UNIVERSITÀ DEGLI STUDI DI MACERATA

CORSO DI DOTTORATO DI RICERCA IN

METODI QUANTITATIVI PER LA POLITICA ECONOMICA

CICLO XXXIV

Essays on Environmental Migration

Supervisore di tesi
Chiar.mo Prof. Luca DE BENEDICTIS

Co-supervisore di tesi
Chiar.ma Prof.ssa Maria CIPOLLINA

Coordinatore
Chiar.mo Prof. Luca DE BENEDICTIS

Dottoranda:
Dott.ssa Elisa SCIBÈ

Anno 2020/2021

Acknowledgements

First and foremost I am extremely grateful to my supervisor, Prof. Luca De Benedictis for his invaluable advice, continuous support, and extreme patience in critical moments throughout these years of academic career at Università di Macerata. Even through hard times, his encouragement has been an essential source of strength to go through these past years. I am also extremely grateful for the precious help and contribution to Prof. Maria Cipollina, and her practical help and extreme availability in countless situations. It is especially and undoubtedly thanks to them and their support I could make it to continue and complete my PhD. Their substantial contribution to the dissertation and their supportive kindness have been essential.

A special thanks also to Prof. Gani Aldashev, for his warm welcome and interesting advise during my stay at ECARES. Thanks for the financial support to FSE Marche and the *Dottorato Innovativo* scholarship. Many thanks to the organisers of conferences in which I had the occasion to present my work, Francesca Pallotti, Tom Stanley, and the participants to various seminars and conferences (EUSN2021, MAER-Net Colloquium 2021) for the insightful comments.

On a personal note, thanks to my many families: the one I have always had, those I had for a longer time than I could remember and the one I found in the process. Far away and apart or locked-down together do not make any difference. A special mention goes to the big Scarron family, who had the hardest task to constantly witness and magnificently support the entire process.

Contents

List of Figures

List of Tables

List of Abbreviations

FAT	**F**unnel **A**symmetry **T**est
FEM	**F**ixed **E**ffects **M**odel
IPCC	**I**ntergorvernmental **P**anel (on) **C**limate **C**hange
JRC	**J**oint **R**esearch **C**enter (European Commission)
INFORM	**In**dex **for** **R**isk **M**anagement
LAC	**L**atin **A**merica (and the) **C**aribbeans
MST	**M**inimal **S**panning **T**ree
MENA	**M**iddle **E**ast (and) **N**orth **A**frica
MA	**M**eta **A**nalysis
MRA	**M**eta-**R**egression **A**nalysis
PET	**P**recision **E**stimate **T**est
REM	**R**andom **E**ffects **M**odel
RUM	**R**andom **U**tility **M**aximisation
SNA	**S**ocial **N**etwork **A**nalysis
UN	**U**nited **N**ations
UNDRR	**U**nited **N**ations (office for) **D**isaster **R**isk **R**eduction
WLS	**W**eighted **L**east **S**quares

Introduction

In a world of changing climate and increasing occurrence of natural hazards, the role of environmental factors in shaping migration patterns throughout the world has become a major importance challenge. The relationship between environmental factors and human mobility has gained visibility and a compelling urge to be addressed during the past few decades in the global policy agenda and more recently within academia. The most recent IPCC Sixth Assessment Report shed light on alarming future scenarios caused by climatic variations and modified environmental conditions all over the world and advised for necessary measures to contain damages and reduce disaster risk. Well-documented scientific evidence shows the increase of extreme and frequent disruptive events, caused by climatic variations. Unfavourable environmental conditions directly impact many aspects of human lives, through livelihoods, economic activities, the habitability of certain areas or development perspectives. This raises the need to address the linkages with human mobility, among other potential impacts. Both sudden and gradual environmental changes may intervene in determining the decision to migrate. However, disentangling the role of determinants to migration has been the object of research efforts for decades, with a general consensus reached around the extreme complexity of factors. The undeniable relevance of altered conditions due to climate change urged the inclusion of environment-related factors in those frameworks. The intricacy of the relationship cannot be only retraced in the many manifestations of climatic and hazardous events in the different parts of the world. Frequency and intensity are accompanied by matters of timing, location and preexisting conditions of populations and areas. Furthermore, mobility can itself take many forms, in a scale that goes from momentary displacement to neighbouring areas to longer-term international migration, in a complex multi-causal combination of factors.

