MAGYC
Migration Governance and Asylum Crises

The influence of long-term environmental trends on migration dynamics

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MAGYC: The MAGYC (**M**igr**A**tion **G**overnance and As**Y**lum **C**rises) project seeks to assess how migration governance has responded to the recent "refugee crises" and has since been influenced by it, and how crises at large shape policy responses to migration. This four-year research project (2018–2022) brings together twelve international partners: the Hugo Observatory from the University of Liège (Coordinator), Sciences Po, the University of Economics in Bratislava, the GIGA institute of Global and Area Studies, Lund University, the IDMC, SOAS University of London, the University of Milan, the Lebanese American University, the University of Macedonia, Sabanci University, IfPO/CNRS.

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MAGYC WORKING PAPER

ABSTRACT

This deliverable aims to lay out the impact of both rapid onset and slow onset environmental changes on migratory movements, and in particular on critical increases in flows of migration using Abel's stock data to flow data conversions with 5 year intervals for the period of 1960-2015. To do so, this working paper first addresses the literature in relation to the impact of both rapid onset and slow onset changes in migratory flows in relation to their potentialdirect and indirect effects and identifies a method of inquiry building upon extant scholary work. Following that, the deliverable lays out and justifies the specific operationalizations of the independent variables that are proxies of both natural disasters and climatic changes, namely temperature and precipitaiton drivers.It then presents the flows and crisis level flows of migration cross sectionally and across time. Having considered the crisis from the perspective of countries of origin, it then incorporates the recipient countries via exploring the main corridors with the help of dyadic data, which takes relationality of the country pairs into consideration. The results contribute to the discussion regarding migratory flows with regards to the role of the disasters taking their impact into consideration as well as temperature and precipitation taking their variability as well as mediating and indirect effects into account. Consistently, many environmental drivers showed statistically significant direct and indirect impact especially through being pull factors in destination countries. The results further underline the value added of this crisis approach to the conventinal flow conceptualization and directions for further research.

Introduction

Workpackage 1 of the Horizon 2020 Project MAGYC aims to quantify the concept of crisis migration and explores its economic, demographic and environmental drivers in an attempt to then predict future crisis based on maximalist and minimalist scenarios. As the last step into examining the drivers of global migratory flows and crisis level flows, this deliverable incorporates the environmental push factors in triggering migration globally for the time span of 1960 to 2015. The fourth assessment report of the Intergovernmental Panel on Climate Change (2007) referred to the potential for populations to migrate as a result of climate related distresses and their later work prioritized the international mobility implications of climate change even further. More recently, the evolution of UN Framewotk Convention on Climate Change set the 2016 Paris Agreement into motion with recommendations to signatory states regarding the potential displacements due to climate change(McLeman and Gemenne, 2018) making the issue ever more real . Research on environment-migration nexus has proliferated with a multitude of studies examining the impact of long term or sudden environmental changes on migration, resulting in a mixed evidence (Hoffman et al., 2019). These efforts were the basis for a multitude of projections ranging from very maximalist to minimalist expectations regarding the number of displacements that are to take place as a result of environmental changes (Adger et al. 2015).

Using a crisis definition as presented in D1.1 with a thorough debate of the ethical and securitized meanings attached to this concept and positioned itself critically vis-à-vis 'crisis' in quantifying migratory flows, D1.3 set an objective criteria to quantify critical level migrations. Also in this deliverable, the focus will be on large migrations taken in relative terms, large enough for the origin country relative to their populations and historical trends. Abel's stock to flow conversions for mobility across the world for 5 year intervals are operationalized based on this definition, and the impact of socioeconomic

(D1.3) and demographic drivers (D1.4) have been explored. These led to the current study where both direct and indirect impact of rapid and slow onset environmental changes will be analyzed and the socioeconomic and demographic drivers from earlier deliverables will be added as control variabless.

Czaika and Reinprecht (2020) point out that in the literature exploring migratory flows, environmental drivers have received relatively less attention leaving their impact understudied. In an attempt to address some of these gaps, the current working paper contributes to the existing literature in a multitude of ways. First, it expands the temporal and spacial dimension of the analysis by exploring the role of environmental drivers on migration for a time period of 1960 to 2015 with no assumptions on the potential destination countries. In other words, all countries in the world are analyzed as both potentially sending and receiving immigrants. Furthermore, it investigates the role of climate related variables on all migratory flows as well as those that are critically high, or as defined in D.1.1. as crisis level flows. This provides avenues to compare the previous findings in the literature on all kinds of migratory flows. In terms of the first set of independent variables, this study differentiates the rapid onset changes in terms of their impact to the lives and livelihoods and explores their direct and interactive effect through economic growth. In terms of the second set, a common operationalization climate variability is adopted and all alternative routes it is shown to affect mobility are examined. Finally, as the dyadic analysis section will further illustrate, as opposed to considering only the characteristics of destination or origin countries, this estimation approach takes the same push and pull factors in both sending and receiving countries, thereby fully utilizing the relational dimension of country dyad.

In the remainder of this deliverable, first, the correlations between the environmental characteristics and migratory movements will be descriptively investigated across different time frames for available data resources. This is to illustrate the time effects as well as to account for issues of missing data.

Consequently, the first two of the three step estimation approach identified in the methodological paper (D.1.1) will be adopted. For the first step, the goal is to estimate both the long and the short term determinants of crisis outflows, with a focus on the environmental indicators in the origin countries in relation to the migratory out flow data for a time period of 1960-2015. This will be followed by an investigation of migration corridors using dyadic data to understand the dynamics of movement vis-à-vis the destination of peak flows. Finally, the concluding remarks will reflect on the value added of this approach to the conventinal flow conceptualization and directions for future research.

THE ROLE OF ENVIRONMENTAL FACTORS AS DRIVERS OF MIGRATION

There is a rich discussion in the literature with regards to the the relative role of various drivers, push and pull factors leading to migration(for a thorough review Czaika and Reinprect 2020). Lately acknowledged as a multicausal phenomena, the debate on determinants of migratory flows has been heavily shaped by the role of different socio-economic and demographic factors. With the Deliverable 1.3, the role of economic drivers such as development, income, poverty, and inequality were explored deeply and the reverse U-shaped relationship between economic growth and migratory flows have been confirmed. Deliverable 1.4 illustrated the comparative role of significant role of urbanization as compared to weak impact of labor market characteristics and human development on these flows using same data and methods. These analysis were instrumental in leading up to the current work as many of the environmental drivers operate through these economic and structural indicators.

The nexus between climate change and migration has been addressed since the early 90's by scholars of various disciplines from economists, environmentalists, demographers to political scientists. According to Reuveny (2007), there are three main ways people adapt to environmental problems, either by accepting the costs and staying in place with inaction or adopt by mitigating the changes and by leaving the territory. When the decision to leave is considered, the efforts to pinpoint the exact causal path and impact of environmental drivers on migration have been challenged by the multitude of channels and ways environment is impacting habitability. On the one hand, the case studies on environment induced migration had an easier time addressing these different factors in shaping migration decisions, yet, their conclusions were not generalizable. On the other the macro studies that have the advantage of external validity, they were challenged by data availability on migratory moves around the work as well as the complexity of causal channels. As discussed by Gemenne (2011), their estimates and predictions may well be misleading due to the sometimes non linear and mostly indirect impact of climate change on migration. As way to address this, a majority of recent studies(see Table 1 in this deliverable for a review) consider both direct and indirect impacts of environmental distress with special emphasis on their effects on habitability such as reducing agricultural yield triggering droughts, sea level rise, rapid urbanization. Hoffmann (2020) further note that of the 25 macro quantitative studies reviewed focusing on environment-induced migration, 23 find a significant correlation between climatic conditions and mobility, but they also emphasize the heterogeneity in these result in that they are very context dependent. In other words, they show how environment induces migration in certain geographies, for countries with high agricultural dependency, for middle income or island states.

As shown by the meta analysis of Hoffman et al (2020), existing studies provide mixed evidence regarding climate induced migration with some earlier studies finding no significant direct effect on international mobility. In addition to diverse explanatory power of environmental drivers depending on the context, they are also shown operate indirectly through affecting other drivers of migration such. For instance in their analysis of migration from 39 Sub-Saharan African countries, Machiori et al. (2170) find that both income differential and the level of urbanization are affected by climate variables, and both are also explaining migration. Others point out to how this process may also depend on anthropogenic processes and mismanagement of global warming leading to a massive the loss of habitat due to systematical use of the neoliberal development models of development via geographically isolated events such as land grabs to poisoning of land of water due to mining and construction (Sassen, 2016). Adger et al. (2015) examined the potential impact of global warming and draughts through the pressures on prices, welfare of individuals and growth rates and Abel et al. (2017) discussed the implications of climate change on migration, through reducing the availability of fresh water resources.

A further discussion on these direct and indirect links to mobility require an initial differentiation of the environmental impact based on their duration. The two sets of drivers found to have an impact on human mobility in latest studies are the rapid onset changes in the environment such as disasters, making livelihoods difficult immediately and slow onset changes having a similar effect gradually, mostly resulting from global warming (Neumann et al. 2015).

Rapid onset changes

According to the meta analysis of Czaika and Reinprecht (2020), about 35 percent of the literature on environmental drivers investigates the role of the variables in this category such as floods, storms, droughts, earthquakes and man-made disasters with mixed evidence. Quite influential in explaining internal migration, potentially stemming from their temporary impact at times, there is limited evidence as to their statistically significant effect in explaining international migratory flows either directly or indirectly (Afifi 2011, Bohra-Mishra et al 2014, Beine and Parsons 2015, Islam 2018)

As to the direct effects, disasters, such as floods, droughts, earthquakes are to impact the habitability of the living areas leading to out-migration. This direct channel suggests the new environment after the rapid onset change is no longer suitable for human survival for instance due to the available water supplies or change in people's perceptions regarding their future where both short and long term effects of a disaster is considered by individuals when deciding to relocate. For instance using bilateral panel migration data dor the years between 1960 and 200, Bettin and Nicolli (2012) find a significant direct impact f disasters but only for Asian countries. Still, as argued by Conglio and Pesce (2014), the link between climate shocks are complex as the decision to relocate depends on several factors such as the nature of the climatic shock, the characteristics of the affected populations and the adaptation vs. vulnerability level of the region's economic system.

For instance, Naude(2008) illustrates this impact for Sub-Saharan Africa, with frequent disasters act as a trigger on migration. Drabo and Mbaye(2011) take a step further and differentiate across different kind of disasters in showing their impact on migration, namely Meteorological, hydrological, and climatological for poor and middle to lower income countries. They also confirm the number of natural disasters to have a positive impact on net migration rates for all except climatological disasters and argue lower adaptation capacities in the case of first two in their analysis for a period from 1950 to 2010. A similar classification is made by Coniglio anf Pesce (2014) where authors further explore the size of the climatic shocks as well as seasonal effects with their analysis of migratory flows from developing countries to OECD countries in the period 1990-2001.

Still, the evidence regarding the direct effect of disasters on especially international displacement is rather mixed, with additional studies that show limited or no impact. For instance, Beine and Parsons (2015) and Cattaneo and Peri (2016, for low and middle income countries) find no statistically significant direct relationship between the national disasters in origin countries and internatonal migration. In this working paper, the direct impact of disasters on migratory movements will be explored with a specific focus on the kind of impact they create in an attempt to measure their impact on habitability of living areas of people in origin countries. This approach is likely to reveal the nuances in terms of disaster effects. In addition, the interactive effects with economic growth will be explored as economic capabilities are expected to play a critical mediating role in establishing the disaster migration link. This is a rare approach in the literature as most studies explore the impact of any disaster or different kind of disasters without much regard to the intensity of the disaster, which should be expected to manifest in varying degress of distress to the population and hence lead to different numbers of successful migration decisions.

Slow onset changes

According to Berleman and Steinhardt (2017), migration is possibly the most direct adaptation strategy to global warming. Even if the climate goals of the Paris Agreement (2015) were to be met internationally, many scholars expect climate change to have a major impact on the living conditions of word populations. These pessimistic expectations along with the availability of data on various indicators of climate change lead to a bourgenoning literature exploring this impact at the macro level, building on the existing case studies illustrating these processes at the regional level (see Table 1 for the related literature).

Either through case studies focusing on one or few regions, or through large-N studies, the majority of the literature exploring the impact of environmental drivers of migration focus on the slow onset changes in the temperature and precipitation levels (Czaika and Reinprecht, 2020). The qualitative and quantitative studies focusing in specific regions illustrate how temperature increases either through direct or indirect impact create draughts, impact health conditions make resources scarce, thereby making migration a viable option (Khavarian et al 2019). Bohra-Mishra et al. (2014) point out to the fact that temperature changes may not have the same effect on migratory moves equally across all temperatures. In particular, authors illustrate that this impact is most visible above 25 degrees Celcius leading to increases in internal migration decision, a direct effect that is statistically significant.

Furthermore, many scholars point out to the indirect effects of climate change in general and temperature and precipitation changes in particular on population movements (McLeman and Gemenne 2018). Beine and Parsons (2015) find indirect effect of climatic change on wage differentials in their meticulous and technically advanced assessment of spatial pattern of environmental drivers of migration. Their results from a cluster analysis on spatially explicit data suggest that land degradation is an important factor of outmigration from drylands globally, and even more important than water availability. On the other hanf, for the case of Mexico, the study by Feng et al (2010) projects that by 2080 climate change, through their effect on agricultural productivity, temperature increases may lead to additional outmigration of 2–10% of the current working age population in Mexico. Similarly, exploring the agricultural linkage in relation to climate variability, in their analysis of bilateral flows from 163 countries of origin to 42 destination countries for the period of 1980 to 2010, Cai et al. (2016) find a statistically significant effect of temperatures on out-flows only in the most agriculture dependent countries.

Combining the climate change data with longitudinal household surveys conducted in Indonesia, Bohra-Mishra et al (2014) show the indirect and non-linear effect of temperature changes on migration decisions through household assets where the relationship starts to be visible at 24 degrees Celsius with this indirect impact growing at each degree temperature increase. On a related note, another indirect effect, this time regarding fresh water resources and rainfall isfound by Abel et al. (2017) in their study of international refugee flows for the years 1951 to 2014 using Heckman selection with a gravity model.

Authors demonstrated that controlling for the economic conditions and political factors, conflict outbreaks are more probably in countries with scarce fresh water resources and lower level of rainfall, hence show the mediated impact of environmental change on migration.

Table 1: Indirect and Interactive Effects of Climate Change

Publication	Variables Interacted with Climate in explaining Migration Flows
Machiori et al 2017	*Show direct and indirect effects* Agriculture: Whether the country has an agricultural value added above the median in 1995 (similar to Dell et al 2009) *****Especially significant for temperature Environmentally Induced income Variability: Intertemporal SD of GDPpc over intertemporal SD of GDPpc in other African countries weighted by distance *NS Urbanization
Coniglio and Pesce 2014	*Show direct and indirect effects* Agriculture:Percentage of Agriculture Share of GDP *Significant GDP per capita *Significant
Beine and Parsons 2013, 2015, 2017	*Find no direct effect show indirect effects* Wages: The wage dif-ferential is proxied as the log of the ratio of per capita GDP in destination and origin countries. *Significant indirect
Neumann et al 2015	*Show indirect effect* Drylands Land degradation (significant) rather than water availability
Hoffmann et al 2020 META ANALYSIS	*Show literature on direct and indirect effect* Agriculture: Income level of the country: (Middle or not (see also Peri et al 2016) , NON-OECD but not low income) Region: Latin America, Sub Saharan Africa Urbanization: Movement towards cities puts more pressure on labor markets and outmig

DATA AND METHODOLOGY

Measurement of the Environmental Drivers

The belowmentioned descriptions relate to the basic measurement of the environmental relationships outlined above and will be recoded for country level and dyadic data differently according to the various stages of estimation. Deliverable 1.1 illustrated the theoretical literature behind these variables and how they have been planned to be measured. The measures for slow onset changes have been further refined based on the review of the recent literature on operationalization of temperature and precipitation. The following section will summarize the measurement of these different set of variables that are included in the final models.

