-state migration and excess precipitation: total effect and agricultural state effect

	(1)	(2)	(3)	(4)	(5)	(6)
ln distance$_{ij}$	−0.660***	−0.658***	−0.661***	−0.730***	−0.731***	−0.730***
	(0.079)	(0.079)	(0.079)	(0.076)	(0.076)	(0.076)
Border$_{ij}$	1.222***	1.219***	1.223***	1.099***	1.097***	1.099***
	(0.149)	(0.149)	(0.149)	(0.117)	(0.116)	(0.116)
Language$_{ij}$	0.376**	0.376**	0.375**	0.032	0.035	0.032
	(0.160)	(0.163)	(0.161)	(0.131)	(0.129)	(0.132)
ln SC_{it}	−20.868	−5.484	−20.927	−0.662	5.103	0.440
	(19.835)	(18.329)	(20.533)	(14.474)	(14.369)	(14.519)
ln ST_{it}	3.316	2.286	2.732	6.305	7.604	8.903
	(6.222)	(6.317)	(6.229)	(10.898)	(10.444)	(10.872)
Network_rate$_{ijt}$	0.064**	0.064**	0.065**	0.082***	0.079***	0.081***
	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)
Flood frequency$_{it}$	−0.014*					
	(0.007)					
Longest flood dur$_{it}$		−0.002				
		(0.006)				
Flood magnitude$_{it}$			−0.010*			
			(0.005)			
flood frequency$_{it}$$(AgrSt)$				−0.015*		
				(0.009)		
longest flood dur$_{it}$$(AgrSt)$					−0.015**	
					(0.007)	
flood magnitude$_{it}$$(AgrSt)$						0.000
						(0.005)
Origin-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1860	1860	1860	1560	1560	1560
R^2	0.699	0.691	0.698	0.668	0.675	0.668

Note: The dependent variable is the bilateral migration rate from state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses.
$^*p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Webber 2010; Piguet 2010). Thus, responses to flood events are different, and if migration occurs, it may be temporary (Perch-Nielsen et al. 2008).

5.3 Robustness tests

5.3.1 Additional measures of climate variability

We test several alternative measures of climate variability to improve the robustness of our results. First, we test the long-run temperature and precipitation anomaly measures used in Table 3. Table 10 Column (1) shows the same estimations as in Table 2 with drought frequency. Column (2) includes positive temperature anomaly to control for temperature in addition to negative precipitation anomalies as measured by drought frequency. All the

Table 10. Inter-state migration and long run anomalies in temperature and precipitation

	(1)	(2)	(3)	(4)
ln distance$_{ij}$	−0.658***	−0.658***	−0.658***	−0.657***
	(0.080)	(0.081)	(0.079)	(0.080)
Border$_{ij}$	1.226***	1.226***	1.220***	1.220***
	(0.150)	(0.150)	(0.149)	(0.149)
Language$_{ij}$	0.377**	0.377**	0.375**	0.385**
	(0.160)	(0.160)	(0.163)	(0.161)
ln SC_{it}	−9.682	−9.725	−5.972	−3.153
	(18.386)	(18.357)	(18.284)	(18.393)
ln ST_{it}	1.540	1.549	1.956	1.667
	(6.352)	(6.358)	(6.245)	(6.231)
Network_rate$_{ijt}$	0.064**	0.064**	0.064**	0.064**
	(0.020)	(0.020)	(0.020)	(0.020)
Drought frequency$_{it}$	0.015*	0.015*		
	(0.008)	(0.008)		
Temperature (+) anomaly$_{it}$		0.552	−1.565	
		(2.466)	(2.317)	
Precipitation (−) anomaly$_{it}$				2.407**
				(0.986)
Origin-state FE	Yes	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes	Yes
N	1860	1860	1860	1860
R^2	0.698	0.698	0.692	0.695

Note: The dependent variable is the bilateral migration rate from state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses. $^*p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

effects—including drought frequency—remain stable, but the temperature anomaly is not statistically significant. Column (3) includes only the positive temperature anomaly. Its effect is negative and not significant. In Column (4) the negative precipitation anomaly replaces the temperature variable. The coefficient is positive, indicating that a deficit in precipitation will increase migration which is in line with the previously reported results on drought measures based on the SPI. Two interesting conclusions can be drawn from these results. First, there is no evidence of omitted variables bias from including only precipitation-based measures and not temperature (Auffhammer et al. 2013). Second, unlike the precipitation variables, the temperature variables are not significant or stable in either magnitude or direction.

Table 11 tests additional climate variability measures. Columns (1)–(3) present the continuous values of the SPI directly. In Column (1), the measure is the value of the annual SPI average 5 years before migration which is aimed at capturing average deviations (positive or negative) in climate variability without distinguishing between positive and negative shocks. The large size of most Indian states limits this measure, however, and we find no statistical significance. Columns (2) and (3) present SPIs superior to +1 and inferior to −1 (in absolute values) to capture positive (excess precipitation) or negative (drought) shocks

Table 11. Inter-state migration and other alternative climate variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln distance$_{ij}$	−0.658***	−0.658***	−0.658***	−0.657***	−0.658***	−0.658***	−0.658***	−0.658***
	(0.079)	(0.079)	(0.080)	(0.079)	(0.079)	(0.079)	(0.080)	(0.080)
Border$_{ij}$	1.219***	1.219***	1.221***	1.218***	1.218***	1.217***	1.220***	1.222***
	(0.149)	(0.149)	(0.149)	(0.149)	(0.149)	(0.149)	(0.149)	(0.149)
Language$_{ij}$	0.375**	0.376**	0.375**	0.378**	0.377**	0.376**	0.379**	0.384**
	(0.163)	(0.163)	(0.161)	(0.162)	(0.162)	(0.162)	(0.162)	(0.160)
ln SC_{it}	−5.361	−6.021	−1.685	−5.156	−5.640	−5.713	−4.135	−2.650
	(17.957)	(18.807)	(18.346)	(18.267)	(18.200)	(18.195)	(18.406)	(18.512)
ln ST_{it}	2.063	2.101	3.002	1.596	1.531	1.282	2.414	1.869
	(6.237)	(6.215)	(6.261)	(6.250)	(6.266)	(6.283)	(6.259)	(6.294)
Network_rate$_{ijt}$	0.064**	0.064**	0.064**	0.065**	0.064**	0.064**	0.064**	0.064**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Average SPI$_{it}$	−0.049							
	(0.288)							
Average SPI$_{it}$ > 1		−0.012						
		(0.133)						
Average SPI$_{it}$ < 1			0.179*					
			(0.107)					
Flood frequency$_{it}$				0.125				
				(0.105)				

(continued)

Table 11. (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood severity$_{it}$					0.116			
					(0.106)			
Flood magnitude$_{it}$						0.055		
						(0.043)		
Monsoon average pre 5y$_{it}$							−6.3e-05	
							(0.000)	
Monsoon average pre 2y$_{it}$								−1.4e-04**
								(0.000)
Origin-state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-state/time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1860	1860	1860	1860	1860	1860	1860	1860
R^2	0.691	0.691	0.695	0.692	0.692	0.692	0.693	0.696

Note: The dependent variable is the bilateral migration rate from state i to state j between year $t-1$ and year t. The subscript t indicates only that the variable varies over time. Robust standard errors in parentheses.