This dissertation moves from the need to address evidence-based indications on the relationship between environmental factors and migration. The starting point is an overview of academic contributions produced until now concerning the subject. Moving away from a canonical literature review, a novel approach is introduced in Chapter 1 and further developed and integrated into Chapter 2. The necessity to overview the extreme heterogeneous outcomes and non-consensual conclusions drawn on the magnitude and sign of the relationship led this dissertation to gather the most extensive ensemble of economic literature in the field and thoroughly analyse it in a three-fold methodological strategy. A preliminary bibliometric analysis of the main features of all contributions collected shows an extreme heterogeneity of approaches, methodologies and, most importantly, outcomes, which raises the assumption of the existence of potential inter-connectivity between the documents and the formation of club-like communities. This assumption is tested and proven by detecting communities of contributions on the citation-based network of the entire sample of documents (Chapter 1). A further step is taken in Chapter 2: to test the validity of the assumption, I built a unique dataset of estimated coefficients included in empirical analyses having a measure of mobility as the dependent variable and environmental factors as regressors to run a meta-analysis and detect the average size effect. Accounting for potential sources of heterogeneity between studies, the emerged clustered structure is applied to separate conditional meta-regressions. Cluster-by-cluster effect sizes converge towards different and opposite outcomes and conclusions.

The following two chapters of the thesis provide two different applications to migration modelling. Chapter 3 capitalises on Social Network Analysis tools to provide a detailed descriptive analysis of international migration flows spanning the last 30 years (1990-2020) by using the most recent data source available to detect factors of evolution or stability. The analysis goes beyond well-known descriptive tools of the network by applying a technique of visualisation of the hierarchical structure of the network which, to the best of my knowledge, has not been used yet to model migration networks. The structure resulting from the extraction of the *minimal spanning tree* displays some important features of the World Migration Network in the last three decades and reveal many linkages with predictions issued from gravity models applied to migration. Exploiting the dyadic structure of data analysed in Chapter 3, a gravity approach to migration and environmental factors is provided in Chapter 4.

The evidence emerged from the three-stage analysis of the literature (Chapter 1-2) motivates the assumptions that underlie the model applied in Chapter 4: occurrence, frequency and intensity might not explain entirely the impact exerted by hazardous events on different regions. Natural disasters interact directly with intrinsic characteristics and conditions of the affected area in a complex interplay of risk dimensions determined by physical, social, economic and environmental factors. The three dimensions of exposure, vulnerability and lack of coping strategy are then analysed and included in a structural gravity model applied to migration to assess their combined and single weight.

Overall, this study provides an extensive framework of analysis on environmentally-driven migration and a picture of the complex heterogeneity of the relations between the two phenomena. Drawing from existing contributions and offering novel methodological and conceptual applications to the analysis, this work is intended as an attempt to contribute to the ongoing debate on the topic.

Chapter 1

Mapping the Literature on Environmental Migration

1.1 Introduction

As opposed to a simplistic vision of a general direct role of environmental factors in determining migration flows from environmentally stressed areas and regions hit by calamities, more complex scenarios have been the result of investigations, with analyses reporting different and sometimes opposite outcomes. This may not only be due to the intrinsic complexity of their extent and scale, but also to differences in specific characteristics of scientific contributions.

This chapter aims at mapping the economic literature on these topics moving away from a classical literature review and offering a methodology that integrates multiple approaches in a sequence. The analysis starts with systematic research of the literature through main bibliographic databases and collecting previous reviews and meta-analyses, followed by a review and bibliometric analysis of all resulting papers. This first step produces a sample of 151 papers empirical and non-empirical contributions, spanning the last 20 years and focusing on different geographical areas, taking into account different socio-economic factors, applying different methodologies and empirical approaches. Most importantly, the sample provides a variety of different outcomes on the impact of climatic changes and hazards on migration, revealing three main possible scenarios: (1) active role of environmental factors as a driver of migration; (2) environmental factors as a constraint to mobility; (3) non-significant role of environmental factors among other drivers of migration.