With regards to the rapid onset changes, as suggested by Berlemann and Steinhardt (2017), one of the most often employed sources of distaster data is the Emergency Events Database, EM-DAT[1]. With the support of the World Heath Organization and the Belgian Government, the Center for Research on the Epidemiology of Disasters at University Catholique de Louvain keeps data on over 22,000 disasters and their impact from 1900 to present. The records of the disasters are kept either if there are at least 10 confirmed deaths, 100 affected individuals, or if there is a rewuest for national and international assistance. In particular, the number of people who lost their lives and went missing, injured, left homeless or required emergency assistance/ basic humanitarian assistance are measured in order to calculate its effect. In addition, estimations of the damage to the property, crops, and livestock caused by the disaster are also coded as part of the effect. Furthermore, disasters are categorized into 17 categories such as geophysical, meteorological, hydrological, climatological, or biological ones.

Considering the measurement of slow onset changes, the most widely used data set is the Standardized Precipitation Evapotranspiration Index (SPEI). Due

[1] http://www.emdat.be

to the country level nature of the data we are employing with regards to other variables, the temperature and precipitation data is aggregated at the country level. The following table illustrates the ways some recent studies in the literature operationalized this climate data. One way of approaching temperature changes could be simply taking the absolute values and changes over time, possibly also standardizing via taking country level averages as Backhaus et al. (2015) or Cai et al (2016) did by taking the population weighted annual average of the monthly mean temperatures. However, Beine and Parsons (2015) convincingly argue against this approach as follows:

> "Measuring precipitation and temperature in absolute levels might not be appropriate because this formulation fails to adequately capture migratory responses to changes from standard climatic conditions. Rather, these would capture whether migration is more prevalent from rainier or warmer countries. This is unlikely to prove useful because tropical countries, for example, are more likely to be poorer on average. Any significant results would instead likely capture part of the effect of GDP per capita at origin, which in turn would be highly correlated with the measure of wage differentials." (Beine and Parsons, 2015; pp.739)

Instead, they suggest a focus on anomalies in temperature and precipitation, as they capture both the changes in overall climate conditions but also seasonal variations. In order to reach that measure, they first calculate deviations which are the differences of countries' decadal averages from their long-run averages. They calculate the long run averages based on Marchiori et al. (2011), referring to the period 1901–2000. They use these indicators to calculate anomalies, which simply take the long run standard deviations into consideration. Calculating anomalies of climatic measures are a superior method because as they argue:

> "..the use of anomalies eliminates scale effects as well as correcting for the fact that climatic variations in more arid regions are typically greater when compared to the mean. Moreover, because the long-term mean can be assumed to capture typical weather conditions in aparticular country, anomalies thus describe how far the weather conditionsdepart from this normal in a given year [...] capturing deviations in the weather from the norm" (Machiori et al. 2011, pp. 18)

This is also one of the climatic measures of Coniglio and Pesce (2014) and Neuman et al (2015) and the advised measurement by Hoffmann et al. (2020). Similarly, we adopt their approach of anomalies which are the deviations of countries' decadal averages (in temperature and precipitation) from their long-run average, divided by the corresponding long-run standard deviation with two minor modifications. As the time span of the data used expands to 2015, the long run averages and standard deviations are calculated taking data until 2015. Also, as the migration flow data derived from stocks is for every five years, five year averages of the anomalies are calculated for the previous 5 years. In other words, the way they are modelled illicits a natural lag with for instance averages of anomalies for a given country for the period 1990 to 1995 is used to estimate the migratory flows between 1995 to 2000.

Table 2: Measurement of Climate Variables and Methods Adopted

Publication	Measure of Climate	Method
Machiori et al 2017	Temperature Anomalies: Deviations from the country's long term mean divided by its long run Standard Deviation Same with precipitation	Two Stage Regressions Both income differential and level of urbanization are affected by the climate vars and are also explaining migration
Coniglio and Pesce 2014	Climatic shocks 1. Absolute levels of prec and temp (yearly average) NS 2. Surplus or deficit prec or temp NS 3. Anomalies above 1 SD with respect to long term values Significant 4. Seasonal effects for dry and rainy seasons	Poisson Pseudo MLE plus an instrumental variable estimation approach instead of using the size of current diasporas
Beine and Parsons 2013, 2015, 2017	Deviations in both temperature and precipitation) are calculated as the differences of countries' decadal averages from their long-run averages. Marchiori et al. (2011), we take the long run to refer to the period 1901–2000, and anomalies are calculated as the deviations of countries' decadal averages (in temperature and precipitation) from their long-run average, divided by the corresponding long-run standard deviation	Fixed Effects Poisson pseudo-maximum likelihood estimations 4 sub-samples: hotter initial climate, countries that are more dependent upon agriculture, countries with low endowments of groundwater, and countries located closer to the equator.
Neumann et al 2015	Drought frequency: Annual precipitation variability within a given year, using monthly precipitation data, variability is the degree of variation of the annual value derived	

	from the 31 year mean divided by the 31 yr SD (a la Machiori et al 2012)	
Hoffmann et al 2020 META ANALYSIS	Changes in the variability, anomalies of rainfall and temperature are suggested	reviews various models
Cai et al 2016	Both Temperature and Precipitation Population-weighted annual average of monthly mean temperature in the origin country in degree Celsius at a given year	country-pair fixed-effects regression model:
Backhaus et al 2015	Temp: Population weighted average annual temperature in degrees celsius in the origin-constant 1990 weights (Dell et al 2008) Precip: Population weighted average annual precipitation in millimeters in the origin -constant 1990 weights	Gravity model

Measurement of the Control Variables

There is a range of demographic and economic drivers that relate to both origin and destination factors being important drivers of migration. Labor market and employment conditions (Migali et al. 2018) along with wages (Beine et al. 2014), levels of economic development as measured by GDP growth rates, per capita income (Bell et al. 2015) and fluctuations are influential in individuals' migration decisions at different rates and mostly in non-linear patterns. Studies repeatedly underlined the inverse U-shaped effect of economic development on migration decisions (Dao et al. 2018, De Haas et al. 2019). In particular, for low income countries, development is shown to increase migration in the short run until the purchasing parity adjusted per income GDP rates of 7,000- 8,000 USD, after which migration rates start to decrease (Carling and Talleraas 2016). While with mixed evidence, poverty and inequality are also concluded to be important drivers of migratory flows.

In order to measure economic development levels, GDP per capita data from World Development Indicators has been collected. GDP per capita is gross domestic product divided by midyear population and GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars. Unfortunately, purchasing povery parity adjusted versions of this data is only available since 1995, hence simple per capita measurement was preferred due to data availability issues. In order to account for the potential non-linearity regarding this driver, a GDP per capita squared variable is created, whose statistical significance would attest to that effect.

Poverty and inequality are measured by the percentage living in poverty in each country (as defined 5 USD per day) compiled from the Worldbank database on Poverty and Equity. The differences between the origin and destination countries are calculated for the dyadic models.

With regards to the measurements and data sources of the demographic drivers, the majority are taken from the World Development Indicators and coded replicating common ways used by aforesaid literature described in D.1.4. In particular, basic demographic indicators such as population statistics and fertility rates are acquired from the UN Population statistics. Urbanization, defined as the percentage of urban population, constructed by dividing the urban population in the given year by the total population of that year and multiplying by 100 is obtained from UN Population Statistics.

Another important variable that may have a joint effect with climate factors is the agricultural dependency of the origin country. As this is an important link in the literature (see Table 1), it is measured three different ways using World Development Indicators in an attempt to capture its full impact. The first operationalization –also the most common measurement in the literature takes the share of agricultural output in the overall GDP. The second one focuses on the geographical dimension and calculates the share of agricultural land over the entire total territory of an origin country. Finally the third one focuses on the demography and measures it as the percentage of population employed in agriculture.

The gravity models to be used in the estimation based on country dyads allow for inclusion of certain set of variables associated with push and pull factors. These related to distances and borders between countries as well historical and cultural ties. To this dataset, a proxy of international conflict has also been added. To construct the contiguity and colonial link variables CEPII dataset has been utilized. We include a variable to capture whether the two states are either contiguous by land or separated by less than 24 or less miles of water(contiguity) since neighbors may be more likely to have population movement across the borders. Land contiguity is defined as the intersection of the homeland territory of the two states in the dyad, either through a land boundary or a river (such as the Rio Grande along the US-Mexico border). Water contiguity is based on whether a straight line of no more than a certain distance can be drawn between a point on the border of one state, across open water (uninterrupted by the territory of a third state),to the closest point on the homeland territory of another state.

The CEPI dataset contains different distance measures and dummy variables indicating whether the two countries are share a common language or a colonial relationship. For this deliverable, the population weighted distances calculated on principal cities in each country has been utilized. Accordingly, the distance between two countries is calculated based on bilateral distances between the largest cities of those two countries, those inter-city distances being weighted by the share of the city in the overall country's population. For our estimation, we measured this in 1000 kms.

Finally, the dataset also provides dummy variables based on whether the countries share a common language, have had a common colonizer after 1945 (comcol), have ever had a colonial link (Head et al. 2010). Based on this data for country dyads constucted two dummy variables are constructed: Whether the origin has been a colony of the destinationand whether the origin has ever colonized the destination.

For external conflict, the Militarized Interstate Dispute Data Version 5.0 within the Correlates of War project has been utilized (Palmer et al. 2020). Accordingly, ‘a militarized dispute is based on a sequence of related militarized incidents, each of which is an outgrowth of or a response to one or more previous incidents.’ For the origin based models, a dummy variabe is constructed to see if the country has been in a MIT for the last five years. For the dyadic models, hostility level is calculated for five years which is the level of hostility reached by states in dyad ranges from no militarized action (1),threat to use force (2), display of force(3), use of force(4), and war(5).

Dependent Variables and Estimation Approach:

As demonstrated in the previous working papers (D1.1 and D1.3), Abel’s estimations of flow data derivied from bilateral flow tables estimates from sequential bilateral stock data via birthplace specific flow tables (Abel 2017: 817) will be used for the dependent variables of this study. This dataset is particularly fit to the purposes of this deliverable due to its large time span, starting with years 1960-65, and its geographical bradth as it covers global flows. This allows for operationalization of the main assumption and one of the important contributions of this study, namely developing countries being both origins and destinations for migratory flows.

These flow estimations utilize the changes over time in bilateral migrant stock sizes for estimations of flows. Abel’s log linear models, a form of Poisson regression model used to predict or explain count variables, in this case number of flows, where each of the parameter values are obtained using the known marginal sums and diagonal cells in stock tables with iterative proportional fitting. These parameters for Abel (2017)’s method of imputation along with his use of three versions of UN stock data along with Özden et al.(2011)’s World Bank data enable a sensitive and comprehensive approach both geographically and temporally in estimating the missing values/gaps of flows. At a two-stage estimation, first flows over 10 year periods with alternative combinations of gender, demographic and stock data are predicted followed by an estimation of 5 year period flows between 1960 and 2015.

To construct the dependent variables of this study, Abel's flow data is first accumulated for each sending country based on outflows in gross numbers from an origin country, by summing up flows to all destinations from a given origin country. Two different dependent variables are constructed with this data, with the first one capturing all flows from the country (all flows one to the other for the dyadic version) and and binary crisis/critical level migration variable, which is discussed thoroughly in the following section.

Regarding the crisis level migration, conceptually, it is defined as ' very high flows from a country which could potentially cause a governance crisis in the origin as well as the recipient country as a result of their critically high number'. As it has been argued in D.1.3, this critical size is either as a high portion of the origin country population (determined as five percent), or as a nominally high number to create a sizable impact on the recipient country.[2] Finally, in order not to exclude similarly sized flows from countries with a high population, their flows were included even though this number was below the 5 percent of their large populations as in the cases of China and India. The flows to be included were determined based on the mean rate of the 5 percent group, which was about 200 thousand people per give year intervals . All outflows from countries exceeding this number were included in the crisis variable as well.

In terms of estimation, following the standard diagnostics such as multi collinearity, hetroscedascity and unit roots, as well as Hausmann tests for the choice of random or fixed effects, the model specification is determined as fixed effects models with robust standard error, clustered at the country level, that allow for intra-group correlation. The first step aims to reveal the origin

[2] As countries with very small populations could also end up in this new variable which would not really have a 'crisis' effect, flows below 100 thousand people were excluded from each five year interval, which were a very small share of the 5 % group (i.e for one of the highest flow years, 1995-2000, these constituted 0,036 percent of the group total of over 11 million migrants).

specific dynamics with cross sectional panel models estimated for all three dependent variables. The second relies on the bilateral flows as the dependent variable to also focus on recipient countries. This time, Abel's flow data will be utilized as consisting of country dyads. This is important in creating a base gravity model to identify the main destinations of the flows which are outlined in detail in the previous section.

Based on the results of the estimates from the previous model, peak predictions of migratory flows will be matched with medium and high outflow countries. As a contribution to the literature, a new dataset will then be compiled with dyadic data, enabling us to identify where this migration influx is likely to be destined, which countries are likely to be hit by these crisis level flows and if certain countries would be easier destinations due to factors such as colonial history, network effects, or other cultural ties. This would also have implications on the potential relative impact of these crisis flows on different destination countries.

DESCRIPTIVE STATISTICS

Before estimating crisis flows, a descriptive investigation of the dependent variables and explanatory demographic variables will be provided as a first step into understanding the data to explore the distribution of the variables, and the temporal dimension. There is reason to expect time effects, such as differences in relationships for different snapshots in time. These could be due to global economic trends, leading to stronger links through multiplied channels among the states or global structural changes, and migration governance.

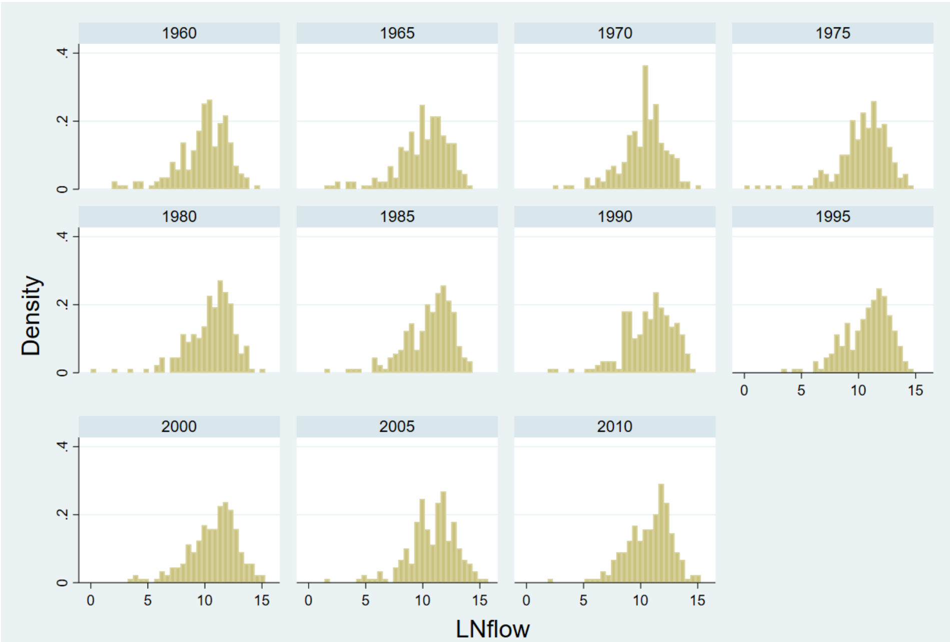
Figure 1 illustrates the distribution of migratory flows derived from stock data across time. As described earlier, this data is derived from the migrant stock data countries hold across 5 years, hence available for five year slots. This data indicates the logarithm of all flows from countries of origin for a given year, not corrected for migrant arrivals. As seen, overall, the data is normally distributed making it fit for a panel estimation. For the years 1990-5, the distribution is distribution is somewhat dispersed, indicating higher out-migration for some countries for these years stemming from various factors. This period also illustrates, both in terms of diversity of origin and magnitude, the influx of Syrians after 2015 is not unprecedented. In the 1990s, initially, the number of asylum seekers soared due to the influx of Bosnians and Croats fleeing the war in Yugoslavia but they were soon numerically superseded by refugees escaping war in the Middle East, notably Iraq, Iran, and Afghanistan as well as Somalia. Therefore this period is expected to show itself as a significant year dummy in them models estimated. For the years 2005-2010 and especially for 2010-2015, the mean and mode has fully shifted to the right, indicating higher numbers of outflows from many countries on average for these years. This is no doubt the source of the 'refugee crisis' discourse with the very high number of intenational forced migration displacing over 5.6 million people internationally[3], due to Syrian civil war. Finally, it is evident that overall the number of migratory outflows have increased over time but as shown repeatedly in the literature its ratio to the world population remained rather stable. For the entire time period the countries which have experienced the highest number of out migration are India, Bangladesh, Mexico and China, followed by Pakistan, Russia, Afghanistan, Great Britain, and Philiphines and many OECD countries such as Germany, France, USA are also in this list as high number of their citizens chose to live elsewhere[4].