*$p<0.10$, **$p<0.05$, ***$p<0.01$.

separately. Again, we find a statistically significant positive impact of drought, but the excess precipitation measure based on the continuous value of the SPI is negative and nonsignificant.

In Columns (4)–(6), we test three types of alternative flood measures based on the Dartmouth Flood Observatory data used in Ghimire and Ferreira (2016). The Observatory records every large flood observed (see definition in Supplementary Appendix Table SA2). In Table 11, all the measures are based on floods occurring 1 year before migration, and we define the variables to be comparable with the previously used excess precipitation frequency measures. The flood frequency variable measures the number of months with a large flood event, flood severity measures the average flood severity index defined by the Observatory, and flood magnitude is the log of the product of frequency and duration. Although the signs of the flood variables are positive as expected ex ante (and in contrast to the SPI-based measures), none of the coefficients is statistically significant.

Columns (7) and (8) present estimations with yearly averaged precipitation for the summer monsoon months only (June through September). The estimation in Column (7) includes the average monsoon precipitation in the 5 years before migration (similar to the climate variability variables), and Column (8) uses the average during the 2 years preceding migration. We construct this measure to account for the rainy season only, since most yearly precipitation falls during the monsoon which is important for the agricultural sector. This avoids the smoothing of the monsoon impact by averaging over 12 months. We observe a significant effect only for the 2-year averaged monsoon, and more importantly, the effect is negative. This result suggests that the negative impact on migration of our measures of excess precipitation is not due to omission of the effects of monsoon periods and that precipitation data on their own do not capture all types of flood events in India.

5.3.2 Alternative specification

Supplementary Appendix Table SD7 presents the same estimations as in Table 2 but with an OLS rather than a PPML estimator and with standard errors clustered at the origin state. Clustering is not possible in PPML estimations, and can be an issue if there is spatial correlation in climatic factors between bordering states.[19] The effect of drought and excess precipitation varies very little, presenting an even larger effect and of higher statistical significance, with the exception of drought magnitude which turns out to be nonsignificant compared to the results in Table 2.

5.4 Discussion: Is drought-induced migration important?

The estimates of the impact of drought frequency and magnitude may seem small in relative terms. Two considerations are necessary before drawing policy implications. The first is that the effect is estimated only on inter-state migration, where migration barriers are high as shown in the estimation results, and the estimate is likely to represent a lower bound for internal migration in India, since intra-state migration represents the larger part of internal migration (see Supplementary Appendix Table SC1). The second point is that our estimates represent the effect on out-migration from one state to another specific state, and not the

19 The principal component analysis of state climatic factors shows that the state-level measures should be independent, though.

Table 12. Estimated drought-induced migration figures

1996–2001					2000–2001		
Migrants	Marginal drought effect	Minimum	Mean	Maximum	Minimum	Mean	Maximum
56,166,947	842,504	0	11,963,560	37,912,689	0	2,392,712	7,582,537

effect on total out-migration. Thus, the marginal effect obtained here is an underestimation of the effect on total internal migration. Table 12 presents a back-of-the-envelope calculation of what the estimates imply for migrant flows.

Table 12 shows the total flow of internal migrants between 1996 and 2001 in India. If we apply the estimated marginal effect of drought of 1.5% to total migrants, we obtain 842,504 migrants over 5 years for each additional month of drought. The summary statistics in Supplementary Appendix Table SA2 show that over 5 years, the number of droughts ranged from 0 and 45 months, with a mean of 14.2 months. We multiply each of the three numbers (minimum, mean, and maximum) by the marginal effect on the migrant population to see how many additional migrants were due to drought frequency in the best, mean, and worst-case scenarios. According to our estimate of the marginal effect of drought, in the mean scenario, over 5 years, there are 11.96 million additional migrants, and in the worst-case, there are 37.91 million migrants due to drought. These numbers correspond to 2.39 million and 7.58 million in 1 year. When converting the marginal effect into numbers of potentially drought-induced migrants, the effect is large.

These indicative numbers of past migrants due to drought frequency can be compared to Internal Displacement Monitoring Centre (IDMC) data which indicate that 3.7 million people were displaced by natural disasters in India in 2015. From the estimated effect for the earlier period 1996–2001, we obtain a yearly mean of 2.4 million displaced by drought alone. We emphasize that these figures are for illustrative purposes only, and are not projections of future migrations induced by drought. Compared to estimates from other neighboring countries, Hassani-Mahmooei and Parris (2012) predict between 3 million and 10 million internal migrants in Bangladesh over the next 40 years.

6. Conclusions

We analyze whether climate variability affects Indian bilateral inter-state migration rates using census data. The analysis in this article is one of the first attempts to investigate the impact of climate variability on internal migration using precise and complete census data at the level of a large and diverse country—India. Use of migration flow data defined between years $t-1$ and t allows us to test and compare the results from different timings of climatic factors prior to migration. This is a novelty compared to the existing literature on climatic factors and migration which mainly average figures over a longer time period. The other main contribution of the article is that we use objective meteorological indicators of climate variability based on the SPI. We created three variables based on the SPI: frequency, duration, and magnitude of drought and excess precipitation. In contrast to most previous studies, our analysis takes account of over-control bias that arises from including migration determinants that are dependent on climatic factors such as average income. We explored separately three important channels through which climate variability could affect migration: average income, agricultural income, and urbanization. The use of census data allowed us to analyze the effect of climate variability on actual migration flows from rural areas, rather than using the urbanization rate as a proxy, as is frequent in the literature.

The estimation results show significant effects on bilateral migration rates from drought frequency, with an average effect of 1.5%. For agricultural states, the effect of drought frequency is 1.7% and bilateral migration rates also increase following an increase in the magnitude of drought in agricultural origin states. We suggest that the findings for drought frequency could be interpreted as evidence of migration induced by expectations of future droughts. Observed drought frequency tends to reinforce future expectations of drought, and hence, may induce migration. However, the relative effect is small compared to the important role of the barriers to migration in the Indian context, which explain the low Indian inter-state migration rates. It is possible that the impact of climate variability on internal migration in India is underestimated. When complete origin-destination district-level data become available, more detailed analysis of inter-district bilateral migration should be conducted. However, by extrapolating the estimated marginal effect on inter-state flows to total migration flows in India, we show that drought may have induced 2 million migrants on average in year 2001, a figure that is compatible with current IDMC estimates of displaced people in India following natural disasters.