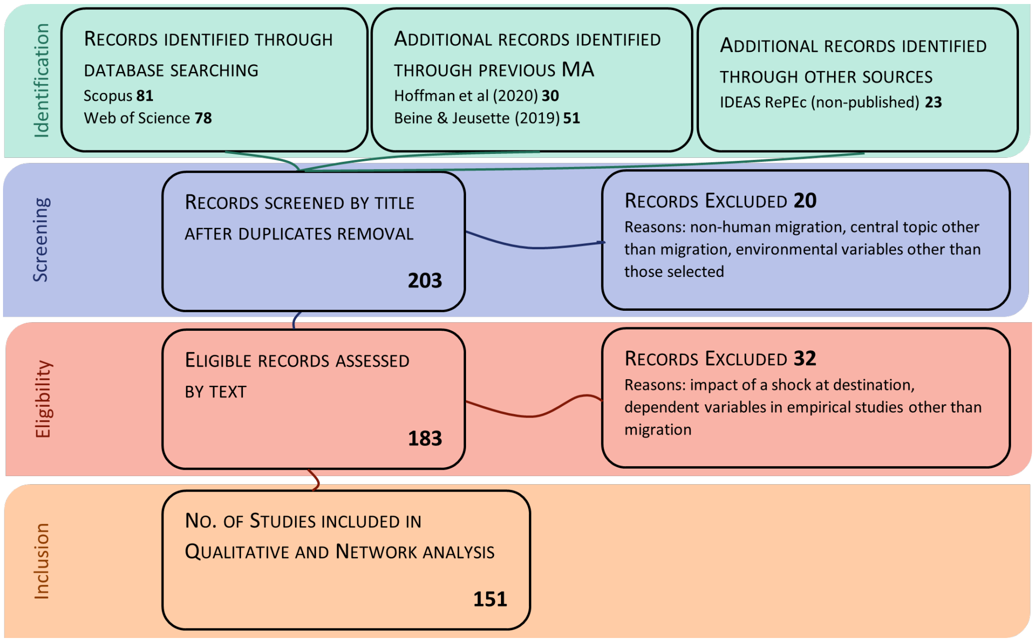
To investigate the determinants of this extreme heterogeneity of outcomes, an assumption is postulated: the inter-connectivity of papers may play a role in shaping such opposite conclusions. Considering the ensemble of papers referenced by each contribution included in the sample, as a second step, a bibliographic coupling network is built, where papers are linked to each other according to the number of shared references. This citation-based method allows for the formation of a network of contributions in the literature space and highlights some potential common grounds among papers. The community detection on the resulting network produces four main clusters that gather papers together according to not only certain characteristics of the analysis but also resulting outcomes.

The clustered structure will then be included in the meta-analysis presented in Chapter 2: estimated effects of environmental variables on human mobility will be tested through meta-analytic tools to summarise and analyse the literature on environmental migration. This chapter is structured as follows: Section 1.2 offers a systematic review of the literature and gives a detailed description of the data collection process; Section 1.3 analyses the structural characteristic of the network of the bibliographically coupled papers; Section 1.4 details the characteristics of clusters and comments on their structure.

1.2 Systematic review

This section details the different phases of the systematic review. Each step is schematically described to facilitate the understanding of the procedure. The main aim of this section is to provide the most comprehensive sample of economic contributions on the relationship between climatic variations and natural hazards on the one side and human mobility in all its different forms on the other. To do so, a systematic review is implemented and aimed at mapping the largest extent of the body of literature and defining the boundaries of our focus. Systematic reviews have become highly recommended to conduct bibliographic overviews of specific literature because they provide a tool to transparently report a synthesis of the state of the art of a field through to a structured methodology (Page et al., 2021). To allow for comparability with previous meta-analyses and reviews, the sample also includes all the articles included in two recent meta-analyses, Hoffmann et al. (2020) and Beine and Jeusette (2021). Systematic reviews begin with the definition of the research question and the main keywords, to gather and collect data in a sample of contributions. The definition of inclusion and exclusion conditions is followed by a screening by title to exclude off-topic contributions and then to a screening of the text to assure the uniformity of contributions. The resulting sample is then the object of a preliminary bibliometric analysis.