Due to Abel's (2017) estimation technique, there are rather very low number of missing values for this variable also evident in the figures especially for earlier years.

[3] UNHCR data https://www.unhcr.org/syria-emergency.html#:~:text=Over%205.6%20million%20people%20have,continues%2C%20hope%20is%20fading%20fast.

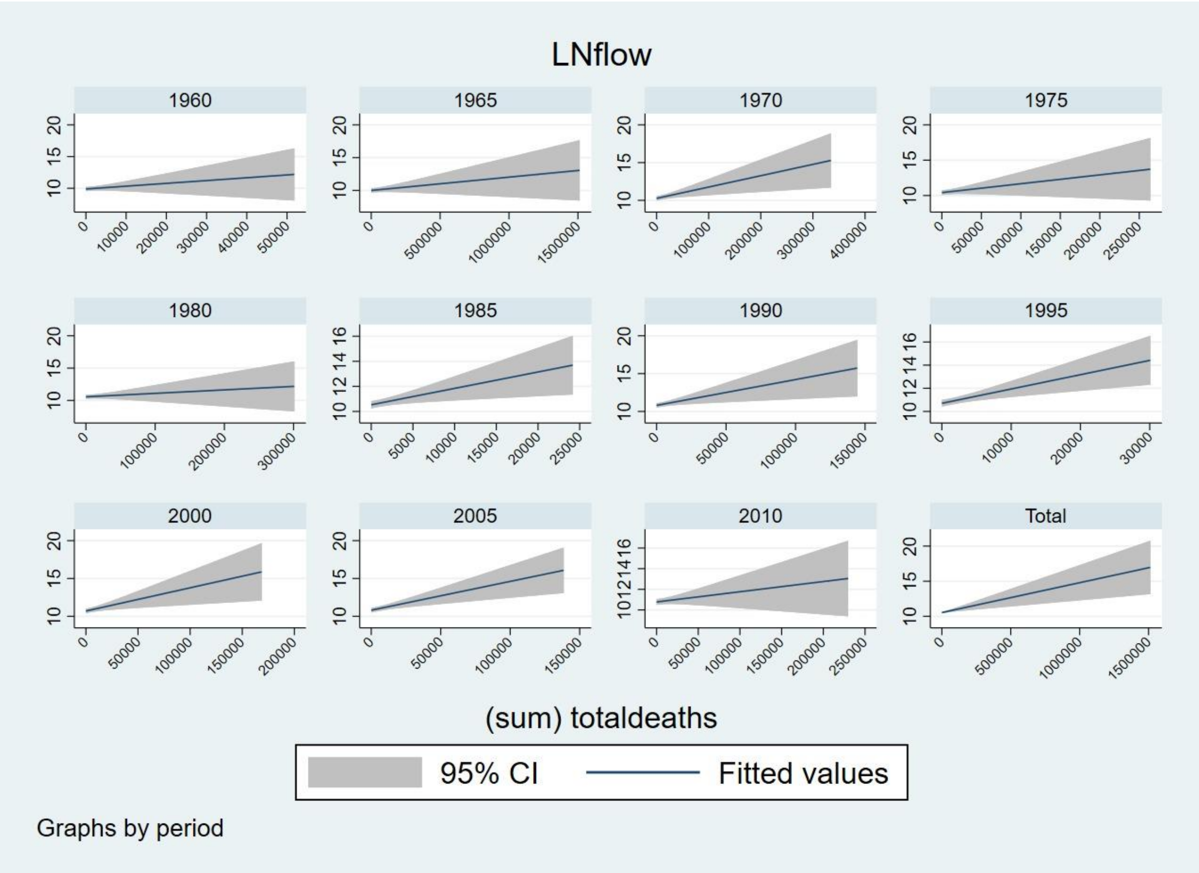
[4] A detailed comparison of these are provided in D 1.3

Figure 1: Distribution of migration out-flows across time



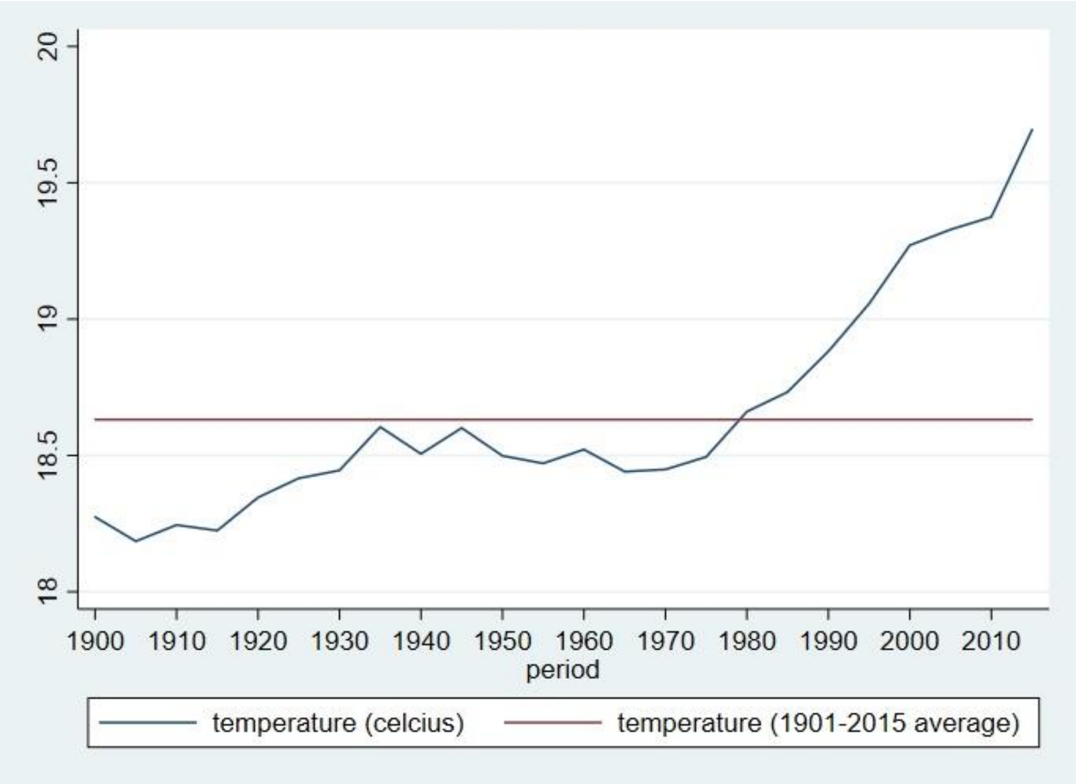
When it comes to the rapid onset changes, the EMDAT data has information regarding the intensity of disasters' effect regarding various dimension. The following figure illustrates how their impact in terms of number of total deaths relates to the out migration from a country. On a first sight, there seems to be some positive relationship between high intensity of disasters in terms of the death toll in a country and the number of people who migrate from that country. The large confidence interval suggests that, this relationship may not be always statistically significant. It should also be kept in mind that this appears to be the case when no other factors are taken into consideration, which is the task in the estimation stage.

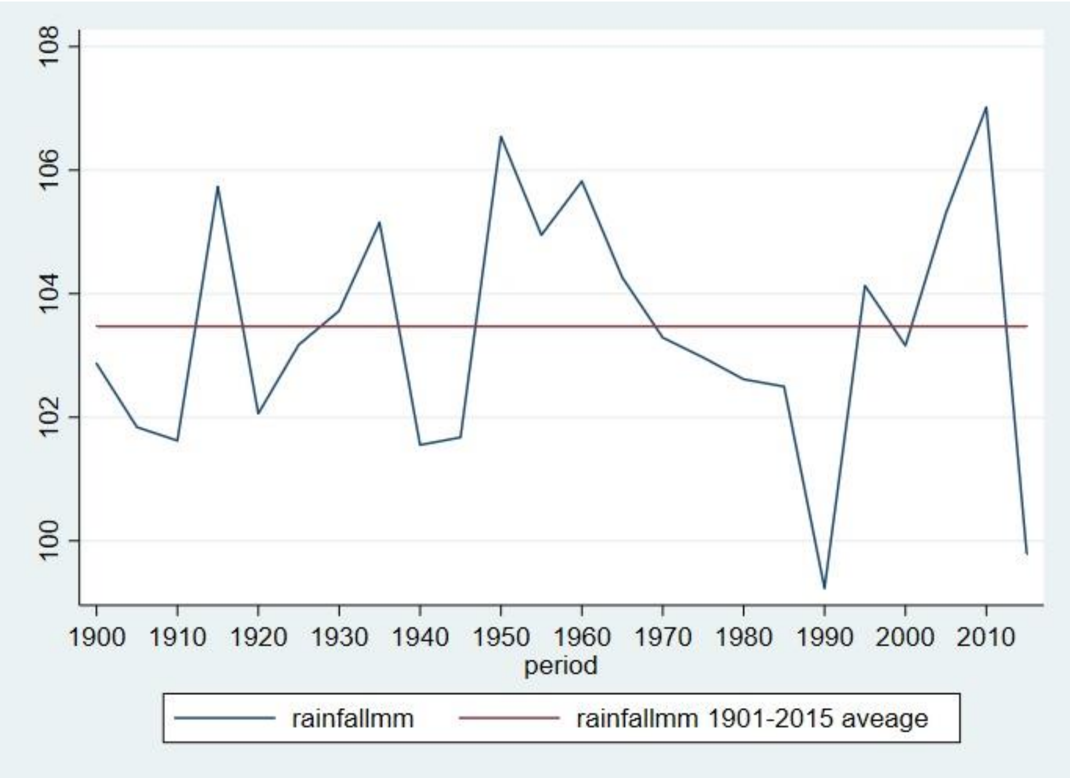
Figure 2: Disaster Intensity and Migration Flows
(example effect: Number of deaths)



The two graphs in Figure 3 illustrate trends in climatic indicators over time. As seen the tempertatures around the world have visibly increased while the changes in the precipitation do not suggest a clear trend except for high variability across the years. This changing dynamic may result in a weak or no relationship in the statistical models, therefore potential time differences should be considered.

Figure 3: Temperature and Precipitation Changes over Time





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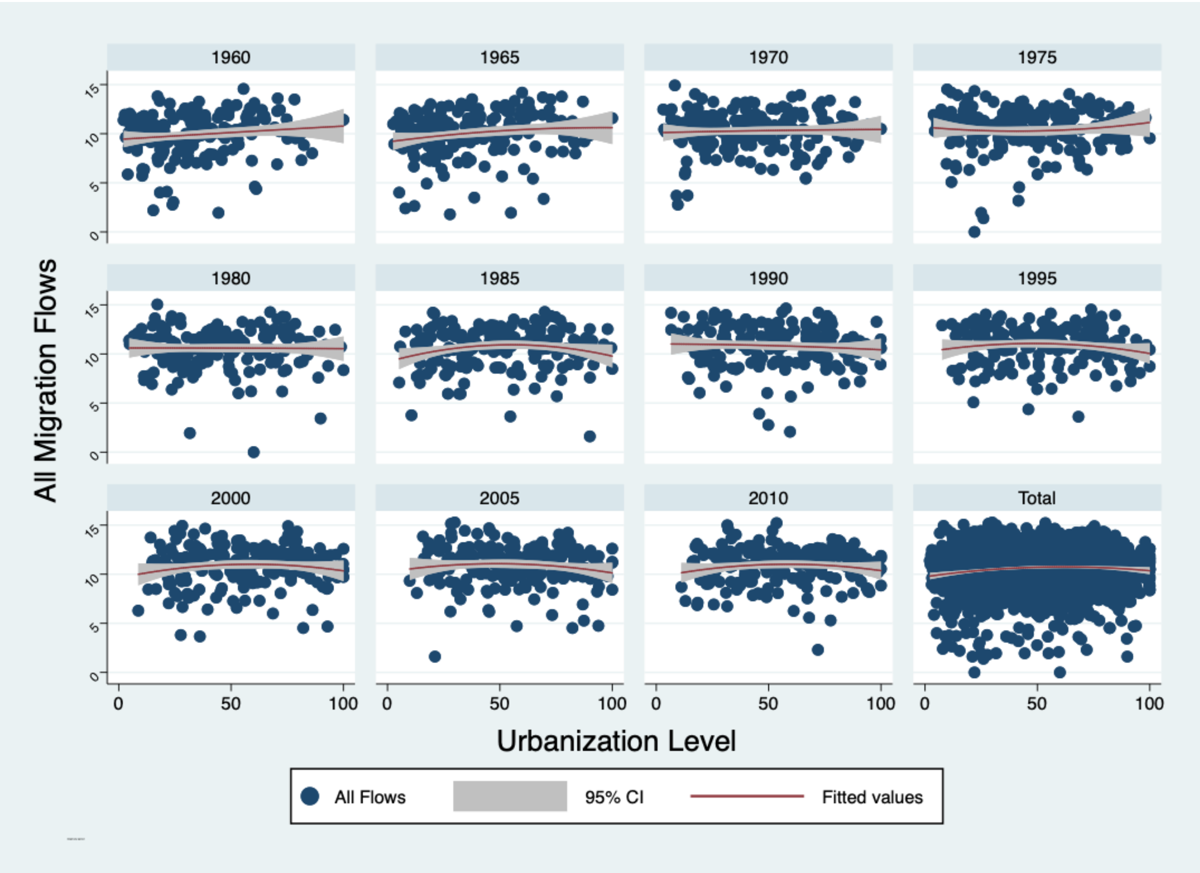
Finally, the relation between urbanization and migration is plotted in Figure 4. Despite the trend for more urbanization over time, the relationship stays similar across time indicating a slight positive correlation between levels of urbanization and flows. Still, urbanization levels in an origin and destination may play out differently, an issue the dyadic models will explore in greater detail.

Figure 4: Urbanization Levels and Migratory Flows



The descriptive discussion in this part has aimed at addressing the time effects, global trends, and missing data. Different measurements of migratory flows has first been explored across the years and countries, and then compared to the trends in different structural drivers. They are not to suggest causality but overall patters across time for the observation of temporal differences with naked eye.

ESTIMATIONS OF MIGRATORY FLOWS AND 'CRISIS' LEVEL FLOWS

In order to statistically test the role of the environmental drivers on migration flows and crisis level flows different fixed effects time series models are estimated with robust standard errors are clustered at the country level, that allow for intra-group correlation. The first set of these models focuses on flows from the origin countries with the aforesaid two dependent variables, namely flows and crisis flows. Due to the missing values in some of the independent variables, first a base model is estimated with the better available ones, and others are added as different models. Nevertheless, it is the only way to explore the impact of different structural drivers. For ease in presentation, each dependent variable two models are estimated, with the first one exploring labor market dimension of demographic factors and the second one incorporating all the remaining ones. Following the origin country models, estimations based on the dyadic dataset were peformed with the usual controls of the gravity models such as distance between the countries in the dyad, colonial links, common languages etc. The climatic anomalies are averaged for the five years preceeding the flows allowing for measuring their lagged effect.

The equations for these models are as follows:

EQUATION for FLOW MODELS (both flow & crisis):

$$Y_{it} = \alpha + \beta X_{it} + D_t + u_i + \varepsilon_{it}$$

where:

Y_{it}= dependent variable (LNflow or Crisis_Dummy)

α = constant

X_{it} = vector of (the model specific set) explanatory variables

β = coefficients vector

D_t = year dummies

ε_{it}= error term

ESTIMATIONS OF MIGRATORY FLOWS AND 'CRISIS' LEVEL FLOWS BASED ON RAPID ONSET CHANGES

ORIGIN COUNTRY FOCUSED MODELS

Table 3 below illustrates the role of rapid onset changes in the environment on migratory flows on their own and their conditional effect through economic growth and urbanization. To start off, no multicollinearity is detected among the variables. Still for most estimations, variables with many missing values were added one by one so as to avoid degress of freedom issues. As expected, the population size of the origin country has a positive and statistically significant effect on migratoey flows. The U shaped size of the effect of GDP is confirmed with a statistically significant effect of its squared value.