Excess precipitation was not found to induce inter-state migration, contrary to what might have been expected ex ante. The only significant effect is that each additional month in a consecutive spell of excessive precipitation reduces bilateral migration rates by 1.5%. Alternative flood measures from the Dartmouth Flood Observatory are also never significant, although they show the expected positive effect on migration. An extended analysis using more exact flood measures, for example based on remote-sensing data as in Guiteras et al. (2015) or in Gröger and Zylberberg (2016), would be a fruitful direction for future research.

We found evidence of two possible channels through which climate variability affects inter-state migration in India: the impact on net state domestic product and the agricultural sector. In particular, the effect of drought frequency on rural out-migration is higher than on total inter-state migration, and the strongest impact is on rural–rural migration. However, a direct effect of drought frequency remains after controlling for these indirect drivers of migration. The analyses in this article could be extended when bilateral migration data from the 2011 Census become available. They could include analysis of potential insurance mechanisms via an institutional channel, in particular from the National Rural Employment Guarantee Act (NREGA) implemented in 2006.

Supplementary material

Supplementary material is available at *Cesifo* online.

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Natural Disasters and Poverty Reduction: Do Remittances Matter?[1]

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Abstract

Do private funds help mitigate poverty in the context of natural disasters? This paper aims to answer this question by looking at the joined effect of migrants' transfers and natural disasters on poverty level in developing countries. Using panel data from developing countries over the period 1984-2010 and a fixed effects model, our results show that private mechanisms, such as remittances, significantly alleviate poverty when natural disasters occur in these countries. Put differently, we find that the effect of remittances on poverty is all the more important when they are received in countries experiencing natural disasters. Our results are confirmed by various robustness tests to mitigate the endogeneity issues.

Keywords: Natural disasters; Remittances; Poverty

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Introduction

There is a growing interest and acknowledgment of natural disasters as likely consequences of climate change (Stern report, 2007; IPCC, 2007). Natural disasters are often present in the news since many regions are more frequently experiencing climate driven disasters such as floods, storms or droughts. Different parts of the world are exposed and the consequences are disastrous, especially for poor regions. The first and immediate pictures of a disaster on a screen are destroyed infrastructure, homeless people and refugees seeking help, highlighting poverty as an inevitable consequence of such events, at least in the short-run.

These natural disasters can trigger important socioeconomic consequences. It has been found that the negative impact of these shocks on economic growth is particularly true for developing countries (Felbermayr and Gröschl, 2014; Noy, 2009; Dell et al., 2012; Loyza et al., 2012). Research also focusing on the specific link between natural disasters and poverty find a negative correlation between these two variables (e.g. Carter et al. 2007; Lal et al., 2009; Rodriguez-Oreggia et al., 201; Arouri et al., 2015). However, there is much less evidence on the role of private mechanisms, such as remittances, on poverty when natural disasters occur in developing countries. Among the few studies which investigated this relationship, it has been shown that in rural Vietnam, remittances help migrants' families to escape from poverty when natural disasters occur (Arouri et al., 2015). It has also been demonstrated in the case of the Philippines that remittances can play an insurance role when countries experience disasters such as rainfall shocks (Yang and Choi, 2007). Moreover, there is evidence showing that remittances improved the responses to natural disasters in countries that have a larger emigrant stock (Mohapatra et al., 2012).

Consequently, this paper contributes to this scarce literature by investigating in a short-term perspective the role of remittances in the mitigation of poverty when natural disasters occur. The value added of this study compared to the previous ones is fourfold. First, while the previous studies are interested in single countries- at the exception of Mohapatra et al., (2012) who use 4 countries- our paper uses panel data from 52 developing nations, in particular low- and lower-middle-income countries over the 1984-2010 period, generalizing the role of remittances in terms of geographical situation. Second, previous studies generally used household level data while this paper goes forwards by using country level observation as unit of analysis. Third, the cross-country and panel structure of the data that we use allow the elimination of the time-invariant unobserved heterogeneity and reduce the potential endogeneity due to the omitted variable bias. Finally, following Felbermayr and

Gröschl (2014), the paper considers measures of physical intensity of disasters. We use a disaster index aggregating different disaster intensity measures. We also use the disaggregated intensity measures such as the wind speed, the difference between the monthly maximum temperature and the monthly mean over the period, the occurrence of drought measured through a dummy equal one if at least for three successive months or five months within a year, rainfall level is below 50% of the period monthly mean, the occurrence of flood captured through the positive difference in precipitation over the long run mean, the maximum value recorded on the Richter scale and the maximum volcanic explosivity index. They help avoiding the potential measurement bias due to the misreporting of the number of affected people or economic damages due to disasters. Another advantage of using these variables is that they allow dealing with the potential endogeneity of the consequences of disasters which could be explained by the poverty level of countries per se. These measures have been compiled and used by Felbermayr and Gröschl (2014) to explore the relationship between natural disasters and economic growth. However, to the best of our knowledge, our study is the first that uses these exogenous measures of disasters to study the relationship between natural disasters, remittances and poverty.

Our estimates primarily focus on the poverty headcount ratio at $1.25 a day (ppp) as dependent variable. We also use an alternative measure of poverty which is the poverty gap at $2 a day (ppp). The interest variable is the interaction term between remittances and natural disasters. We are particularly interested in the latter to determine whether remittances play a role in mitigating poverty in the context of natural disasters. By doing so, we would like to test the assumption that because of their vulnerability, developing countries may not have the ability to deal with poverty issues in the context of disasters which will induce people to rely on migrants' transfers.

Although we use country fixed effects and exogenous measures of natural disasters, the study still faces challenges due to other source of bias. Subsequently, we also control for time fixed effects to capture the aggregate trends between natural disasters and poverty. Moreover, it is possible that remittances and natural disasters of the previous years also affect the poverty level. Subsequently, in addition of remittances and disasters at time t, we control for these variables at t-1. Another concern which remains is the endogeneity of remittances. It is likely that the poorest people are those who cannot afford migration costs, which means that poverty may determine the location choice and thus the ensuing amount of remittances received. More generally, the amount of remittances received can also be explained by the poverty level. We test the robustness of our results to this source of bias by using in our specifications the logarithm of the lagged amount of remittances instead of the contemporaneous one. Indeed if the amount of remittances received in t-1 can influence the level of poverty in t, it is very unlikely to observe the opposite relationship. Finally, we used a GMM system estimator to test the robustness of our results. Interestingly, the results show that in the context of natural disaster, the amount of remittances received contributes to decrease the level of poverty. More precisely, we found that for countries experiencing an increase in the disaster index by 1% and receiving the average logarithm of remittances, the poverty headcount ratio at $1.25 a day decreases by 1.145 percentage points. These results suggest that the reducing effect of remittances on poverty is even more important in countries which experience natural disaster. A more detailed analysis shows that the results are mainly driven by storms and hurricanes as well as extreme temperature events.