FIGURE 1.1: PRISMA Diagram



Note: PRISMA Diagram (Liberati et al., 2009) of identification, screening, eligibility and inclusion stages of academic contributions. The resulting sample is obtained through search on Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2019).

Figure 2.1 shows the PRISMA diagram (Liberati et al., 2009) of the process of identification, screening, eligibility, and inclusion of contributions in the final sample. The following paragraphs describe each step in detail. The resulting sample includes all kinds of economic contributions, both quantitative and non-quantitative[1]. For the purpose of the analysis hereby presented, the choice is to keep every eligible contribution that can be of interest in building the taxonomy of the whole concerned literature, as they may play a role in building links between different contributions. Non-quantitative (policy, qualitative or theoretical) papers may participate as well in the development of research fronts or to give a direction to a certain thread of contributions and incidentally affect the detection of clusters. These reasons led to building the citation-based network and performing the network analysis and the community detection on the whole sample, while the sample for the MA is restricted only to quantitative contributions that meet the coding requirements.

[1] In Chapter 2 an additional level of inclusion is included: the first level hereby considered identifies the sample of contributions included in our network analysis, while the second level will restrict to quantitative analyses suitable for the meta-analysis. The motivation behind this choice is that to conduct a meta-analysis it is crucial to select only comparable papers that provide complete information, which implies the exclusion of papers that do not comply with the requirements of a meta-analysis.

1.2.1 Definition of the research question and keywords

The purpose of the systematic research is to collect all economic contributions on the impact of environmental factors on migration determinants. Three main keywords are defined, capturing in a general way the three main phenomena under study. The first keyword is "*climate change*". As part of the environmental factors, the role of climate change is widely the most investigated across the literature on migration determinants. The events connected to climate change are hereby intended as slow-onset events that gradually modify climatic conditions in the long run. The focus is specifically on the variation of temperature, precipitation, and soil quality (such as desertification, salinity, or erosion), factors that are not expected to cause an immediate and sudden expected impact, but slowly modify environmental conditions. The second category is identified by the keyword *"natural disasters"*, defining fast-onset events that present themselves as a hardly predictable sudden shock. The classification is drawn on the classification made within the framework of the EM-DAT (*Emergency Events Database*) developed by the Centre for Research on the Epidemiology of Disasters (CRED): geophysical, meteorological, hydrological, climatological and others (see table C.1 for a detailed list of categories and relative events).

Finally, "*migration*" is the last keyword. The intent is to observe the phenomenon under a large spectrum of possible patterns of human mobility. Along with international migration, internal mobility is also included (within the borders of a country) which is very likely to be a potential response to environmental change. Internal mobility includes also the process of urbanisation, the specific channel of population moving out of rural areas to settle in cities.

1.2.2 Data collection and initial search results

The data collection process is articulated in three main groups: database sources, working papers, previous meta-analyses. The first collection step implies the choice of the database to search on. Two main databases of literature are selected: Scopus, a database created by Elsevier, and Web of Science, a service provided by Clarivate Analytics. They collect, respectively, more than 12 thousand and 8 thousand journals, including social sciences (thus economics). Compared to other common sources (such as Google Scholar), they have many advantages: they allow for restricting the search to specific areas, provide detailed information about the specific contribution and allow for the extraction of the full list of references cited by the