The variables that are proxies of the disasters' magnitude are mostly significant, with the disasters actually deterring people from mobility. This is contrary to the models which only control their direct effects, see Appendix A for an example. For instance, as the total deaths or number of injured increase, outflows for that origin country increases in the absence of interaction effects but decreases once they are added. Put differently, the positive effect of intensity of a disaster in terms of total deaths is mediated by the country's GDP, in that disasters with the aforesaid effects in higher GDP countries result in more migration, a finding emphasizing the importance of capabilities. Same goes for disaster's effects regarding number of injured. In terms of the direct effects of disasters, only for countries with disasters where the insured damages can be measured, their higher vaue results in more migration. Regarding the time effects, the years 1990 onwards have a separate impact resulting in more outflows as compared to 1960 levels. About 40 percent of the variance in the migratory flows is explained by these models.

TABLE 3: Rapid Onset Changes on Migratory Flows (Origin Focused Model)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
LNPopulation	0.6414***	0.6454***	0.6474***	0.6478***	0.6474***	0.6465***	0.6414***	0.6407***
	(0.0354)	(0.0351)	(0.0361)	(0.0350)	(0.0361)	(0.0347)	(0.0352)	(0.0358)
Landlocked	0.0664	0.0609	0.0518	0.0580	0.0516	0.0638	0.0652	0.0613
	(0.1746)	(0.1746)	(0.1745)	(0.1750)	(0.1745)	(0.1745)	(0.1751)	(0.1748)
LNGDPpc	0.6489	0.6743	0.6335	0.6817	0.6325	0.7032*	0.6950	0.6437
	(0.4223)	(0.4217)	(0.4366)	(0.4328)	(0.4368)	(0.4217)	(0.4250)	(0.4428)
LNGDPpc * LNGDPpc	-0.0446*	-0.0461*	-0.0439*	-0.0465*	-0.0438*	-0.0477*	-0.0475*	-0.0443*
	(0.0250)	(0.0250)	(0.0258)	(0.0256)	(0.0258)	(0.0249)	(0.0252)	(0.0262)
Totaldeaths	-21.0858**							
	(9.4381)							
LNGDPpc *totaldeaths	3.5869**							
	(1.5939)							
Injured		-5.8895**						
		(2.9227)						
LNGDPpc*injured		0.8337**						
		(0.3778)						
Affected			-0.0127***					
			(0.0028)					
LNGDPpc *Affected			0.0017***					
			(0.0004)					
LeftHomeless				-0.3066				
				(0.3194)				
LNGDPpc * LeftHomeless				0.0421				
				(0.0434)				
TotalAffected					-0.0127***			
					(0.0028)			
LNGDPpc * TotalAffected					0.0017***			
					(0.0004)			
ReconstructionCosts						0.0001		
						(0.0001)		
LNGDPpc * ReconstructionCosts						-0.0000		
						(0.0000)		
InsuredDamages							0.0007***	
							(0.0003)	
LNGDPpc*insureddamages							-0.0001***	
							(0.0000)	
TotalDamages								0.0000
								(0.0000)
LNGDPpc *totaldamages								-0.0000
								(0.0000)
1965.year	-0.0528	-0.0451	-0.0479	-0.0494	-0.0478	-0.0520	-0.0514	-0.0517
	(0.1827)	(0.1831)	(0.1818)	(0.1817)	(0.1818)	(0.1817)	(0.1816)	(0.1816)
1970.year	0.2130	0.2170	0.2251	0.2204	0.2252	0.2171	0.2187	0.2178
	(0.2021)	(0.2026)	(0.2031)	(0.2031)	(0.2031)	(0.2026)	(0.2027)	(0.2027)
1975.year	0.2746	0.2765	0.2802	0.2814	0.2805	0.2743	0.2766	0.2746
	(0.2332)	(0.2333)	(0.2335)	(0.2343)	(0.2335)	(0.2335)	(0.2334)	(0.2335)
1980.year	0.2312	0.2276	0.2338	0.2280	0.2338	0.2263	0.2269	0.2248
	(0.2380)	(0.2379)	(0.2384)	(0.2382)	(0.2384)	(0.2382)	(0.2381)	(0.2382)
1985.year	0.1779	0.1786	0.1898	0.1823	0.1899	0.1781	0.1768	0.1767
	(0.2293)	(0.2292)	(0.2301)	(0.2296)	(0.2301)	(0.2295)	(0.2295)	(0.2295)
1990.year	0.4288**	0.4313**	0.4391**	0.4352**	0.4392**	0.4311**	0.4220**	0.4257**
	(0.2068)	(0.2071)	(0.2078)	(0.2076)	(0.2079)	(0.2073)	(0.2081)	(0.2078)
1995.year	0.4176**	0.4212**	0.4263**	0.4237**	0.4263**	0.4172**	0.4148**	0.4137**

	(0.2058)	(0.2057)	(0.2064)	(0.2065)	(0.2064)	(0.2066)	(0.2063)	(0.2068)
2000.year	0.2956	0.3017	0.3159	0.3125	0.3158	0.3112	0.3067	0.3077
	(0.2052)	(0.2048)	(0.2057)	(0.2047)	(0.2057)	(0.2047)	(0.2050)	(0.2052)
2005.year	0.3314*	0.3367*	0.3377*	0.3405*	0.3377*	0.3368*	0.3293	0.3294
	(0.2010)	(0.2010)	(0.2015)	(0.2010)	(0.2015)	(0.2011)	(0.2020)	(0.2022)
2010.year	0.2327	0.2400	0.2375	0.2412	0.2375	0.2369	0.2204	0.2288
	(0.2029)	(0.2030)	(0.2034)	(0.2029)	(0.2034)	(0.2035)	(0.2045)	(0.2048)
Constant	-1.6984	-1.8656	-1.7132	-1.9282	-1.7093	-2.0052	-1.8724	-1.6630
	(1.9800)	(1.9680)	(2.0572)	(2.0175)	(2.0579)	(1.9657)	(1.9859)	(2.0815)
Observations	1,520	1,520	1,520	1,520	1,520	1,520	1,520	1,520
R-squared	0.383	0.383	0.382	0.383	0.382	0.383	0.383	0.382
Number of orig_n	174	174	174	174	174	174	174	174

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The following table estimates the same model only for crisis level flows. For these models the magnitude of the rapid onset changes is more pronounced as evidenced by higher coefficient values. This time, the numbef of the injuries occured due disasters in the origin country have an even higher immobility effect but the same effect is not statistically significant for the other variables except for reconstruction costs. The mitigating effects of GDP are also present for damages in reconstruction costs andn number of injured. However this time, the model is better at explaining the variation in the flows as evidenced by limited temporal effects.

Tabel 4: The Direct and Interactive Effect of Disaster Effects on Crisis Level Migration

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
LNPopulation	1.2215***	1.2313***	1.2336***	1.2282***	1.2339***	1.2373***	1.2251***	1.2001***
	(0.1454)	(0.1471)	(0.1428)	(0.1488)	(0.1429)	(0.1449)	(0.1440)	(0.1465)
Landlocked	-0.4210	-0.4451	-0.4495	-0.4557	-0.4503	-0.4357	-0.4322	-0.4381
	(0.4779)	(0.4803)	(0.4765)	(0.4794)	(0.4766)	(0.4758)	(0.4774)	(0.4783)
LNGDPpc	2.6922**	2.5995**	2.5863**	2.4847*	2.5814*	2.8029**	2.7777**	2.4500*
	(1.2563)	(1.3115)	(1.3181)	(1.3148)	(1.3187)	(1.3001)	(1.3068)	(1.3391)
LNGDPpc * LNGDPpc	-0.1863**	-0.1815**	-0.1803**	-0.1743**	-0.1800**	-0.1935**	-0.1927**	-0.1722**
	(0.0775)	(0.0808)	(0.0811)	(0.0809)	(0.0811)	(0.0802)	(0.0807)	(0.0826)
Totaldeaths	-26.5097							
	(29.4391)							
LNGDPpc *totaldeaths	5.3747							
	(4.7514)							
Injured		-40.6111**						
		(16.3198)						
LNGDPpc*injured		6.0298**						

		(2.5397)						
Affected			-0.0228					
			(0.0458)					
LNGDPpc *Affected			0.0033					
			(0.0062)					
LeftHomeless				-2.0025				
				(1.6173)				
LNGDPpc * LeftHomeless				0.3076				
				(0.2631)				
TotalAffected					-0.0241			
					(0.0453)			
LNGDPpc * TotalAffected					0.0035			
					(0.0061)			
ReconstructionCosts						-0.0046**		
						(0.0022)		
LNGDPpc * ReconstructionCosts						0.0007**		
						(0.0003)		
InsuredDamages							0.0020*	
							(0.0010)	
LNGDPpc*insureddamages							-0.0002*	
							(0.0001)	
TotalDamages								0.0000
								(0.0000)
LNGDPpc *totaldamages								-0.0000
								(0.0000)
1965.year	0.2675	0.3543	0.2845	0.2775	0.2849	0.2794	0.2800	0.2701
	(0.4298)	(0.4521)	(0.4241)	(0.4431)	(0.4241)	(0.4279)	(0.4257)	(0.4216)
1970.year	0.0181	0.0499	0.0807	0.0772	0.0814	0.0719	0.0785	0.0638
	(0.4864)	(0.4987)	(0.4878)	(0.4973)	(0.4882)	(0.4892)	(0.4852)	(0.4806)
1975.year	0.0442	0.0788	0.0728	0.0744	0.0733	0.0661	0.0751	0.0456
	(0.5551)	(0.5599)	(0.5512)	(0.5606)	(0.5515)	(0.5527)	(0.5480)	(0.5452)
1980.year	-0.3137	-0.3009	-0.2911	-0.3179	-0.2906	-0.3019	-0.2915	-0.3373
	(0.5822)	(0.5885)	(0.5792)	(0.5865)	(0.5796)	(0.5811)	(0.5750)	(0.5778)
1985.year	0.1486	0.1518	0.1634	0.1510	0.1643	0.1501	0.1475	0.1144
	(0.5221)	(0.5280)	(0.5116)	(0.5290)	(0.5120)	(0.5202)	(0.5161)	(0.5118)
1990.year	0.8616*	0.8516	0.8798*	0.8647	0.8800*	0.8749*	0.8592*	0.8203
	(0.5224)	(0.5327)	(0.5234)	(0.5314)	(0.5237)	(0.5239)	(0.5212)	(0.5158)
1995.year	0.4426	0.4389	0.4522	0.4262	0.4519	0.4141	0.4280	0.3771
	(0.5236)	(0.5337)	(0.5249)	(0.5353)	(0.5253)	(0.5297)	(0.5220)	(0.5230)
2000.year	0.1246	0.1354	0.1888	0.1729	0.1887	0.1864	0.1653	0.1305
	(0.5488)	(0.5525)	(0.5456)	(0.5515)	(0.5459)	(0.5456)	(0.5428)	(0.5417)
2005.year	0.5658	0.5689	0.5824	0.5764	0.5826	0.5670	0.5625	0.5317
	(0.5474)	(0.5550)	(0.5469)	(0.5520)	(0.5472)	(0.5496)	(0.5465)	(0.5415)
2010.year	-0.1898	-0.1914	-0.1686	-0.1708	-0.1689	-0.2058	-0.2455	-0.2642
	(0.5518)	(0.5616)	(0.5552)	(0.5577)	(0.5554)	(0.5677)	(0.5546)	(0.5545)
lnsig2u	1.0506***	1.0573***	1.0417***	1.0411***	1.0424***	1.0374***	1.0430***	1.0430***
	(0.2435)	(0.2404)	(0.2438)	(0.2459)	(0.2438)	(0.2468)	(0.2431)	(0.2435)
Constant	-31.1250***	-30.8505***	-30.8620***	-30.3534***	-30.8443***	-31.7746***	-31.4368***	-29.7499***
	(6.0292)	(6.2941)	(6.3664)	(6.3533)	(6.3693)	(6.2177)	(6.2218)	(6.4084)
Observations	1,548	1,548	1,548	1,548	1,548	1,548	1,548	1,548
Number of orig_n	174	174	174	174	174	174	174	174

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

COUNTRY DYAD MODELS

Having estimated out-flows and crisis level out-flows taking the direct and interactive effects of the rapid onset changes into account, it is important to explore these flows more relationally, by incorporating both origin and destination indicators and looking at the interactions between country dyads. Table 5 below illustrates the results of a gravity model taking these dimensions into account. Accordingly, contiguity, colonial ties and common language between the origin and destination countries are both statistically significant predictors of flows. Surprisingly, distance does not seem to have a visible effect, part of which may be captured by contiguity. Moreover, as their differences in poverty and conflict rates increase, so do migratory flows from origin to destination. Considering the rapid onset changes, controlling for the effect of GDP, an increase in the difference in total deaths people left homeless and insured damages between the pairs results in an increase in migratory flows. Nevertheless, the model fits are not particularly high indicating there is quite some the variables in these models cannot explain.

Table 5: Rapid onset drivers on Migration for Country Dyads

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Contiguity	3.7299***	3.6660***	3.6901***	3.6985***	3.6906***	3.7119***	3.6634***	3.6412***
	(0.6607)	(0.6689)	(0.6823)	(0.6666)	(0.6790)	(0.6623)	(0.6639)	(0.6888)
Common Language	2.1579***	2.1107***	2.1301***	2.1171***	2.1265***	2.1054***	2.1056***	2.1239***
	(0.4188)	(0.4099)	(0.4114)	(0.4144)	(0.4108)	(0.4114)	(0.4173)	(0.4309)
Colony of Dest.	5.8980***	5.8739***	5.8130***	5.8111***	5.8241***	5.8695***	5.8563***	5.7610***
	(2.0640)	(2.0882)	(2.0883)	(2.0828)	(2.0918)	(2.0902)	(2.0885)	(2.0654)
Colonizer of Dest.	5.0938***	5.8069***	5.7975***	5.7904***	5.7972***	5.7457***	6.0339***	6.1877***
	(1.0440)	(1.0385)	(1.0449)	(1.0408)	(1.0439)	(1.0342)	(1.0703)	(1.1148)
Distance	-0.0036	-0.0066	-0.0050	-0.0050	-0.0051	-0.0053	-0.0049	-0.0064
	(0.0318)	(0.0332)	(0.0319)	(0.0330)	(0.0320)	(0.0325)	(0.0328)	(0.0310)
LN Population Orig	-0.1074	-0.0206	-0.0843	0.0265	-0.0700	-0.0302	-0.0197	-0.1169
	(0.1867)	(0.1912)	(0.2201)	(0.2141)	(0.2269)	(0.1970)	(0.1950)	(0.1839)
LN Population Dest	0.4174***	0.3834***	0.4050***	0.3603***	0.3993***	0.3870***	0.3822***	0.4306***
	(0.0744)	(0.0705)	(0.0807)	(0.0671)	(0.0827)	(0.0722)	(0.0698)	(0.0613)
Fertility Diff	0.0804	0.0486	0.0439	0.1298	0.0456	0.0535	0.0701	0.0776
	(0.1128)	(0.1130)	(0.1229)	(0.1079)	(0.1221)	(0.1143)	(0.1143)	(0.1077)
GDPpcDifference	-0.0001	0.0040	0.0026	0.0030	0.0032	0.0042	0.0266	0.0363
	(0.0435)	(0.0435)	(0.0423)	(0.0428)	(0.0424)	(0.0437)	(0.0518)	(0.0509)
Landlocked_orig	-1.5519***	-1.5165***	-1.5238***	-1.6652***	-1.5260***	-1.5526***	-1.5381***	-1.5123***
	(0.3981)	(0.4431)	(0.4151)	(0.4799)	(0.4183)	(0.4241)	(0.4191)	(0.3853)
Landlocked_dest	-0.7220**	-0.6980**	-0.7045***	-0.6644**	-0.7005***	-0.6974**	-0.6648**	-0.6688**
	(0.2844)	(0.2774)	(0.2683)	(0.2767)	(0.2690)	(0.2766)	(0.2885)	(0.2854)