The remainder of the paper is organized as follows. Section 2 presents the literature related to the relationship between natural disasters, remittances and poverty. Section 3 presents the empirical framework by discussing the methodology, endogeneity issues and presenting the data. Section 4 discusses the results and Section 5 concludes.

2. Related literature

This paper draws upon the literature on the impact of natural disasters on economic growth and poverty as well as the role of remittances in the aftermath of natural disasters.

2.1 Natural disasters, economic growth and poverty

Some studies demonstrated that natural disasters are positively correlated with higher rate of human capital accumulation, higher productivity and thus economic growth (Skidmore and Toya, 2002). However, this positive relationship between natural disasters and economic growth has been challenged in the literature. It has been documented that disasters can have a short-term negative impact on GDP (Noy and Nualsri, 2007; Raddatz, 2009, and Loayza et al., 2009). Indeed, Natural disasters can destroy productive and social infrastructures, reduce economic activities and increased fiscal deficit at the moment when affected countries need more income to respond to the damages caused by disasters (to build infrastructure, increase social expenditure and implement redistribution policies). The economic productivity, economic growth and status of economic development are thus negatively affected (Felbermayr and Gröschl, 2014). The adverse effects of disasters on economic growth are particularly observed in the developing countries which are the most vulnerable (Noy, 2009;

Dell et al., 2012; Loayza et al., 2012). For instance, from a cross-country analysis, Barrios et al. (2010) use data from 1960 to 1990 of 60 countries including 22 African countries and find that since the sixties a decrease in rainfall is responsible of the reduction between 15 and 40% of the gap in the African GDP per capita compared to other developing countries.

These studies suggest that the negative effect of natural disasters on economic growth can push people into poverty and trigger important socioeconomic consequences. For instance, the destruction of assets of people belonging to the middle class can induce households towards chronic poverty, whereby they lack the required income to revert to their previous situation. These households do not have the capacity to rebuild their homes, substitute lost assets and fulfill the conditions to secure their basic needs. Moreover, since it is difficult for them to quickly replace their lost assets, this could put them into a poverty trap (Carter et al. 2007). Other findings show that disasters exacerbate poverty because the most vulnerable generally live in unfavorable and exposed conditions such as marginal lands and poorly constructed houses. This is often synonymous of their unsafe living environment and sensitivity to disasters which increase their poor economic status. Consequently, poor people are unable to take advantage of disaster-proof technology, relocation to less dangerous regions or benefit from insurance mechanisms (Lal et al. 2009). For instance, studies in Ethiopia and Honduras showed that the poorest households are those which struggle most with shocks and adopt costly coping strategies in terms of both short- and long-term well-being (Carter et al., 2007). From a panel of Indonesian household data, Silbert and Useche (2012) found that natural disaster risk increases projected poverty rates and economic development factors such as income, urbanization and institutional strength. Another example from a household survey data from Phillipines in 1998 assess the distributional impact of the recent economic crisis and found that the largest share of the overall impact on poverty is attributable to the El-Niño shock as opposed to shocks mediated through the labor market (Datt and Hoogeveen, 2003). Rodriguez-Oreggia et al. (2013) investigate the effects of natural disasters on human development and poverty levels at the municipal level in Mexico. Using panel data, they show that the occurrence of natural disasters exacerbates food and extreme poverty by about 3.7 percent, capacities poverty by 3 percent and assets poverty by 1.5 percent. More recently, Arouri et al. (2015) assess the effect of natural disasters on the welfare and poverty of rural households in Vietnam, as well as their resilience to disasters using commune-fixed effect regressions. They found that storms, floods and droughts have negative effects on household income and expenditure.

2.2 Heterogeneity in the effect of natural disasters on poverty

Another issue in the relationship between natural disasters and poverty is the heterogeneity of the former's impact. Karim and Noy (2014) evaluated the poverty consequences of natural disasters through a meta-regression analysis of the existing literature. They found strong heterogeneity in the impacts of disasters on poverty even though several general patterns emerge. More precisely, they found that incomes are negatively affected after natural disasters, while consumption is also reduced, albeit to a lesser extent than income. Accordingly, poor households smooth their food consumption by reducing their consumption of non-food items (spending on housing, health and education). However, the authors did not find any consistent long-term effects. This is also similar to results found by Gignoux and Menendez (2016). The latter assesses the effects of earthquakes in rural Indonesia since 1985. They found that in the short-term, meaning two years after the shock, the earthquake caused some economic losses. However, individuals started recovering between two and five years after the earthquake. Between six and twelve years after the shock, individuals' total expenditure per capita was 10% higher than before the shock. The positive impact of the earthquake on the total expenditure, in the long term, was explained by the external aid which allows reconstituting physical assets and investing in public infrastructures. They did not find any large population movement or reallocation of labor across sectors. These studies show that the impact of disasters on poverty is not necessarily the same between the short and long term. Moreover, the heterogeneity in the impact of disasters on poverty also depends on the transfers received by the communities after the shocks and which help mitigating the negative consequence of the earthquake.

2.3 Role of remittances

Countries affected by the same kind of disaster do not suffer to the same degree, and some households within the same country are more resilient than others because of the availability of insurance mechanisms such as remittances. For instance, Silbert and Useche (2012) show that natural disaster risk disproportionately affects consumption-constrained households. Households with greater self-insurance strategies and higher levels of human capital are better protected against repeated shocks than less-endowed and -educated ones. Arouri et al. (2015) find that higher mean expenditure and more equal expenditure distribution in the commune in Vietnam through access to micro-credit, internal remittances and social allowances increase resilience to natural disasters. Consequently, migrants' remittances help their families left-behind escaping from poverty in general and the consequences of natural disasters in particular. Studies show that remittances increase in the aftermath of disasters and help reducing the negative effect of shocks by playing an insurance role for households (Mohapatra et al., 2012; Yang and Choi, 2007; Yang, 2008). Moreover, it is generally accepted in the literature that sending money back to the home country reduces poverty through the accumulation of human and physical capital, reduced income inequalities and increased consumption (Adams and Page, 2005; Gupta and al., 2009; Adams and Cuecuecha, 2013). Remittances can thus be considered as channels mediating the effect of natural disasters on poverty and well-being. For instance, Prakash (2007) investigates the consequences of remittances inflows from Gulf regions on the Kerala economy and shows that remittances not only strongly increase the levels of income, consumption and acquisition of assets, but also reduce poverty. However, this effect may adversely affect the poor since the prices of land, construction materials, consumer foods, charges for health, education and transport subsequently increase. Using data for 59 industrial and developing countries over 1970–2000, Acosta et al. (2008) analyzed the effect of workers' remittances on economic growth, inequality and poverty reduction in Latin American and Caribbean (LAC) countries and find that remittances increase growth and reduce inequality and poverty.