TABLE 1.1: Classification of natural hazards

Category	Definition	Type of hazard
Geophysical	Hazard originating from solid earth	Earthquake Mass movement (rock fall, landslide) Volcanic activity.
Meteorological	Hazard caused by short-lived extreme weather and atmospheric conditions that last form minutes to days	Storm (tropical and extra-tropical storm, convective storm) Extreme temperature (cold wave, heat wave, severe winter) Fog
Hydrological	Hazard caused by the occurrence, movement, and distribution of water	Flood Landslide (wet) Wave action
Climatological	Hazard caused by atmospheric processed ranging from intra-seasonal to multi-decadal climate variability	Drought Glacial lake Wildfire
Others	Hazard caused by other causes, such as exposure to toxic substances, vector-borne diseases carried by living organisms, impact of extraterrestrial objects	Epidemics Insect infection Miscellaneous*

Note: Classification made within the framework of the EM-DAT (*Emergency Events Database*) developed by the Centre for Research on the Epidemiology of Disasters (CRED). https://www.emdat.be/classification
*This category includes biological and extraterrestrial events which, however, are marginally covered by the literature in a small number of contributions.

paper.[2] Exploiting the specific indexing and keyword definition of both sources[3], the search is run allowing for any kind of document type (articles in journal, book chapters, etc.) but limiting the area to economic literature in English[4]. The results of the research are then be downloaded in bulk and include exclusively published documents. An additional source, the bibliographic database IDEAS, based on RePEc and dedicated to Economics, is added to include working papers that have not been published yet or at all.[5]. A selection of the contributions is made manually through

[2] This feature will be important for the next steps of the bibliometric analysis and more importantly to build the citation-based network. The extraction is made through bibliometrix, an R tool for science mapping analysis that reads and elaborates the information exported by Scopus and Web of Science (Aria and Cuccurullo, 2017).

[3] The code ”KEY” in Scopus' Advanced Research tool is a combined field that searches the author keywords and controlled vocabulary terms assigned to the document; in Web of Science the code ”AK” refers to author keywords, while ”KP” refers to ”Keyword plus” a feature of WoS that assigns words and phrases that appear frequently in the titles of an article's references.

[4] Scopus: KEY(”migration” AND (”natural disasters” OR ”climate change”)) AND (LIMIT-TO(SUBJAREA,”ECON”)) AND (LIMIT-TO(LANGUAGE,”English”)), Date: 24/11/2020.
Web of Science: ((AK=(migration AND (”natural disasters” OR ”climate change”))) OR (KP = (migration AND (”natural disasters” OR ”climate change”)))) AND LANGUAGE: (English) Refined by: WEB OF SCIENCE CATEGORIES: (ECONOMICS), Date: 24/11/2020.

[5] The main limitation of results from Scopus and Web of Science is that the sources only contain published documents. Keeping in mind that the sample will be used to perform a MA in the next

TABLE 1.2: Results of data collection across sources

Source		**Records**
Published documents		
	Scopus	81
	Web of Science	78
Non-published documents		
	IDEAS RePEc	23
Previous reviews		
	Beine and Jeusette (2021)	51
	Hoffmann et al. (2020)	30
Records after duplicate removal		203

the searching tool[6]. Finally, to meet the purpose of comparability with other recent meta-analyses, I also include all the contributions that have been reviewed in two main meta-analytic articles on the topic. Hoffmann et al. (2020) provide a meta-analysis on 30 empirical papers on the impact of climate change and natural disasters on migration. Their work specifically focuses only on country-level studies relying on a uniform sample that allows for a specific standardisation process. All 51 papers reviewed in Beine and Jeusette (2019) (recently published Beine and Jeusette, 2021) are also included, which offers an investigation of the role of methodological choices of empirical studies (at any level) on the sign and magnitude of estimated results. Merging the results together gives a sample of 203 records (Table 1.2).