%Below Poverty Diff	-0.0201***	-0.0181***	-0.0178***	-0.0229***	-0.0178***	-0.0179***	-0.0167**	-0.0162***
	(0.0061)	(0.0062)	(0.0067)	(0.0060)	(0.0067)	(0.0064)	(0.0068)	(0.0058)
Conflict 5yrs Diff	-0.0453***	-0.0468***	-0.0477***	-0.0439***	-0.0477***	-0.0506***	-0.0450***	-0.0484***
	(0.0096)	(0.0100)	(0.0102)	(0.0109)	(0.0103)	(0.0108)	(0.0103)	(0.0098)
Totaldeaths Diff	-0.0121***							
	(0.0036)							
Injured Diff		-0.0004						
		(0.0003)						
Affected Diff			-0.0000					
			(0.0000)					
Left Homeless Diff				0.0001***				
				(0.0000)				
Total Affected Diff					-0.0000			
					(0.0000)			
Reconst Costs Diff						-0.1813***		
						(0.0595)		
Insured Damages Diff							-0.0115	
							(0.0070)	
Total Damages Diff								-0.0088**
								(0.0036)
1975.year	0.3367	0.3909	0.3689	0.3896	0.3664	0.3801	0.5135	0.5916
	(0.9593)	(0.9352)	(0.9079)	(0.7994)	(0.9147)	(0.9190)	(1.0042)	(0.9803)
1980.year	-0.9085***	-0.9102***	-0.8865***	-1.1247***	-0.8912***	-0.8727***	-0.9458***	-0.8417***
	(0.1570)	(0.1530)	(0.1498)	(0.2050)	(0.1553)	(0.1673)	(0.1698)	(0.1697)
1985.year	1.1906***	1.2142***	1.1782***	1.1776***	1.1809***	1.2223***	1.3100***	1.3756***
	(0.2822)	(0.3107)	(0.3344)	(0.3330)	(0.3307)	(0.2939)	(0.3554)	(0.3439)
1990.year	0.6573**	0.6747**	0.6787**	0.6351**	0.6722**	0.6693**	0.6754**	0.7217**
	(0.3164)	(0.3281)	(0.3299)	(0.2956)	(0.3314)	(0.3298)	(0.3368)	(0.3056)
1995.year	0.1758	0.1341	0.1057	0.3011	0.1053	0.1409	0.1033	0.0818
	(0.5188)	(0.5273)	(0.5218)	(0.4504)	(0.5207)	(0.5251)	(0.5192)	(0.5205)
2000.year	0.3001	0.2442	0.2555	0.2324	0.2599	0.2943	0.3053	0.3696
	(0.2008)	(0.2248)	(0.2217)	(0.2126)	(0.2254)	(0.2105)	(0.2303)	(0.2358)
2005.year	-0.0124	0.1051	0.1092	0.0537	0.1032	0.0169	0.0165	-0.0491
	(0.3002)	(0.3068)	(0.3181)	(0.3219)	(0.3168)	(0.2834)	(0.3555)	(0.3502)
2010.year	-0.2031	-0.2572	-0.2369	-0.3122	-0.2460	-0.2649	-0.2852	-0.3391
	(0.3462)	(0.3220)	(0.3416)	(0.3108)	(0.3419)	(0.3239)	(0.3309)	(0.3274)
Constant	-2.8976	-3.8226	-3.0605	-4.2443	-3.2131	-3.7024	-3.8147	-2.9020
	(2.5316)	(2.6843)	(2.9265)	(3.0883)	(3.0041)	(2.7156)	(2.6668)	(2.4947)
Observations	1,571	1,571	1,571	1,571	1,571	1,571	1,571	1,571
R-squared	0.294	0.290	0.293	0.288	0.292	0.288	0.296	0.310
Number of dyads	671	671	671	671	671	671	671	671

Robust standard errors, clustered at the origin country level, are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of this section have illustrated that there is more to the impact of disasters on migration than whether or not a disaster has happened. The impact of the particular disaster on mobility depends on the magnitude of damage it creates and in a negative way. In other words, disasters with high impact create additional pressures on economic well being of individuals, making migration outcomes even harder. On the other hand, when looked relationally, countries capabilities to cope with disaster also acts as a push factor for those countries who cannot and a pull factor for those who can. This analysis brings a fresh perspective into the debate on the migration generating effects of rapid onset changes and shelds further light on resilience mechanisms that are in place. Disasters may induce migration but only when people have the means to do so.

ESTIMATIONS OF MIGRATORY FLOWS AND 'CRISIS' LEVEL FLOWS BASED ON SLOW ONSET CHANGES

ORIGIN COUNTRY FOCUSED MODELS

Table 6 below illustrates the role of of climate variables on migratory flows on their own and conditional on economic growth and urbanization. To start off, no multicollinearity is detected among the variables. Still for most estimations, variables with many missing values were added one by one so as to avoid degress of freedom issues. As expected, population size has a statistically significant positive impact on flows. In terms of the main control variable for economic drivers, GDP's non linear effect as tapped by the squared per capita variable is statistically signigicant only for Model 3. The effect of precipitation anomalies on migratory flows is significant for models without the interactions with urbanization, but surprisingly, in the opposite direction than expected where more precipitation anomalies in the origin seem to lead to less out-migration. This may well be due to the high level of anomalies in low income countries as suggested by the positive and significant sign of the interaction effect with GDP suggesting that in places with higher GDP, precipitation anomalies actually do lead to more migration. The statistically significant impact of urbanization on international mobility has been illustrated in D1.4. This time, both on its own and conditional on climate impacts, it holds its statistically significant impact in that, migration rates from urbanized countries are higher and this effect is magnified in countries with precipitation anomalies.

When it comes to the temporal effects, the period between 1990 to 2000 exert a separate positive effect in some models, when controlling for the drivers and as compared to the base year/reference category, -here 1960-65. This is not surprising and has also been confirmed in earlier deliverables due to the high high mobility rates for these years. This actually reiterates the high level of flows in 1990, which have not really been considered as 'crisis' by policy makers, as also argued by Lucassen (2018). Finally, as to the overall explanatory powers of the estimations, the model fits as illustrated by R-Squared valueas are above .38 and are comparable across the models, indicating the addition of new variables contribute little to the initial base model.

Table 6: Slow onset drivers conditional on urbanization and economic growth

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LN Population	0.6580***	0.6512***	0.6567***	0.6392***	0.6352***	0.6405***
	(0.0358)	(0.0372)	(0.0378)	(0.0395)	(0.0392)	(0.0403)
Landlocked_orig	0.0631	0.0522	0.0820	0.1312	0.1148	0.1323
	(0.1740)	(0.1749)	(0.1771)	(0.1805)	(0.1775)	(0.1802)
LNGDPpc	0.5617	0.5015	0.6546	0.4886	0.4344	0.4639
	(0.4235)	(0.4324)	(0.4377)	(0.4692)	(0.4730)	(0.4792)
LNGDPpc * LNGDPpc	-0.0391	-0.0358	-0.0460*	-0.0431	-0.0384	-0.0420
	(0.0250)	(0.0256)	(0.0264)	(0.0272)	(0.0272)	(0.0276)
temp_anomaly		-0.2576	-1.0044	-1.1422	-0.3069	-1.3797
		(0.2098)	(1.4504)	(1.4368)	(0.4388)	(1.8851)
LNGDPpc * Temp_anomaly			0.0936	0.1186		0.1655
			(0.1707)	(0.1691)		(0.2777)
Prec_anomaly		0.0100	-3.5185*	-3.5870*	-1.1480	-2.7972
		(0.2995)	(2.0602)	(2.0611)	(0.7579)	(2.5724)
LNGDPpc * Prec_anomaly			0.4103*	0.4194*		0.2518
			(0.2357)	(0.2362)		(0.3928)
Urbanization				0.0096*	0.0086*	0.0100**
				(0.0051)	(0.0050)	(0.0051)
Urbanization * Temp_anomaly					0.0027	-0.0031
					(0.0070)	(0.0116)
Urbanization * Prec_anomaly					0.0216*	0.0119
					(0.0120)	(0.0202)
1965.period	-0.0537	-0.0839	-0.1014	-0.1049	-0.1138	-0.1119
	(0.1815)	(0.1816)	(0.1810)	(0.1811)	(0.1811)	(0.1810)
1970.period	0.2347	0.2047	0.1945	0.1829	0.1671	0.1738
	(0.2032)	(0.2035)	(0.2010)	(0.2003)	(0.2023)	(0.2021)
1975.period	0.2851	0.2676	0.2619	0.2383	0.2203	0.2295
	(0.2326)	(0.2337)	(0.2321)	(0.2305)	(0.2326)	(0.2330)
1980.period	0.2019	0.2206	0.1824	0.1339	0.1225	0.1215
	(0.2380)	(0.2392)	(0.2355)	(0.2311)	(0.2341)	(0.2330)
1985.period	0.1499	0.1669	0.1434	0.0781	0.0741	0.0706
	(0.2308)	(0.2326)	(0.2316)	(0.2305)	(0.2321)	(0.2313)
1990.period	0.4052*	0.4848**	0.4480**	0.3644*	0.3586*	0.3520*
	(0.2083)	(0.2110)	(0.2094)	(0.2100)	(0.2140)	(0.2127)
1995.period	0.4148**	0.4881**	0.4600**	0.3647*	0.3609*	0.3564
	(0.2051)	(0.2129)	(0.2119)	(0.2164)	(0.2193)	(0.2181)
2000.period	0.2995	0.3780*	0.3539*	0.2538	0.2399	0.2418

	(0.2051)	(0.2119)	(0.2073)	(0.2063)	(0.2097)	(0.2099)
2005.period	0.3207	0.4057*	0.3814*	0.2831	0.2757	0.2736
	(0.2006)	(0.2098)	(0.2079)	(0.2083)	(0.2095)	(0.2092)
2010.period	0.2470	0.3454	0.3138	0.2085	0.2102	0.2017
	(0.2024)	(0.2158)	(0.2125)	(0.2132)	(0.2153)	(0.2142)
Constant	-1.6168	-1.2653	-1.8995	-0.8905	-0.6428	-0.7970
	(1.9682)	(2.0105)	(2.0388)	(2.2059)	(2.2036)	(2.2328)
Observations	1,545	1,523	1,523	1,523	1,523	1,523
R-squared	0.389	0.385	0.386	0.388	0.388	0.388
Number of countries	178	175	175	175	175	175

Robust standard errors, adjusted for country clusters, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In addition to these first set of interaction of growth and urbanization, environment induced migration is found to be more pronounced agricultural dependent countries. To capture these potential relationships, the following models in Table 7 are estimated with different measures of agricultural dependency. The first model illustrates that the share of the agricultural land of the territory of an origin country is a direct predictor of out-migration, which is also a possible predictor of development. Temperature anomalies in highly agriculture dependent countries in terms of GDP also result in less migration, possibly because these are very low income countries at the same time. When it comes to the temporal effects, the decade of 90's continue to have a separate positive effect on flows for the models were the point of reference is 1960.

Table 7: All environmental drivers of all migratory flows

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LN Population	0.6337***	0.6342***	0.6649***	0.6651***	0.7049***	0.7077***
	(0.0390)	(0.0390)	(0.0397)	(0.0398)	(0.0473)	(0.0465)
Landlocked_orig	0.0215	0.0184	0.0711	0.0653	0.0201	0.0435
	(0.1821)	(0.1819)	(0.1764)	(0.1738)	(0.1938)	(0.1949)
LNGDPpc	0.5258	0.5247	0.4452	0.4309	0.1553	0.2887
	(0.4509)	(0.4486)	(0.5413)	(0.5372)	(0.6752)	(0.6771)
LNGDPpc *LNGDPpc	-0.0380	-0.0380	-0.0348	-0.0317	-0.0228	-0.0234
	(0.0272)	(0.0270)	(0.0311)	(0.0312)	(0.0369)	(0.0368)
Temp_anomaly	-1.2885	-1.7304	-1.3436	2.9520	-2.5645	3.8616
	(1.5213)	(1.7408)	(1.5094)	(2.9284)	(1.9325)	(4.3344)
LNGDPpc * Temp_anomaly	0.1288	0.1709	0.1459	-0.2845	0.2860	-0.3522
	(0.1793)	(0.1926)	(0.1736)	(0.3026)	(0.2276)	(0.4468)
Prec_anomaly	-3.5447*	-4.4975*	-3.2815	-8.3511	-1.7606	-5.6573
	(2.1292)	(2.3018)	(2.2166)	(5.0986)	(2.2227)	(4.9603)
LNGDPpc * Prec_anomaly	0.4108*	0.4490*	0.3950	0.8838*	0.2201	0.5944
	(0.2453)	(0.2476)	(0.2573)	(0.5049)	(0.2462)	(0.4886)
%of AgrLand *	0.0059*	0.0055				
	(0.0036)	(0.0036)				

%of AgrLand * Temp_anomaly		0.0039				
		(0.0101)				
%of AgrLand * Prec_anomaly		0.0168				
		(0.0125)				
Agr%ofGDP			-0.0017	0.0032		
			(0.0074)	(0.0075)		
Agr%ofGDP * Temp_anomaly				-0.0496*		
				(0.0271)		
Agr%ofGDP * Prec_anomaly				0.0648		
				(0.0666)		
AgrEmploy					-0.0039	0.0037
					(0.0080)	(0.0098)
AgrEmploy * Temp_anomaly						-0.0361
						(0.0237)
AgrEmploy * Prec_anomaly						0.0283
						(0.0277)
1965.period	-0.1237	-0.1208	0.0476	0.1053		
	(0.1853)	(0.1855)	(0.2724)	(0.2806)		
1970.period	0.1754	0.1927	0.3748	0.4559		
	(0.2058)	(0.2052)	(0.3106)	(0.3322)		
1975.period	0.2346	0.2357	0.6501**	0.7397**		
	(0.2375)	(0.2374)	(0.3256)	(0.3486)		
1980.period	0.1606	0.1626	0.2374	0.3534		
	(0.2408)	(0.2408)	(0.3882)	(0.3938)		
1985.period	0.0642	0.0689	0.1270	0.2394		
	(0.2383)	(0.2367)	(0.3673)	(0.3851)		
1990.period	0.4298**	0.4324**	0.5839*	0.6859*		
	(0.2130)	(0.2130)	(0.3426)	(0.3589)		
1995.period	0.4411**	0.4419**	0.6051*	0.7104*	-0.0099	-0.0201
	(0.2161)	(0.2148)	(0.3510)	(0.3645)	(0.1423)	(0.1408)
2000.period	0.3348	0.3269	0.4833	0.5725	-0.1200	-0.1300
	(0.2114)	(0.2110)	(0.3437)	(0.3523)	(0.1672)	(0.1663)
2005.period	0.3636*	0.3619*	0.5094	0.6078*	-0.0888	-0.0986
	(0.2136)	(0.2150)	(0.3504)	(0.3591)	(0.1589)	(0.1583)
2010.period	0.2870	0.2774	0.4285	0.5293	-0.1932	-0.2127
	(0.2183)	(0.2196)	(0.3557)	(0.3660)	(0.1696)	(0.1675)
Constant	-1.2403	-1.2310	-1.2162	-1.4970	0.4576	-0.8919
	(2.0917)	(2.0879)	(2.5524)	(2.5218)	(3.2746)	(3.3907)
Observations	1,493	1,493	1,278	1,278	806	806
R-squared	0.384	0.385	0.387	0.389	0.424	0.428
Number of countries	174	174	174	174	169	169

Finally, the very same models have been estimated for the crisis level migratory outflows, the calculation of which has been laid out earlier in the deliverable. As the dependent variable is a binary one indicating whether or not there is a crisis level flow, the estimation method is a fixed effects logit model, therefore, the sizes of the coefficients cannot be interpreted in a straightforward way. Accordingly, as in the previous estimation, population size has a stiatistically significant effect on crisis level outflows. The nonlinear GDP impact is confirmed for the first two models in Figure 8, while the population effect is visible for all. Also when the statistically coefficient for the interaction of the GDP per capita and temperature anomalies in the last full model with all the control variables is considered, temperature variability seems to lead to crisis level out-migration for countries with higher GDP per capita. The interaction of temperature anomalies with urbanization also yields to a statistically significant impact with termperature anomalies in higher urbanized countries leading to less migration. The year 1990 continues to exert a statistically significant positive time effect on crisis level migratory flows as compared to 1960. None of the other variables exert a statistically significant effect on crisis level flows from an origin country, possibly because only the driving factors in the origin are taken into consideration and the model fits do not vary much across the models.