The question that the study at hand addresses is related to the role of the amount remittances in poverty reduction when natural disaster occurs. Consequently, we develop an empirical framework where we discuss the methodology used as well as the endogeneity issues and data.

3. Empirical framework

3.1 Data

We use 2 different measures of poverty from the World Development Indicators (World Bank Databases): the poverty headcount ratio at $ 1.25 a day (PPP), the percentage of population living in households with consumption or income per person below the poverty line of $1.25 a day, adjusted for purchasing power parity (PPP); and the poverty gap at $2 a day (PPP) which is the mean shortfall from the poverty line expressed as a percentage of the poverty line of $2 a day, adjusted for purchasing power parity (PPP). This measure reflects the depth of poverty as well as its incidence.

Our natural disaster variables are from the GeoMet data (Game) constructed by Felbermayr and Gröschl (2014). We use the plain disaster index which aggregates the different disaster intensity measures. We also used the disaggregated intensity measures to assess the relationship between natural disasters, remittances and poverty by disaster type. The first component of the disaster index is the wind speed measuring the maximum total wind speed in knots for storms and hurricanes. The second component is the disaster index which measures extreme temperature events through the percentage difference between the monthly maximum temperature and the monthly mean over the period (1979-2010). The third component of the disaster index is drought, a dummy taking the value 1 if at least for three successive months or five months within a year, rainfall level is below 50% of the period monthly mean. The fourth component is flood measured as the positive difference in precipitation over the long run mean. The fifth component of the disaster index is the Richter scale which measures the maximum value recorded on the Richter scale. Finally the last component of the Disaster Index is the volcanic eruption measured as the maximum volcanic explosivity Index.[4] For comparison purpose we use in our estimates the standardized values of the various disaster types. The remittance variable measures the logarithm of the transfers received in the countries during the period analyzed.

In our estimates, we control for country characteristics such as the total population and the population density. Population variables capture the size of the country which both can affect the level of poverty as well as the incidence of both disaster and remittances on the poverty level. We also control for the urbanization rate. Indeed, although the share of poor living in urban areas is increasing, there is the view that urbanization decreases poverty with most of the poor people still living in rural areas (e.g Ravallion et al., 2007; Chen and Ravallion, 2010). However, it has also been demonstrated that urbanization rate could decrease poverty around rural areas due to the positive spillover effects arising from internal remittances or non-farm employment in rural areas (Calì and Menon, 2013). Moreover, urbanization rate is also a proxy for internal migration. In all cases, it is important to capture these rural-urban demographic dynamics that could affect poverty. Following Felbermayr and Gröschl (2014), we take into account the quality of the institutions through a polity index normalized between 0 standing for the most autocratic countries and 1 standing for the most democratic ones. Finally, we also control for the growth rate of real GDP per capita which captures the economic factors of the country such as unemployment or infrastructure. This

[4] Please see Felbermayr and Gröschl (2014) for a detailed explanation of the methodology used to create the Disaster Index.

variable is defined as the difference between the logarithm of GDP per capita in t and $t-1$, adjusted in purchasing power parity. [5]

3.2 Methodology

In this paper we investigate the relationship between natural disasters, remittances and poverty by using a panel data from 52 developing countries, in particular low and lower middle income countries over the period 1984 to 2010. The countries were selected following World Bank classification of the level of development of countries. [6] We focus on the following country-fixed effects regression, where the unit of observation is the country i at year t:

$$Poverty_{i,t} = \alpha_1 disaster_{i,t} * remit_{i,t} + \alpha_2 disaster_{i,t} + \alpha_3 remit_{i,t} + \alpha_{ki} X_{k,i,t-1} + \mu_i + \kappa_t + \varepsilon_{i,t} \quad (1)$$

$Poverty_{i,t}$ reflects the different outcomes measuring poverty. Since we mainly focus on the incidence of remittances and natural disaster on poverty, our main interest variable is the interaction term between natural disasters ($disaster_{i,t}$) and logarithm of remittances ($remit_{i,t}$). $X_{k,i,t-1}$ is the vector of variables controlling for the characteristics of the country with one year lag. μ_i stands for the country-fixed effects which control for the time-invariant country characteristics that may be related to poverty. We also include time fixed effects through the variable κ_t to capture additional variation. $\varepsilon_{i,t}$ is the unexplained residual.

3.3 Endogeneity issues

Although we use country fixed effects which control for unobservable time invariant country characteristics, we still have to address some endogeneity issues related to the main interest variables. The first issue is related to the choice of exogenous natural disasters variables. Unlike the number of people killed or affected as well as the economic costs of the damages caused by disasters[7] which could be misreported or misevaluated, and which could also be influenced by the level of poverty of countries, we use exogenous measures of natural

[5] See Appendix A for the Descriptive statistics and Appendix B for variable definitions and sources.

[6] The countries are low and lower middle income countries for which we have data for the various variables considered over the period.

[7] These variables are available in EM-DAT database provided by the Centre for Research on the Epidemiology of Disaster (CRED).

disasters from the Geomet-data (GAME) compiled over the period 1979-2010 by Felbermayr and Gröschl (2014). Using primary data from geophysics and climatology, these authors constructed the physical intensity measures of disasters events depending on the month, year and country in which they occur. For the purpose of our paper we use the country-year level data set.

However, using an exogeneous measure of disaster may not be enough to deal with other sources of bias. Consequently, we also control for time fixed effects. It is likely that poverty at time t is affected not only by disasters and remittances at t but also at t-1. Subsequently, we use an alternative specification controlling for natural disasters and remittances which happened at t-1, in addition to the t level variables.

The other concern is related to the endogeneity of remittances. The amount of remittances received can also be explained by the level of poverty. Ideally we would use an instrumental variable which has to be correlated to poverty only through its effect on remittances. Unfortunately we have not found such strong instrument which respects this exclusion restriction and with data covering the period studied. Subsequently, we use various alternative specifications to test the robustness of our results. First, we use the interaction term between natural disaster and the logarithm of the amount of remittances received in t -1 which is assumed to be more exogenous than the contemporaneous amount. If the amount of remittances received in t-1 can influence the level of poverty in t, it is very unlikely to observe the opposite relationship. Another concern which remains here is that estimating such dynamic model with the use of fixed effects may lead to a Nickell bias (Nickell, 1981). However, since this bias is minimized in long panel (Judson and Owen, 1999), this is not a major issue due to the fact that we have 26 years of observations.[8] Finally, we further account for dynamics in the model and check the robustness of our results by instrumenting the endogenous explanatory variables with their lagged values through a GMM model.