Table 8: The Impact of Climate vars interacted with GDP and Urbanization on Crisis Level Migrations

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LN Population	1.1603***	1.1721***	1.1570***	1.1533***	1.1526***	1.2042***
	(0.1375)	(0.1419)	(0.1417)	(0.1415)	(0.1365)	(0.1512)
Landlocked_orig	-0.4985	-0.5139	-0.5747	-0.5207	-0.6215	-0.5176
	(0.4669)	(0.4694)	(0.4881)	(0.4997)	(0.4980)	(0.5107)
LNGDPpc	1.9638	1.9501	1.8236	1.6638	1.2800	1.3015
	(1.2650)	(1.3012)	(1.2636)	(1.3479)	(1.3154)	(1.4123)
LNGDPpc * LNGDPpc	-0.1369*	-0.1382*	-0.1272	-0.1239	-0.1037	-0.1157
	(0.0779)	(0.0805)	(0.0779)	(0.0799)	(0.0785)	(0.0832)
temp_anomaly		-0.4495	3.0606	3.1416	1.8207	-6.4663
		(0.8310)	(3.2429)	(3.2350)	(1.2838)	(4.4187)
LNGDPpc * Temp_anomaly			-0.4654	-0.4732		1.4034*
			(0.4423)	(0.4400)		(0.7543)
Prec_anomaly		1.3067	-0.1619	-0.2492	2.0696	-2.8294
		(0.8826)	(6.0195)	(5.9972)	(2.3938)	(7.3147)
LNGDPpc * Prec_anomaly			0.1827	0.1924		0.7768
			(0.7007)	(0.6978)		(1.1623)
Urbanization				0.0088	0.0149	0.0221
				(0.0154)	(0.0142)	(0.0153)
Urbanization * Temp_anomaly					-0.0560**	-0.1122***
					(0.0248)	(0.0369)
Urbanization * Prec_anomaly					-0.0112	-0.0407
					(0.0369)	(0.0615)
1965.period	0.2711	0.1561	0.1226	0.1212	0.1132	0.1520
	(0.4216)	(0.4113)	(0.4118)	(0.4145)	(0.4146)	(0.4254)
1970.period	0.0595	-0.0402	-0.0936	-0.1029	-0.1477	-0.0738
	(0.4839)	(0.4730)	(0.4801)	(0.4812)	(0.4848)	(0.4859)
1975.period	0.0499	-0.0614	-0.1254	-0.1400	-0.1748	-0.1274
	(0.5458)	(0.5460)	(0.5518)	(0.5511)	(0.5528)	(0.5599)
1980.period	-0.3125	-0.2382	-0.2907	-0.3221	-0.3305	-0.3259
	(0.5734)	(0.5812)	(0.5879)	(0.5857)	(0.5792)	(0.5800)
1985.period	0.1341	0.2418	0.2007	0.1529	0.1210	0.1052
	(0.5119)	(0.5290)	(0.5316)	(0.5284)	(0.5311)	(0.5417)
1990.period	0.9082*	1.0900**	1.0692**	1.0000*	1.0027*	0.9539*
	(0.5180)	(0.5357)	(0.5395)	(0.5391)	(0.5434)	(0.5519)
1995.period	0.4320	0.5511	0.5263	0.4480	0.4407	0.4038

	(0.5175)	(0.5436)	(0.5453)	(0.5562)	(0.5574)	(0.5684)
2000.period	0.2297	0.3244	0.2950	0.2136	0.2153	0.2149
	(0.5400)	(0.5671)	(0.5656)	(0.5670)	(0.5692)	(0.5785)
2005.period	0.5396	0.6326	0.6155	0.5359	0.5448	0.5283
	(0.5401)	(0.5807)	(0.5798)	(0.5803)	(0.5828)	(0.5923)
2010.period	-0.1269	0.0041	0.0119	-0.0684	-0.0298	-0.0848
	(0.5422)	(0.6055)	(0.6080)	(0.6182)	(0.6202)	(0.6351)
Constant	-27.4709***	-27.5180***	-26.9351***	-26.2113***	-24.7171***	-25.3308***
	(6.0881)	(6.2463)	(6.0943)	(6.3909)	(6.1951)	(6.5996)
lnsig2u	0.9989***	1.0062***	0.9898***	0.9890***	0.9802***	1.0080***
	(0.2464)	(0.2511)	(0.2483)	(0.2474)	(0.2458)	(0.2440)
Observations	1,574	1,550	1,550	1,550	1,550	1,550
Number of countries	178	175	175	175	175	175

Robust standard errors, adjusted for country clusters, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Finally, the results for the models with interactions of climate variables with agricultural dependency are shown in Table 8. Similar to the flow models, the population size and share of agricultural yield to higher out migration in Model 2. Different than refular flow models, when crisis level migrations are considered, precipitation anomaly is positively correlated with mobility as the origin country's share of GDP increases, which is a finding in the expected direction in Model 4. Regarding the temporal effects, only the time period between 1990-1995 seems to exert a separate effect resulting in higher likelihood of crisis level migrations.

Table 9: Impact of climate variables interacted with GDP and Agriculture on Crisis Level Migrations

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LN Population	1.1193***	1.1101***	1.2372***	1.2496***	1.4011***	1.4110***
	(0.1373)	(0.1355)	(0.1588)	(0.1614)	(0.2149)	(0.2194)
Landlocked_orig	-0.6458	-0.6964	-0.6443	-0.7071	-0.6703	-0.7312
	(0.4816)	(0.4824)	(0.5180)	(0.5167)	(0.6230)	(0.6212)
LNGDPpc	1.6380	1.3097	1.1483	1.1044	0.8599	0.7519
	(1.2758)	(1.2652)	(1.6662)	(1.6516)	(1.9414)	(1.9796)
LNGDPpc *LNGDPpc	-0.1148	-0.0945	-0.0876	-0.0865	-0.0586	-0.0599
	(0.0791)	(0.0789)	(0.0959)	(0.0956)	(0.1115)	(0.1137)
Temp_anomaly	2.2158	6.8855	1.2765	2.2626	-1.4443	-7.5225
	(3.2951)	(5.1410)	(3.0064)	(7.4022)	(3.6623)	(15.9872)
LNGDPpc * Temp_anomaly	-0.3521	-0.7333	-0.2244	-0.3224	-0.0102	0.6072
	(0.4503)	(0.5567)	(0.4088)	(0.7618)	(0.4974)	(1.6225)
Prec_anomaly	-0.9429	-1.2536	-2.6321	-28.9433**	-1.1111	-22.9433
	(6.1030)	(6.4921)	(7.0819)	(12.8198)	(8.8321)	(18.2791)
LNGDPpc * Prec_anomaly	0.2733	0.1966	0.4799	3.0461**	0.3689	2.4755
	(0.7143)	(0.7235)	(0.8211)	(1.3277)	(1.0195)	(1.8384)
%of AgrLand *	0.0150	0.0197*				
	(0.0094)	(0.0103)				
%of AgrLand * Temp_anomaly		-0.0454				

		(0.0353)				
%of AgrLand * Prec_anomaly		0.0226				
		(0.0417)				
Agr%ofGDP			0.0051	0.0060		
			(0.0235)	(0.0265)		
Agr%ofGDP * Temp_anomaly				-0.0125		
				(0.0818)		
Agr%ofGDP * Prec_anomaly				0.3434**		
				(0.1364)		
AgrEmploy					0.0240	0.0187
					(0.0206)	(0.0242)
AgrEmploy * Temp_anomaly						0.0284
						(0.0812)
AgrEmploy * Prec_anomaly						0.1523
						(0.1130)
1965.period	0.1703	0.1453	0.8841	0.9431		
	(0.4186)	(0.4301)	(0.7128)	(0.7226)		
1970.period	-0.0578	-0.0928	0.7354	0.8749		
	(0.4829)	(0.4973)	(0.7661)	(0.7354)		
1975.period	-0.0998	-0.1462	0.9085	1.0928		
	(0.5579)	(0.5719)	(0.8625)	(0.8660)		
1980.period	-0.2663	-0.2892	0.4229	0.5429		
	(0.5958)	(0.6110)	(0.9685)	(0.9726)		
1985.period	0.1100	0.0881	0.7314	0.8883		
	(0.5468)	(0.5587)	(0.8985)	(0.8972)		
1990.period	1.0141*	1.0194*	1.8438**	2.0189**		
	(0.5373)	(0.5422)	(0.8874)	(0.8849)		
1995.period	0.4654	0.4492	1.2847	1.3943*	-0.5740	-0.6439*
	(0.5436)	(0.5511)	(0.8484)	(0.8414)	(0.3680)	(0.3721)
2000.period	0.2245	0.2490	1.1342	1.2875	-0.7378	-0.7761*
	(0.5640)	(0.5672)	(0.9140)	(0.9055)	(0.4541)	(0.4582)
2005.period	0.5461	0.6065	1.4123	1.5681*	-0.3420	-0.3875
	(0.5780)	(0.5772)	(0.9320)	(0.9213)	(0.4068)	(0.4098)
2010.period	-0.1011	-0.0246	0.7014	0.8391	-1.0526**	-1.1333**
	(0.6097)	(0.6106)	(0.9686)	(0.9528)	(0.5046)	(0.5163)
Constant	-26.2447***	-24.9804***	-26.4519***	-26.5353***	-27.5888***	-26.5252**
	(6.1032)	(5.9858)	(8.0962)	(8.0567)	(10.1203)	(10.4646)
lnsig2u	1.0357***	1.0524***	1.0367***	1.0365***	1.4855***	1.4935***
	(0.2519)	(0.2486)	(0.2809)	(0.2830)	(0.3016)	(0.3028)
Observations	1,519	1,519	1,298	1,298	827	827
Number of countries	174	174	175	175	170	170

Robust standard errors, adjusted for country clusters, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

COUNTRY DYAD MODELS

Having estimated out-flows and crisis level out-flows taking the direct and interactive effects of the climatic drivers into account, it is important to explore these flows more relationally, by incorporating both origin and destination indicators and looking at the interactions between country dyads. Previous deliverables of this work package showed these models yield to better model specifications in relation to socioeconomic and demographic drivers as compared to origin only models. To this end, a dyadic dataset is constructed, consisting of country dyads for the five year intervals between 1960 and 2015. The independent variables refer to indicators in origin and destination countries separately[5]. With this data, fixed effect models with clustered robust standard errors were estimated first for overeall flows and then for crisis flows.

Table 10 below illustrates the direct effect of slow onset changes, followed by their interactive role in explaining all migratory flows as well as crisis level flows between dyads of countries from 1960 to 2015. One striking result is the high number of variables that have a statistically significant impact on flows, indicating a better model specification as compared to models based on outflows from origins only. Accordingly, consistent with the previous findings in the literature, being contiguous, sharing a common language, being a colony of the destination or having colonized the destination all have statistically significant positive impact on migration. Similarly, an increase in the distance between country dyads as well as being from a landlocked country results in lower levels of migratory flows indicating the importance of geographical location and sea borders. In their analysis of migration patterns between 1960-2000 also based on census data, Czaika and Haas(2014) have argued decreasing significance of post-colonial migration patterns and distances, nevertheless, these findings illustrate that they still exert and important influence on people's ability to migrate internationally, even more so for crisis level migrations, which will be discussed below. The difference between the GDP per capitas is also statistically significant for all the estimated models with higher difference between the dyad countries results in higher flows.

Regarding the slow onset changes, starting with the temperature anomalies, while their impact is negligible for the origin country as a push factor, low anomalies serve as a pull factor to destination countries as evidenced by the negative sign of the statistically significant coefficient. The precipitation

[5] Alternative models were also estimated with a relational definition of these independent variables by subtracting the origin values from the destination values but the results remained similar. The variables are incorporated into the models separately to make better use of the full variation of the data as well as considering potential inconsistencies of data in low income countries making comparisons with higher income countries difficult.

anomalies in the destination country also seems to have a statistically significant effect but it interestingly opposite of expected in that high anomalies attract more flows. This may be partly due to the developed countries having their fair share of the precipitation variability, however their higher resilience and lower dependency on agriculture may assuage fears of migrants. As the population of the country origin, as well as the country of destination, increase, so does the magnitude of migration flows. The next set of variables are included one by one, to show their sole impact to the base models as well as to make sure not to lose much data due to missing cases. Higher urbanization rates at both origin and destination result in higher migration in a statistically significant way. This finding suggests, from the perspective of the origin, a continuance of mobility that starts with urbanization -potentially an unplanned one, reducing habitability. From the perspective of the destination, it is consistent with the literature which posits that potentially multicultural urban centers are more attractive destinations for migrants due to the ease in social and economic cohesion than other areas. Average secondary education attainment is also both a push and a pull factor, with higher values at the origin leading to more migration but high values at the destination serve as an even higher attraction for people globally as indicated by the high and statistically significant coefficient of the variable. High urbanization rates are both an important push and pull factor and similarly high dependency on agriculture is neither a push or a pull factor. The models estimated also illustrate that the variance explained is slightly increased with the inclusion of climate and urbanization variables. Through all models considerable time effects are observable for the period after 1990 as compared to the migration levels of 1960. The effect is negative indicating that there is a negative impact exerted by events during these years as compared to 1960, which cannot be accounted for by thevariables models estimated.

Table 10: Direct effect of slow onset changes on migration flows

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Contiguity	2.8190***	2.8034***	2.8463***	2.7961***	2.8436***	2.8740***
	(0.1793)	(0.1852)	(0.1814)	(0.1856)	(0.1969)	(0.2147)
Common Language	0.6189***	0.6577***	0.7970***	0.8064***	0.7866***	0.8276***
	(0.0563)	(0.0579)	(0.0599)	(0.0612)	(0.0643)	(0.0740)
ColonyofDest	3.5783***	3.5370***	3.2327***	3.2192***	3.5260***	3.3232***
	(0.1569)	(0.1570)	(0.1510)	(0.1497)	(0.1740)	(0.1740)
ColonizerofDest	1.0276***	0.9721***	0.7221**	0.7840*	0.7720**	0.6844
	(0.3510)	(0.3488)	(0.3434)	(0.4030)	(0.3170)	(0.4208)
Distance	-0.0914***	-0.0894***	-0.0797***	-0.0825***	-0.0790***	-0.0812***
	(0.0066)	(0.0066)	(0.0056)	(0.0060)	(0.0065)	(0.0072)
LNPopulation_orig	0.2600***	0.2601***	0.2552***	0.2737***	0.2760***	0.3327***
	(0.0241)	(0.0241)	(0.0235)	(0.0254)	(0.0262)	(0.0326)
LNPopulation_dest	0.2508***	0.2488***	0.2401***	0.2486***	0.2431***	0.2773***
	(0.0085)	(0.0084)	(0.0079)	(0.0085)	(0.0085)	(0.0100)
rGDPpcDifference	0.0191***	0.0193***	0.0183***	0.0199***	0.0194***	0.0179***
	(0.0028)	(0.0028)	(0.0026)	(0.0026)	(0.0026)	(0.0025)
Landlocked_orig	-0.4819***	-0.4823***	-0.2623***	-0.1882*	-0.2410**	-0.2249*
	(0.1124)	(0.1119)	(0.1005)	(0.1108)	(0.1138)	(0.1198)
Landlocked_dest	-0.3715***	-0.3803***	-0.1005***	-0.1190***	-0.0421	0.0297
	(0.0263)	(0.0266)	(0.0248)	(0.0250)	(0.0279)	(0.0296)
Temp_anomaly_orig		-0.2550*	-0.1630	-0.1527	-0.0306	0.1524
		(0.1317)	(0.1308)	(0.1293)	(0.1229)	(0.1300)
Temp_anomaly_dest		-0.3609***	-0.2550***	-0.2301***	-0.2973***	-0.4762***
		(0.0394)	(0.0363)	(0.0358)	(0.0326)	(0.0490)
Prec_anomaly_orig		0.3361*	0.2785	0.2728	0.2874	0.3288
		(0.1836)	(0.1806)	(0.1828)	(0.1888)	(0.2035)
Prec_anomaly_dest		0.3890***	0.3381***	0.3244***	0.2584***	0.1992***
		(0.0429)	(0.0399)	(0.0411)	(0.0406)	(0.0453)
Urbanization_orig			0.0117***	0.0124***	0.0106***	0.0096***
			(0.0019)	(0.0020)	(0.0026)	(0.0034)
Urbanization_dest			0.0156***	0.0153***	0.0142***	0.0036***
			(0.0012)	(0.0012)	(0.0012)	(0.0009)
%ofAgrLand_orig				-0.0058***		
				(0.0021)		
%ofAgrLand_dest				-0.0012*		
				(0.0006)		
Agr%GDP_orig					-0.0074*	
					(0.0039)	
Agr%GDP_dest					-0.0072***	
					(0.0012)	
AgrEmploy_orig						-0.0066**
						(0.0031)
AgrEmploy_dest						-0.0204***
						(0.0012)
1965.period	-0.0461	-0.0808	-0.1374	-0.1423	-0.1229	
	(0.0871)	(0.0873)	(0.0880)	(0.0894)	(0.1362)	
1970.period	-0.0094	-0.0286	-0.1787*	-0.1948*	-0.3370***	
	(0.1030)	(0.1023)	(0.1049)	(0.1060)	(0.1289)	
1975.period	0.0151	-0.0055	-0.2348**	-0.2503**	-0.4166***	
	(0.1131)	(0.1140)	(0.1157)	(0.1158)	(0.1525)	
1980.period	0.0301	0.1107	-0.1962	-0.2204*	-0.5699***	
	(0.1200)	(0.1250)	(0.1287)	(0.1292)	(0.1690)	
1985.period	0.0260	0.1279	-0.2530*	-0.2617**	-0.6660***	
	(0.1175)	(0.1235)	(0.1305)	(0.1326)	(0.1634)	
1990.period	-0.2786***	-0.1111	-0.5622***	-0.5994***	-0.9604***	
	(0.1017)	(0.1128)	(0.1175)	(0.1167)	(0.1478)	
1995.period	-0.2958***	-0.1216	-0.6257***	-0.6666***	-1.0292***	-0.0928
	(0.1055)	(0.1211)	(0.1289)	(0.1267)	(0.1565)	(0.0704)
2000.period	-0.3286***	-0.1060	-0.6635***	-0.7154***	-1.0944***	-0.1661**

	(0.1005)	(0.1241)	(0.1305)	(0.1297)	(0.1608)	(0.0722)
2005.period	-0.3003***	-0.0873	-0.6883***	-0.7447***	-1.1388***	-0.2366***
	(0.1044)	(0.1303)	(0.1378)	(0.1373)	(0.1642)	(0.0772)
2010.period	-0.4656***	-0.2443*	-0.8919***	-0.9469***	-1.3614***	-0.4903***
	(0.1001)	(0.1274)	(0.1378)	(0.1357)	(0.1670)	(0.0857)
Constant	-5.6004***	-5.6577***	-6.5947***	-6.7069***	-6.2479***	-7.3576***
	(0.4175)	(0.4184)	(0.4271)	(0.4425)	(0.4558)	(0.5474)
Observations	234,055	228,930	228,930	220,813	174,874	136,893
R-squared	0.267	0.272	0.316	0.317	0.304	0.325
Number of dyads	31,329	30,625	30,625	30,276	30,601	28,900

Robust standard errors, adjusted for country clusters, in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Following the initial exploration of the direct effects of climate variability, a second set of models are estimated with their interactive effect through agriculture dependency and economic growth. First off, the gravity model variables such as contiguity, distance, colonial links, cultural links as well as the proxy of economic growth GDP continue to exert similar and statistically significant effect as in the previous models. When it comes to the interactive effects, none of them either relating to the origin country yield to expected results, even when they are statistically significant except GDP per capita effects. In particular, the impact of the difference between the origin and destination in regards to GDP per capita has a higher impact on mobilities when temperature anomalies' in the origins increase, whereas the effect is in the opposite direction for precipitation. When it comes to destination effects, both the direct and interactive effects seem in the expected direction. For instance, temperature anomalies in destination are a negative pull factor when destination is an agriculturally dependent country. The R –Squared value of the models has slightly increased which is attributable to the inclusion of the interaction effects.

Table 11: Interactive effect of climatic drivers of migratory all flows based on country dyads

VARIABLES	Model 1	Model 2	Model 3	Model 4
Contiguity	2.8627*** (0.1772)	2.8030*** (0.1853)	2.8457*** (0.1970)	2.8867*** (0.2160)
Common Language	0.7786*** (0.0591)	0.8099*** (0.0601)	0.7963*** (0.0625)	0.8288*** (0.0725)
ColonyofDest	3.2429*** (0.1516)	3.1956*** (0.1488)	3.4722*** (0.1737)	3.2695*** (0.1743)
ColonizerofDest	0.7412** (0.3405)	0.7522* (0.3912)	0.7402** (0.3086)	0.6521 (0.4144)
Distancew	-0.0809*** (0.0055)	-0.0824*** (0.0058)	-0.0798*** (0.0064)	-0.0814*** (0.0071)
LN Population_orig	0.2559*** (0.0235)	0.2753*** (0.0247)	0.2842*** (0.0258)	0.3308*** (0.0321)
LN Population_dest	0.2416*** (0.0079)	0.2500*** (0.0085)	0.2482*** (0.0087)	0.2826*** (0.0100)
Landlocked_orig	-0.2661*** (0.0997)	-0.1814* (0.1094)	-0.2117* (0.1102)	-0.2330** (0.1159)
Landlocked_dest	-0.0806*** (0.0245)	-0.1159*** (0.0249)	-0.0256 (0.0281)	0.0579** (0.0284)
rGDPpcdiff	0.0179*** (0.0028)	0.0190*** (0.0027)	0.0170*** (0.0027)	0.0130*** (0.0027)
Temp_anomaly_orig	-0.1800 (0.1236)	0.0380 (0.1884)	0.2396 (0.1809)	0.0732 (0.1910)
rGDPpcdiff1000 * Temp_anomaly_orig	0.0061 (0.0048)	0.0090* (0.0053)	0.0133*** (0.0047)	0.0194*** (0.0055)
Prec_anomaly_orig	0.2602 (0.1810)	-0.1322 (0.3257)	0.5671 (0.3464)	0.3937 (0.3472)
rGDPpcdiff1000 * Prec _anomaly_orig	-0.0161** (0.0073)	-0.0206*** (0.0076)	-0.0068 (0.0082)	-0.0030 (0.0073)
Urbanization_orig	0.0116*** (0.0019)	0.0122*** (0.0020)	0.0104*** (0.0026)	0.0091*** (0.0033)
Urbanization_dest	0.0161*** (0.0012)	0.0153*** (0.0012)	0.0138*** (0.0011)	0.0035*** (0.0009)
%Agr Land_orig		-0.0048** (0.0022)		
%Agr Land_orig * Temp _anomaly_orig		-0.0067 (0.0044)		
%Agr Land_orig * Prec _anomaly_orig		0.0096 (0.0077)		
%Agr Land _dest		-0.0006 (0.0006)		
Temp _anomaly_dest		-0.1646*** (0.0497)	-0.2434*** (0.0575)	-0.4608*** (0.0569)
%Agr Land _dest * Temp _anomaly_dest		-0.0018* (0.0011)		
Prec_anomaly_dest		0.5431*** (0.0697)	0.6330*** (0.0816)	0.8052*** (0.0690)
%Agr Land _dest * Prec_anomaly_dest		-0.0063*** (0.0012)		
Agr%ofGDP _orig			-0.0045 (0.0041)	
Agr%ofGDP _orig *Temp_anomaly_orig			-0.0191*** (0.0074)	
Agr%ofGDP _orig * Prec _anomaly_orig			-0.0234 (0.0182)	
Agr%ofGDP _dest			-0.0078*** (0.0013)	
Agr%ofGDP _dest *Temp_anomaly_dest			-0.0027	

			(0.0032)	
Agr%ofGDP _dest * Prec _anomaly_dest			-0.0284***	
			(0.0043)	
AgrEmploy _orig				-0.0062*
				(0.0033)
AgrEmploy _orig * Temp_anomaly_orig				-0.0003
				(0.0036)
AgrEmploy _orig * Prec_anomaly_orig				-0.0030
				(0.0095)
AgrEmploy _dest				-0.0212***
				(0.0013)
AgrEmploy _dest *Temp_anomaly_dest				0.0007
				(0.0017)
AgrEmploy _dest *Prec_anomaly_dest				-0.0239***
				(0.0020)
1965.period	-0.1211	-0.1477*	-0.1563	
	(0.0879)	(0.0896)	(0.1405)	
1970.period	-0.1872*	-0.1963*	-0.3701***	
	(0.1041)	(0.1055)	(0.1334)	
1975.period	-0.2313**	-0.2588**	-0.4303***	
	(0.1153)	(0.1156)	(0.1556)	
1980.period	-0.2452*	-0.2351*	-0.5920***	
	(0.1265)	(0.1287)	(0.1683)	
1985.period	-0.3123**	-0.2724**	-0.6783***	
	(0.1281)	(0.1328)	(0.1643)	
1990.period	-0.6539***	-0.6127***	-0.9757***	
	(0.1134)	(0.1160)	(0.1542)	
1995.period	-0.7120***	-0.6817***	-1.0252***	-0.0799
	(0.1224)	(0.1260)	(0.1609)	(0.0711)
2000.period	-0.7830***	-0.7241***	-1.0971***	-0.1520**
	(0.1224)	(0.1281)	(0.1624)	(0.0739)
2005.period	-0.8034***	-0.7488***	-1.1470***	-0.2217***
	(0.1297)	(0.1356)	(0.1650)	(0.0791)
2010.period	-1.0049***	-0.9514***	-1.3756***	-0.4713***
	(0.1295)	(0.1344)	(0.1675)	(0.0871)
Constant	-6.5993***	-6.8024***	-6.4821***	-7.4031***
	(0.4257)	(0.4331)	(0.4651)	(0.5517)
Observations	231,478	220,813	174,874	136,893
R-squared	0.316	0.320	0.308	0.329
Number of dyads	30,975	30,276	30,601	28,900

Robust standard errors, adjusted for country clusters, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Having illustrated the impact of slow onset changes on migratory flows based on country dyads, similar models are estimated for origin countries with crisis level out-flows, yielding to the results in the following table. Accordingly, contiguity, distance, common language and colonization history all seem to be significantly affecting the variation in flows from crisis origin countries, much like the overall flow models. The coefficients of certain drivers are different, and overall have higher values. This suggests they are better at explaining variation at higher flows as opposed to the ones in lower numbers. For instance, the difference in GDP per capitas beween the countries is almost double of what it was for all flows. Similary, contiguity, colonization past, fertility, distance between the countries in the dyad also exert a higher influence and also continues to be statistically significant. The direct aversion effect destination temperature anomalies continue, albeit even more strongly for crisis flows. Yet, neither origin anomalies in temperature nor any anomalies of precipitation have the expected effect on flows even for the crisis countries. Still, the stronger coefficients resulted in a better model fit compared to the overall flow models.

Table 12: Direct effects of slow onset changes on flows based on country dyads for crisis origin

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Contiguity	3.1674***	3.1421***	3.2031***	3.1065***	3.2530***	3.0313***
	(0.3056)	(0.3202)	(0.3128)	(0.3213)	(0.3456)	(0.3588)
Common Language	0.8612***	0.9046***	1.0347***	1.0597***	1.0266***	1.1717***
	(0.1492)	(0.1500)	(0.1428)	(0.1440)	(0.1580)	(0.1632)
ColonyofDest	4.3827***	4.3444***	3.8381***	3.9385***	4.2358***	3.6695***
	(0.2481)	(0.2463)	(0.2412)	(0.2248)	(0.2859)	(0.3161)
ColonizerofDest	1.1476***	1.0738***	0.5827**	0.7099**	0.8897**	0.7751*
	(0.2675)	(0.2645)	(0.2563)	(0.3380)	(0.3530)	(0.4252)
Distance	-0.1107***	-0.1067***	-0.1021***	-0.1062***	-0.1045***	-0.1026***
	(0.0164)	(0.0165)	(0.0132)	(0.0147)	(0.0148)	(0.0153)
LNPopulation_orig	0.2459***	0.2629***	0.3122***	0.3390***	0.3402***	0.3563***
	(0.0803)	(0.0818)	(0.0613)	(0.0612)	(0.0706)	(0.0707)
LNPopulation_dest	0.3961***	0.3878***	0.3690***	0.3772***	0.3686***	0.4227***
	(0.0135)	(0.0130)	(0.0119)	(0.0133)	(0.0133)	(0.0153)
rGDPpcDifference	0.0383***	0.0386***	0.0319***	0.0332***	0.0314***	0.0277***
	(0.0062)	(0.0062)	(0.0059)	(0.0060)	(0.0060)	(0.0052)
Landlocked_orig	-0.9010***	-0.8192***	-0.2651	-0.1966	-0.0450	-0.0938
	(0.2080)	(0.1944)	(0.2182)	(0.2102)	(0.2661)	(0.2356)
Landlocked_dest	-0.6041***	-0.6120***	-0.1029	-0.1106*	-0.0255	0.0554
	(0.0608)	(0.0613)	(0.0678)	(0.0641)	(0.0745)	(0.0696)
Temp_anomaly_orig		-0.9896***	-0.4651	-0.4277	-0.2860	0.0228
		(0.3156)	(0.2938)	(0.2799)	(0.2736)	(0.3149)
Temp_anomaly_dest		-0.5341***	-0.2467***	-0.2489***	-0.3325***	-0.5443***
		(0.0910)	(0.0718)	(0.0721)	(0.0637)	(0.1005)
Prec_anomaly_orig		0.4089	0.2713	0.3423	0.4347	0.2121
		(0.4224)	(0.4254)	(0.4143)	(0.4571)	(0.4540)
Prec_anomaly_dest		0.5466***	0.4128***	0.3867***	0.2477**	0.1358
		(0.1163)	(0.1049)	(0.1076)	(0.1176)	(0.1289)
Urbanization_orig			0.0191***	0.0187***	0.0140*	0.0058
			(0.0042)	(0.0042)	(0.0075)	(0.0098)
Urbanization_dest			0.0298***	0.0295***	0.0241***	0.0102***
			(0.0027)	(0.0028)	(0.0025)	(0.0019)
%ofAgrLand_orig				-0.0113**		
				(0.0050)		
%ofAgrLand_dest				-0.0021		
				(0.0013)		
Agr%GDP_orig					-0.0194	
					(0.0130)	
Agr%GDP_dest					-0.0203***	
					(0.0026)	
AgrEmploy_orig						-0.0208***
						(0.0081)

AgrEmploy_dest						-0.0320***
						(0.0018)
1965.period	-0.0522	-0.1157	-0.2326	-0.2263	-0.4840	
	(0.2065)	(0.2075)	(0.2182)	(0.2091)	(0.4382)	
1970.period	-0.1154	-0.2645	-0.4571	-0.4786	-0.9333*	
	(0.3210)	(0.3186)	(0.3301)	(0.3214)	(0.4795)	
1975.period	-0.5540*	-0.6254*	-0.9885***	-1.0022***	-1.7188***	
	(0.3330)	(0.3405)	(0.3427)	(0.3268)	(0.4663)	
1980.period	-0.2848	-0.2108	-0.7164*	-0.7233*	-1.5991***	
	(0.3709)	(0.3725)	(0.3890)	(0.3701)	(0.5698)	
1985.period	-0.1426	0.0124	-0.6962**	-0.6736**	-1.7526***	
	(0.3239)	(0.3300)	(0.3457)	(0.3372)	(0.4814)	
1990.period	-0.3003	-0.0880	-0.8871***	-0.8881***	-1.8822***	
	(0.3119)	(0.3176)	(0.3265)	(0.3092)	(0.4717)	
1995.period	-0.5368	-0.2755	-1.2106***	-1.2079***	-2.2212***	-0.4054***
	(0.3357)	(0.3510)	(0.3586)	(0.3405)	(0.5181)	(0.1148)
2000.period	-0.4498	-0.0800	-1.1354***	-1.1566***	-2.2029***	-0.3314**
	(0.2939)	(0.3255)	(0.3340)	(0.3154)	(0.4929)	(0.1560)
2005.period	-0.4226	-0.0637	-1.1677***	-1.1796***	-2.2847***	-0.4495***
	(0.3083)	(0.3391)	(0.3480)	(0.3294)	(0.5070)	(0.1457)
2010.period	-0.8457***	-0.4492	-1.6770***	-1.7104***	-2.8697***	-1.0988***
	(0.3147)	(0.3504)	(0.3542)	(0.3389)	(0.5014)	(0.1438)
Constant	-6.6919***	-6.9327***	-9.4278***	-9.3657***	-7.7379***	-8.4456***
	(1.3838)	(1.4221)	(1.1579)	(1.1084)	(1.4980)	(1.4028)
Observations	48,164	46,952	46,952	45,584	35,933	31,518
R-squared	0.279	0.288	0.362	0.364	0.357	0.390
Number of dyads	14,524	14,183	14,183	13,841	12,389	12,199

Robust standard errors, adjusted for country clusters, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Finally, the dyad models with only crisis origins were replicated also for the interactive effect of growth and agriculture dependency drivers and illustrated Table 13. Overall, variables contiguity, common language, colonization past, an differences in GDP per capita exert higher influence on flows for the crisis countries as evidenced by higher values of their coefficients. When it comes to the interaction of temperature with growth rates, the differences between origin and destination GDP per capita rates have a higher effect on mobility for origins with high teperature anomalies but the effect ceases to be statistically significant for precipitation.