4. Results

The main results of the relationship between natural disaster, remittances and the poverty headcount ratio at $ 1.25 a day (ppp) are presented in Table 1. Column 1 presents the simple correlation between the interaction term Log remittances*Disaster Index, the specific variable of disaster, Log remittances and poverty. The interaction term is significant and

[8] This explanation also holds for the use of the lagged control variables which are assumed to be more exogenous than the contemporaneous ones.

negative, the disaster index is significant and positive while the specific variable log remittances is significant and negative. In terms of interpretation, the significant and negative sign of the interaction term suggests that remittances decrease poverty in the context of natural disasters. The previous results remain while we introduce in Column 3 the control variables, such as the type of regime (democratic or autocratic), the total population, the population density, the urbanization rate and the growth rate of the GDP per capita, with one year lag. However, these estimates do not take into account the unobservable time invariant characteristics which can bias the results. Consequently, to rule out this source of bias, we use a country fixed effects model (Column 4 to 5 of Table 2). The results in Column 4 are similar to what we found with the random effects. Moreover, they are robust to the inclusion of the time trend, except for the log remittances which still has the expected negative sign but becomes insignificant (Column 5 of Table 2).[9] However, the fact that this variable is not statistically significant anymore should not be interpreted as if remittances do not have an effect on poverty. The effect of remittances should be put into perspective with the effect of the interaction term. The fact that remittances loses its significance while the interaction term remains negative and significant means that the reducing effect of migrants' transfers on poverty is even more important in countries which experience natural disaster. When we focus on the country and time fixed-effect specification as our benchmark, the result indicates that for a country where the disaster index increases by 1% within a year, the poverty headcount ratio at $1.25 a day changes by 24.667-1.301*Log Remittances, on average. Consequently, for countries experiencing an increase in the disaster index by 1% and receiving the average logarithm of remittances, the poverty headcount ratio at $1.25 a day is expected to decrease by 1.145 percentage points (24.667-1.301*19.84=-1.145). This result is very interesting because it means that when a shock occurs, remittances allow countries to decrease their poverty level. This should be put into perspective with results found in the literature and showing that transfers (such as aid) after disaster can be beneficial to the communities, in the long term (Gignoux and Menendez, 2016). It is likely that public transfers benefit to communities many years after a shock, because they require time and organization before reaching the communities and starting producing effect. In our case, we show that private transfers such as remittances occurring in the aftermath of natural disasters are beneficial even in the short term.

[9] The probability of the Hausman test is lower than 10% confirming that the fixed effects model is better than the random effects model.

In Table 2 we look at the combined effect of the disaggregated measures of the disaster and remittances on poverty. Results show that the coefficient associated to the interaction term of each of the disaster type is negative. However, only results from Column 1 to 3 including the interaction term log remittances*wind speed, log remittances *Δ temperature and log remittances*drought are significant. Coefficients associated with the interaction term between log remittances and flood, Richter scale and volcanic explosivity, respectively are not statistically significant (Column 3 to 6). These findings suggest that the effect of remittances in terms of poverty reduction is higher when countries experience storms and hurricanes (measured through wind speed), extreme temperature events and drought.

To test the robustness of our results, we start by adding to the previous estimate the logarithm of remittances as well the natural disasters which happened the previous year, as control variables. Overall the results presented in Table 3 (Column 1 to 7) are similar to the ones found in Table 2 except for Column 1 and 2 where the logarithm of remittances at t becomes significant.

We further test the robustness if our results to the endogeneity of remittances. We start by replacing the log of remittances at t by the log remittances at t-1 which is assumed to be more exogenous than the contemporaneous measure. Unlike the estimates of Table 3 where we control both for log remittances at t and t-1 as well as disasters at t-1, we only consider here remittances at t-1 and disasters at t. Overall, results from previous table are confirmed, except for the interaction term between drought and log remittances which becomes insignificant. A more conservative approach would thus consider that the effect of remittances on poverty when disasters occur is only mainly driven by storms and hurricanes as well as extremes temperature events.

To further test the robustness of our estimations, we use a GMM system estimator (Blundel and Bond, 1998). The GMM system allows to further account for dynamics in the model instrumenting the endogenous variables with their lagged values. However, because of the use of lags, countries in our sample which have missing variables before the period studied will be dropped which will dramatically reduce the number of observations. Consequently, to avoid losing too many countries, we run the GMM estimates based upon a 5 years average over 1986 to 2010 will lead to 5 periods of 5 years each. We run the GMM estimates by introducing the poverty variable with one period lag, in addition to the explanatory variables at time t. For remittances, the interaction term between remittances and natural disasters, GDP growth, lagged poverty as well as the population variables, we use at least 2 period lags for their instruments. For the other explanatory variables such as natural disasters and institutions quality which we consider as predetermined, we use one period lag for their instruments. Moreover, since all lags of variables have been used as instruments and because of the small sample size, we also limit the bias of over-instrumentation[10].

The Hansen test of overidentification restrictions and the Arellano–Bond test for second-order autocorrelation (column 1 to 7 of table 5) do not allow rejection of the hypothesis concerning the validity of the lagged variables in level and in difference as instruments, nor the hypothesis of no second-order autocorrelation. Results presented in Table 5 confirm the negative effect of the interaction term between remittances and the disaster index as well as the effects of wind speed and difference in temperature.[11]

Finally, we test the robustness of our estimations with an alternative measure of poverty, which is the poverty gap at $2 a day (Table 6). The results for the fixed effects model are similar in terms of significance and sign, but the size of the coefficient is smaller. For countries experiencing an increase in the disaster index by 1% within a year and receiving the average logarithm of remittances, the poverty gap at $2 a day is expected to decrease by 0.638 percentage points (19.063-0.993*19.84=-0.638).

5. Conclusion

The occurrence of natural disasters generally destroys the population's living conditions and plunges them into poverty. Many strategies and methods are implemented to mitigate the consequences of natural disasters on poverty at the individual, household, country and more global level. One way to escape from these likely disastrous new living conditions is thus to rely on private mechanisms such as migrants' transfers. This paper has investigated this issue and analyzed the relationship between natural disasters, remittances and poverty. Interestingly, the findings obtained through a fixed effects model approach shows that private transfers such as remittances significantly contribute to decrease poverty in the context of natural disasters. Findings also show that this effect is mainly driven by storms and hurricanes as well as extreme temperatures events. These results are robust to the use of alternative specifications and the GMM system estimator. This implies that in the aftermath of natural disasters, private funds and remittances, in particular, are beneficial to countries.

[10] We limit the bias of over-instrumentation by using the GMM option collapse of stata

[11] We have less observations and countries in the GMM system due to the missing data, in particular when we use two year lag. This also explains that we could not run the estimates for the variable drought.

Subsequently, migrants' transfers are an important channel in terms of helping origin countries to deal with poverty when they experience natural disasters and are at their most vulnerable.

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Table 1: Natural disasters, remittances and poverty: Main results

Dependent variable: Poverty headcount ratio at $1.25 a day (ppp)

	Random effects		Country fixed effects		
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)
Log remittances*Disaster Index	-1.102***	-0.965***	-1.226***	-1.295***	-1.301***
	(0.42)	(0.31)	(0.44)	(0.35)	(0.40)
Disaster Index	21.452**	18.218***	23.894***	24.606***	24.667***
	(8.41)	(6.10)	(8.71)	(6.97)	(8.14)
Log remittances	-4.256***	-3.270***	-4.121***	-2.813***	-1.308
	(0.75)	(0.84)	(0.78)	(0.82)	(0.97)
Polity Index (lag)		1.183		1.994	-1.865
		(6.07)		(7.27)	(7.09)
Log population (lag)		2.105		-7.966	-1.601
		(2.31)		(15.98)	(16.55)
Population density (lag)		-0.017		-0.050	-0.047
		(0.02)		(0.03)	(0.03)
Urban population (lag)		-0.737***		-0.414	-0.142
		(0.16)		(0.41)	(0.45)
GDP growth per capita (lag)		5.986		4.004	0.541
		(8.23)		(8.46)	(9.52)
Time fixed effects	No	No	No	No	Yes
Observations	313	312	313	312	312
R-squared	0.17	0.5	0.33	0.41	0.52
Number of countries	51	51	51	51	51
Hausman test				chi2 (7)=22.23	
				Prob>chi2=0.0045	

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. Overall R-squared presented in Column 1 and 2 and within R-squared presented from Column 3 to 5. All estimates include a constant.

Table 2: Effects of Natural disasters and remittances on poverty according to the type of disasters

Dependent variable: Poverty headcount ratio at $1.25 a day (ppp)

	Country fixed effects					
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log remittances*Wind speed	-1.254*					
	(0.73)					
Wind speed	24.524*					
	(14.61)					
Log remittances*Δ temperature		-0.308***				
		(0.07)				
Δ temperature		5.515***				
		(1.38)				
Log remittances*drought			-0.579**			
			(0.27)			
Drought			11.823**			
			(5.66)			
Log remittances*flood				-0.330		
				(0.29)		
Flood				5.596		
				(5.63)		
Log remittances*Richter scale					-0.591	
					(0.44)	
Richter scale					9.041	
					(8.69)	
Log remittances*Volcanic explosivity						-0.384
						(0.45)
Volcanic explosivity						7.690
						(9.32)
Log remittances	-1.685	-0.596	-1.128	-0.963	-0.626	-0.888
	(1.23)	(1.01)	(1.12)	(1.10)	(1.02)	(1.10)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312	312	312	312	312	312
R-squared	0.50	0.50	0.49	0.49	0.50	0.49
Number of countries	51	51	51	51	51	51

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. All estimates include a constant.

Table 3: Robustness checks: Effects of natural disasters and remittances on poverty controlling for remittances and disasters variables in t and t-1

Dependent variable: Poverty headcount ratio at $ 1.25 a day (ppp)

	Country Fixed effects						
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log remittances*Disaster Index	-1.398***						
	(0.41)						
Disaster Index	26.589***						
	(8.34)						
Disaster Index (lag)	0.118						
	(0.82)						
Log remittances*Wind speed		-1.431*					
		(0.74)					
Wind speed		28.088*					
		(14.95)					
Wind speed (lag)		0.100					
		(0.83)					
Log remittances*Δ temperature			-0.317***				
			(0.08)				
Δ temperature			5.651***				
			(1.60)				
Δ temperature (lag)			0.047				
			(0.31)				
Log remittances *drought				-0.594**			
				(0.26)			
Drought				12.154**			
				(5.47)			
Drought (lag)				0.019			
				(0.63)			
Log remittances *flood					-0.301		
					(0.31)		
Flood					5.101		
					(6.13)		
Flood (lag)					-0.157		
					(0.66)		
Log remittances *Richter scale						-0.684	
						(0.41)	
Richter scale						10.990	
						(8.10)	
Richter scale (lag)						-2.294*	
						(1.29)	
Log remittances*Volcanic explosivity							-0.376
							(0.46)
Volcanic explosivity							7.497
							(9.38)
Volcanic explosivity (lag)							-0.059
							(0.72)
Log remittances	-2.393**	-2.714**	-1.462	-2.016	-1.340	-1.232	-1.425
	(1.13)	(1.33)	(1.15)	(1.44)	(1.34)	(1.11)	(1.14)
Log remittances (lag)	1.316	1.146	1.073	1.061	0.469	0.927	0.693
	(0.93)	(1.04)	(1.11)	(1.44)	(1.33)	(1.08)	(1.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	308	308	308	308	308	308	308
R-squared	0.53	0.51	0.51	0.5	0.49	0.52	0.49
Number of countries	50	50	50	50	50	50	50

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. All estimates include a constant.

Table 4: Robustness checks for the endogeneity of remittances: Effect of natural disasters and remittances on poverty using the lagged of the logarithm of remittances

Dependent variable: Poverty headcount ratio at $1.25 a day (ppp)

	Country fixed effects						
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log remittances (lag)*Disaster Index	-1.145***						
	(0.39)						
Disaster Index	21.350***						
	(7.80)						
Log remittances (lag)*Wind speed		-1.130*					
		(0.61)					
Wind speed		22.021*					
		(12.29)					
Log remittances (lag)*Δ temperature			-0.265***				
			(0.06)				
Δ temperature			4.475***				
			(1.17)				
Log remittances (lag)*drought				-0.432			
				(0.30)			
Drought				8.707			
				(6.38)			
Log remittances (lag)*flood					-0.123		
					(0.29)		
Flood					1.786		
					(5.51)		
Log remittances (lag)*Richter scale						-0.696*	
						(0.40)	
Richter scale						10.958	
						(7.71)	
Log remittances (lag)*Volcanic explosivity							-0.347
							(0.42)
Volcanic explosivity							6.881
							(8.49)
Log remittances (lag)	-0.744	-1.137	-0.249	-0.719	-0.691	-0.220	-0.628
	(0.96)	(1.12)	(1.04)	(1.16)	(1.13)	(1.04)	(1.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	308	308	308	308	308	308	308
R-squared	0.51	0.50	0.50	0.49	0.49	0.50	0.49
Number of countries	50	50	50	50	50	50	50

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. All estimates include a constant.