One difference with the models that take flow as their dependent variable is the impact of population growth, which ceases to exert a statistically significant effect. Still it may have a gradual effect once it reaches a tipping point, which is not the focus of this working paper. As was the case with all flows, destination country demographic charactersitics seem to play a larger role as shown in the full Model (7). As in the case of tthe models illustrated with the basic drivers, also suggested by the the higher impact of the coefficients of the same drivers, these models have a better fit to the data as evidenced by high R-Squared values. This result indicates that many of the same drivers predicting overall flows are actually more influential in our understanding of crisis flows. As in the previous models, the panel effects are visible, in that independent time effects are observed on crisis level migrations after 1975 as compared to 1960 levels. For the final model, as compared to 1990, negative time effects are detected from 2000 to 2015 with increasing magnitude as evidenced by the big changes in the related coefficients. Precipitation anomalies in destination exert a higher aversion effect when destination is an agriculturally dependent country. Finally the inclusion of interaction effects slightly improved the variance explained by the models.

Table 13: : Interactive effect of climatic drivers of crisis level flows based on country dyads

VARIABLES	Model 1	Model 2	Model 3	Model 4
Contiguity	3.0313***	3.1124***	3.2614***	3.0580***
	(0.3588)	(0.3226)	(0.3494)	(0.3611)
Common Language	1.1717***	1.0645***	1.0175***	1.1378***
	(0.1632)	(0.1416)	(0.1553)	(0.1651)
ColonyofDest	3.6695***	3.9139***	4.1510***	3.5815***
	(0.3161)	(0.2230)	(0.2844)	(0.3150)
ColonizerofDest	0.7751*	0.6786**	0.8683**	0.7758*
	(0.4252)	(0.3345)	(0.3468)	(0.4208)
Distancew1000	-0.1026***	-0.1071***	-0.1072***	-0.1025***
	(0.0153)	(0.0145)	(0.0144)	(0.0145)
LN Population_orig	0.3563***	0.3249***	0.3415***	0.3554***
	(0.0707)	(0.0613)	(0.0675)	(0.0676)
LN Population_dest	0.4227***	0.3789***	0.3728***	0.4219***
	(0.0153)	(0.0135)	(0.0141)	(0.0154)
Landlocked_orig	-0.0938	-0.1788	-0.0195	-0.1203
	(0.2356)	(0.2145)	(0.2748)	(0.2419)
Landlocked_dest	0.0554	-0.1015	-0.0085	0.0635
	(0.0696)	(0.0634)	(0.0724)	(0.0667)
rGDPpcdiff1000	0.0277***	0.0284***	0.0244***	0.0219***
	(0.0052)	(0.0064)	(0.0065)	(0.0055)
Temp_anomaly_orig	0.0228	-0.0357	-0.2475	-0.5713
	(0.3149)	(0.5256)	(0.4864)	(0.6731)
rGDPpcdiff1000 * Temp_anomaly_orig		0.0274**	0.0368***	0.0275**
		(0.0123)	(0.0108)	(0.0108)
Prec_anomaly_orig	0.2121	0.8720	0.5801	0.0830

	(0.4540)	(0.9755)	(0.9996)	(0.9152)
rGDPpcdiff1000 * Prec _anomaly_orig		-0.0111	0.0018	0.0020
		(0.0172)	(0.0182)	(0.0148)
Urbanization_orig	0.0058	0.0176***	0.0131*	0.0048
	(0.0098)	(0.0043)	(0.0075)	(0.0098)
Urbanization_dest	0.0102***	0.0299***	0.0238***	0.0096***
	(0.0019)	(0.0028)	(0.0025)	(0.0018)
Temp_anomaly_dest	-0.5443***	-0.0716	-0.2338	-0.9430***
	(0.1005)	(0.1053)	(0.2054)	(0.1755)
Prec_anomaly_dest	0.1358	0.7021***	0.6403***	1.0105***
	(0.1289)	(0.1711)	(0.2483)	(0.2103)
%Agr Land_orig		-0.0091*		
		(0.0050)		
%Agr Land_orig * Temp _anomaly_orig		-0.0140		
		(0.0103)		
%Agr Land_orig * Prec _anomaly_orig		-0.0115		
		(0.0200)		
%Agr Land _dest		-0.0012		
		(0.0012)		
%Agr Land _dest * Temp _anomaly_dest		-0.0049**		
		(0.0025)		
%Agr Land _dest * Prec _anomaly_dest		-0.0086***		
		(0.0031)		
Agr%ofGDP _orig			-0.0168	
			(0.0130)	
Agr%ofGDP _orig *Temp_anomaly_orig			-0.0163	
			(0.0188)	
Agr%ofGDP _orig * Prec _anomaly_orig			-0.0123	
			(0.0422)	
Agr%ofGDP _dest			-0.0211***	
			(0.0039)	
Agr%ofGDP _dest *Temp_anomaly_dest			-0.0043	
			(0.0113)	
Agr%ofGDP _dest * Prec _anomaly_dest			-0.0295**	
			(0.0131)	
AgrEmploy_orig	-0.0208***			-0.0219**
	(0.0081)			(0.0088)
AgrEmploy _dest	-0.0320***			-0.0359***
	(0.0018)			(0.0022)
AgrEmploy _orig * Temp_anomaly_orig				0.0071
				(0.0139)
AgrEmploy _orig * Prec _anomaly_orig				0.0020
				(0.0204)
AgrEmploy _dest * Temp_anomaly_dest				0.0123**
				(0.0051)
AgrEmploy _dest * Prec_anomaly_dest				-0.0348***
				(0.0052)
1965.period		-0.2271	-0.4982	
		(0.2070)	(0.4493)	
1970.period		-0.4941	-0.9837**	
		(0.3148)	(0.4803)	
1975.period		-0.9812***	-1.7321***	
		(0.3254)	(0.4631)	
1980.period		-0.7074*	-1.5902***	
		(0.3769)	(0.5796)	
1985.period		-0.6536*	-1.7402***	

		(0.3348)	(0.4812)	
1990.period		-0.8716***	-1.8744***	
		(0.3105)	(0.4840)	
1995.period	-0.4054***	-1.1793***	-2.1839***	-0.3804***
	(0.1148)	(0.3413)	(0.5316)	(0.1138)
2000.period	-0.3314**	-1.1058***	-2.1766***	-0.2986*
	(0.1560)	(0.3160)	(0.5027)	(0.1577)
2005.period	-0.4495***	-1.1261***	-2.2579***	-0.4145***
	(0.1457)	(0.3287)	(0.5177)	(0.1495)
2010.period	-1.0988***	-1.6517***	-2.8434***	-1.0440***
	(0.1438)	(0.3412)	(0.5112)	(0.1447)
Constant	-8.4456***	-9.2554***	-7.7993***	-8.1723***
	(1.4028)	(1.0856)	(1.4511)	(1.3886)
Observations	31,518	45,584	35,933	31,518
R-squared	0.390	0.367	0.362	0.397
Number of dyads	12,199	13,841	12,389	12,199

Robust standard errors, adjusted for country clusters, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

DISCUSSION AND CONCLUDING REMARKS

This deliverable aimed at exploring the magnitude of environment induced migration in relation to crisis level flows based on rapid and slow onset climatic changes. In doing this, Abel (2017)'s stock to flow conversions were used with a global dataset created covering 187 countries as both countries of origin and destination for the years 1960 to 2015. In doing this, environment induced migration effects are tested for the longest available timespan and largest available scope, for all bilateral flows in the world. Furthermore, in addition to all flows, higher intensity fllows/crisis flows based on the country of origin are defined and provided an additional testing ground for exploring the effects of the environmental drivers of migration.

The findings regarding both slow and rapid onset changes are mixed, reflecting the extant literature. First, differentiating rapid onset changes based on their impact provides a more nuanced approach and underlines the importance of resilience and capabilities. The impact of rapid onset changes seem more consistent than slow onset changes and while some such as number ofdeaths seem to be correlated with more outflows, this effect disappears once controlled for an interaction with GDP. It then becomes an inhibitor to mobility rather than a push factor. This is consistent with the studies on immobility (Zickgraf 2018) and further supported by the mediating role of GDP per capita. Put differently, the migration inducing effect of the disasters depends on their intensity. A highly damaging disaster both in terms of human lives and in reconstruction costs impose further pressures on economic growth and also mobility. This is also evidenced by the mediating role of the GDP interactions of these effects. Hence the suggestion follows that rather than only looking at an existence of a disaster, future studies should try differentiating the impact of the disaster.

While origin country models allow for a deeper analysis of the factors in place from the perspective of push factors regarding environment induced migration, dyadic models for both changes but especially regarding slow onset ones, yield to better model specifications. This is due to our ability to include additional variables to tap the linkages between the countries such as such as economic growth, inequality, geographical distances, cultural and colonial ties between countries.

Equally importantly, the results contribute to the discussion on the conditional role of agriculture dependency, economic growth, and urbanization on environmentally induced migration. While inconsistent across models, there is some support to the effect of precipitation anomalies in urbanized or more developed countries in pushing mobility. More strikingly, climate related characteristics in the destination country such as low temperature anomalies seem to pull higher international migration. The predictors of regular flows and crisis level flows have similar effects but their magnitude is larger for crisis level flows.

The mixed result also point to various avenues for further research. First of all, the measures of climate anomalies may not fully capture the pressures stemming from climate change and alternative methods could be explored to the actual distress they create in countries of origin. The significant interaction variables attenuating their impact attest to importance of resilience. An alternative way to anayze the data could be categorizing the countries based on income level as a way to approximate considering their capabilities. Furtermore, issues of data availability is a potential threat to our results especially considering the missing data is non random and stems systematically from developing countries, that are largely sources of this out-migration. Furthermore, while Abel's estimates, albeit for five year intervals, considerably improved our ability to explore the temporal dimensions of the data, but only insofar as the measurement of our independent variables allow. As this issue limits our ability to explore more cumulative effects of the environmental drivers in a nuanced way, research on improving this data in terms of filling the year gaps is highly valuable.

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APPENDIX A: DIRECT EFFECT OF DISASTER INTENSITIES ON MIGRATION FLOWS

VARIABLES	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8
LNpop	0.6466***	0.6450***	0.6466***	0.6477***	0.6466***	0.6465***	0.6456***	0.6439***
	(0.0348)	(0.0350)	(0.0360)	(0.0350)	(0.0360)	(0.0347)	(0.0346)	(0.0348)
landlocked_orig	0.0635	0.0650	0.0625	0.0620	0.0625	0.0633	0.0650	0.0642
	(0.1745)	(0.1744)	(0.1744)	(0.1744)	(0.1744)	(0.1744)	(0.1748)	(0.1747)
LNgdppc	0.7097*	0.6901	0.7009	0.7098*	0.7013	0.7030*	0.7309*	0.7112*
	(0.4214)	(0.4208)	(0.4319)	(0.4252)	(0.4319)	(0.4216)	(0.4253)	(0.4194)
LNgdppc#LNgdppc	-0.0481*	-0.0469*	-0.0476*	-0.0481*	-0.0476*	-0.0477*	-0.0495**	-0.0484*
	(0.0249)	(0.0249)	(0.0256)	(0.0252)	(0.0256)	(0.0249)	(0.0252)	(0.0248)
totaldeaths	0.1871							
	(0.5104)							
noinjured		0.5390**						
		(0.2572)						
noaffected			0.0001					
			(0.0004)					
nohomeless				-0.0071				
				(0.0146)				
totalaffected					0.0001			
					(0.0004)			
Reconstructioncosts						0.0000***		
						(0.0000)		
Insureddamages							0.0000*	
							(0.0000)	
totaldamages								0.0000
								(0.0000)
1965.year	-0.0548	-0.0560	-0.0519	-0.0512	-0.0519	-0.0519	-0.0517	-0.0516
	(0.1828)	(0.1819)	(0.1817)	(0.1817)	(0.1817)	(0.1816)	(0.1816)	(0.1816)
1970.year	0.2165	0.2159	0.2171	0.2178	0.2172	0.2172	0.2179	0.2180
	(0.2023)	(0.2026)	(0.2028)	(0.2027)	(0.2028)	(0.2026)	(0.2026)	(0.2026)
1975.year	0.2739	0.2727	0.2745	0.2756	0.2745	0.2744	0.2752	0.2751
	(0.2334)	(0.2335)	(0.2336)	(0.2337)	(0.2336)	(0.2335)	(0.2334)	(0.2334)
1980.year	0.2261	0.2254	0.2265	0.2273	0.2266	0.2265	0.2274	0.2263
	(0.2379)	(0.2381)	(0.2384)	(0.2382)	(0.2384)	(0.2380)	(0.2380)	(0.2381)
1985.year	0.1784	0.1772	0.1782	0.1794	0.1783	0.1783	0.1789	0.1784
	(0.2293)	(0.2294)	(0.2299)	(0.2295)	(0.2299)	(0.2294)	(0.2294)	(0.2294)
1990.year	0.4313**	0.4280**	0.4313**	0.4328**	0.4313**	0.4313**	0.4298**	0.4292**
	(0.2071)	(0.2072)	(0.2079)	(0.2075)	(0.2079)	(0.2072)	(0.2074)	(0.2075)
1995.year	0.4223**	0.4191**	0.4220**	0.4247**	0.4220**	0.4168**	0.4214**	0.4185**
	(0.2057)	(0.2059)	(0.2065)	(0.2064)	(0.2066)	(0.2065)	(0.2059)	(0.2065)

2000.year	0.3114	0.3031	0.3113	0.3124	0.3114	0.3115	0.3104	0.3094
	(0.2044)	(0.2049)	(0.2056)	(0.2046)	(0.2056)	(0.2046)	(0.2047)	(0.2050)
2005.year	0.3382*	0.3350*	0.3383*	0.3395*	0.3384*	0.3374*	0.3345*	0.3338*
	(0.2006)	(0.2010)	(0.2014)	(0.2009)	(0.2014)	(0.2009)	(0.2015)	(0.2019)
2010.year	0.2399	0.2363	0.2401	0.2407	0.2402	0.2382	0.2357	0.2322
	(0.2028)	(0.2031)	(0.2032)	(0.2029)	(0.2032)	(0.2028)	(0.2035)	(0.2045)
Constant	-2.0331	-1.9312	-1.9961	-2.0486	-1.9985	-2.0033	-2.0942	-1.9851
	(1.9635)	(1.9662)	(2.0359)	(1.9868)	(2.0357)	(1.9650)	(1.9750)	(1.9536)
Observations	1,520	1,520	1,520	1,520	1,520	1,520	1,520	1,520
R-squared	0.383	0.383	0.383	0.383	0.383	0.383	0.383	0.383
Number of orig_n	174	174	174	174	174	174	174	174

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1