Table 5: Robustness checks: GMM system estimates of the relationship between natural disasters, remittances and poverty

Dependent variable: Poverty headcount ratio at $1.25 a day (ppp)

	GMM						
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log remittances*Disaster Index	-1.202**						
	(0.59)						
Disaster Index	25.721**						
	(12.21)						
Log remittances*Wind speed		-1.554*					
		(0.94)					
Wind speed		34.967*					
		(19.62)					
Log remittances*Δ temperature			-0.208**				
			(0.09)				
Δ temperature			3.449*				
			(1.91)				
Log remittances *drought				-0.428			
				(0.51)			
Drought				4.955			
				(10.22)			
Log remittances*flood					0.924		
					(0.80)		
Flood					-17.604		
					(14.52)		
Log remittances*Richter scale						1.124	
						(1.35)	
Richter scale						-24.008	
						(26.72)	
Log remittances*Volcanic explosivity							1.055
							(0.76)
Volcanic explosivity							-18.241
							(15.32)
Log remittances	-3.010	-2.726	-1.486	-1.472	0.219	-2.149	-1.486
	(1.85)	(1.77)	(1.35)	(1.33)	(1.50)	(1.70)	(1.53)
Poverty headcount ratio at $1.25 a day (lag)	0.834***	0.838***	0.811***	0.840***	0.811***	0.752***	0.724***
	(0.13)	(0.11)	(0.10)	(0.11)	(0.12)	(0.12)	(0.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114	114	114	114	114	114	114
Number of countries	42	42	42	42	42	42	42
Hansen test for overidentification : chi2(19)	22.91	23.32	17.71	20.25	15.45	18.20	16.89
Prob > chi2	0.241	0.223	0.542	0.380	0.694	0.509	0.597
Arellano-Bond test for AR(2): z	-1.17	-1.21	-1.65	-1.52	-1.61	-1.51	-1.24
Pr > z	0.242	0.227	0.100	0.128	0.107	0.132	0.214

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively.

Table 6: Robustness checks: Effect of natural disasters and remittances on poverty using an alternative measure of poverty

Dependent variable: Poverty gap at $2 a day (ppp)

	Country fixed effects						
EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log remittances*Disaster Index	-0.993***						
	(0.29)						
Disaster Index	19.063***						
	(5.93)						
Log remittances*Wind speed		-1.117**					
		(0.50)					
Wind speed		22.157**					
		(10.17)					
Log remittances*Δ temperature			-0.207***				
			(0.05)				
Δ temperature			3.713***				
			(0.97)				
Log remittances*drought				-0.355*			
				(0.19)			
Drought				7.296*			
				(4.04)			
Log remittances*flood					-0.183		
					(0.21)		
Flood					2.852		
					(4.10)		
Log remittances*Richter scale						-0.205	
						(0.36)	
Richter scale						1.878	
						(7.13)	
Log remittances*Volcanic explosivity							-0.290
							(0.31)
Volcanic explosivity							5.822
							(6.22)
Log remittances	-1.017*	-1.404*	-0.495	-0.814	-0.742	-0.634	-0.655
	(0.63)	(0.81)	(0.64)	(0.71)	(0.70)	(0.68)	(0.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	317	317	317	317	317	317	317
R-squared	0.521	0.51	0.50	0.49	0.49	0.50	0.49
Number of countries	52	52	52	52	52	52	52

Notes: Robust standard errors in parentheses. Superscripts ***, **, * indicate significance at the 1, 5, 10% level, respectively. All estimates include a constant.

Appendix A: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Poverty headcount ratio at $1.25 a day (ppp)	24.71	22.58	0	85.92	313
Poverty gap at $2 a day (ppp)	18.9	15.9	0	67.13	317
Disaster Index (Standardized values)	-0.21	0.87	-2.55	3.27	313
Wind speed (Standardized values)	-0.31	0.73	-2.72	3.55	312
Δ temperature (Standardized values)	0.32	2.48	-0.23	18.04	312
Drought (Standardized values)	0.01	1.02	-0.26	3.92	312
Flood (Standardized values)	0.02	0.99	-0.93	7.45	312
Richter scale (Standardized values)	0.12	0.98	-1.68	2.08	312
Volcanic explosivity (Standardized values)	0.1	1.2	-0.31	8.19	312
Log remittances	19.84	2.16	9.35	24.62	313
Polity Index	0.62	0.3	0.05	0.95	312
Log population	9.76	1.44	7.5	14.1	312
Population density	118.89	153.52	1.79	1142.29	312
Urban population	43.24	16.82	4.99	82.47	312
GDP growth per capita (lag) (ppp)	0.06	0.06	-0.22	0.39	312

Appendix B: Variables definition and source

Variables	Definition	Source
Poverty headcount ratio at $ 1,25 a day (PPP) (% of population)	Percentage of population living in households with consumption or income per person below the poverty line of $1.25 a day, adjusted for purchasing power parity (PPP)	PovcalNet database-World Bank
Poverty gap at $2 a day (PPP) (%)	Poverty gap is the mean shortfall from the poverty line (counting the non poor as having zero shortfall), expressed as a percentage of the poverty line of $2 a day, adjusted for purchasing power parity (PPP). This measure reflects the depth of poverty as well as its incidence.	Online World Bank WDI
Disaster Index	Sum of disaster types	Geomet data (Game), Felbermayr and Gröschl (2014)
Wind speed	Maximum wind speed in knots for storms and hurricanes, combined measure	Geomet data (Game), Felbermayr and Gröschl (2014)
Δ temperature	Difference of monthly temperature over the long run mean	Geomet data (Game), Felbermayr and Gröschl (2014)
Drought	Dummy equal 1 if for 3 month in a row or 5 months within year, rainfall level is below 50% of the long run mean, 0 otherwise	Geomet data (Game), Felbermayr and Gröschl (2014)
Flood	Positive difference in precipitation over the long run mean	Geomet data (Game), Felbermayr and Gröschl (2014)
Richter scale	Maximum Richter scale for earthquakes	Geomet data (Game), Felbermayr and Gröschl (2014)
Volcanic explosivity	Maximum Volcanic Explosivity Index for volcanoes	Geomet data (Game), Felbermayr and Gröschl (2014)
Remittances	Personal remittances, received (Current US$)	Online World Bank WDI
Polity Index	Polity Index between 0 and 1	Polity IV
Population	Total population (in thousands)	Penn World Table
Population density	Number of inhabitants per km²	Online World Bank WDI
Urban population	Urbanization rate	Online World Bank WDI
GDP growth per capita (ppp)	difference between the logarithm of GDP per capita in t and $t-1$, adjusted in purchasing power parity	Penn World Table

Appendix C: List of countries

Albania	Honduras	Paraguay
Angola	India	Philippines
Armenia	Indonesia	Rwanda
Azerbaijan	Jordan	Senegal
Bangladesh	Kenya	Sri Lanka
Bolivia	Kyrgyz Republic	Syrian Arab Republic
Burkina Faso	Lao PDR	Tajikistan
Burundi	Liberia	Tanzania
Cameroon	Madagascar	Thailand
China	Mali	Togo
Congo, Rep.	Mauritania	Tunisia
Cote d'Ivoire	Morocco	Uganda
Ecuador	Mozambique	Ukraine
Egypt, Arab Rep.	Nepal	Vietnam
El Salvador	Nicaragua	Yemen, Rep.
Ethiopia	Niger	Zambia
Guatemala	Pakistan	
Haiti	Papua New Guinea	