1.2.3 Screening of the results

The sample may contain some contributions that do not correspond to the definition of the reference literature. As in canonical systematic reviews, I proceed to screen the collected items in two steps: the first screening by title, and a subsequent screening by text of the remaining documents. This step is only applied to the contributions collected through Scopus and Web of Science. All the papers in Beine and Jeusette (2021), Hoffmann et al. (2020) and those manually selected from IDEAS RePEc are automatically included in the sample with no concern of incoherence. The screening by title leads to the exclusion of 20 papers. At this stage, excluded papers are: those treating migration other than human (i.e. plants and animal species), those analysing the impact of environmental variables other than the selected ones (i.e. air pollution, mineral resources), and those focusing on topics different from human mobility (i.e. discrimination, crime, war). The remaining 183 documents are then

chapter, it is important to take into account also non-published documents, to control for a well-known reporting bias in meta-analytic methodology, the publication bias (which will be discussed in section 2.2.1).

[6] The Advanced Search tool allows to search by Keywords and Title: migration AND (”natural disasters” OR ”climate change”).

screened by text in order to isolate eligible contents. This stage leads to the removal of additional 32 documents covering, on the one hand, the analysis of the impact of environmental variables at destination countries (thus not focusing on their role on migration determinants at origin). On the other hand, it excludes all the papers in which the dependent variable of the empirical exercise is not a measure of human mobility (i.e. remittances, poverty, wealth, employment, etc.). After duplicates removal, the sample results in 151 documents of different kinds. The screening by text is also made to identify the various group contributions: 116 records are categorised as empirical and 35 as non-empirical. The former category includes all documents that empirically estimate a model in which the dependent variable is a measure of human mobility and at least one environmental variable enters the model as the independent variable. Non-empirical records contain the ensemble of literature reviews, qualitative analysis, theoretical modelling, and policy papers[7].

1.2.4 Bibliometric Analysis

This section summarises the most relevant features of the ensemble of economic literature collected.[8] Thanks to the R tool bibliometrix (Aria and Cuccurullo, 2017) all records can be uploaded and summary statistics regarding their main features produced. Scopus and Web of Science allow for the download in bulk of records in .bibtex format, ready to be converted in R objects.[9] All the remaining records are manually entered, depending on the publication status of the single record: for published documents an additional research of the specific document is made on Scopus and the relative .bibtex file is downloaded and added to the other results; for unpublished papers, which cannot be found in the two sources, a .bibtex is manually created following the structure of fields and information in the downloaded ready-to-use files. After merging each file and removing duplicates the overall data source contains the bibliographic information of all articles, including publication year/latest draft, author(s), title, journal, keywords, affiliations, and references.

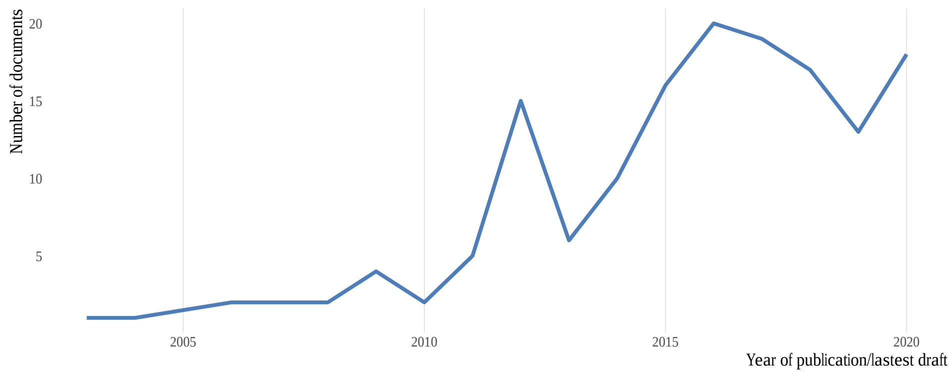
Time-span. The first result is that the scientific production in the specific field is quite recent. Economic literature has started to pay attention to the potential relevance of environmental events on migration in the early 2000s, although the topic

[7] A further screening of empirical contributions eligible for the meta-analysis is made to ensure a correct and homogeneous codification. As it will be described more in detail in the next chapter, 96 out of 116 empirical contributions made it to the meta-analysis

[8] The complete list of articles is provided in section **??** of the Appendix

[9] The ensemble of records found in the two databases contains all the main information related to each document: citation information, bibliographical information, abstract & keywords, funding details, and other information, including the list of cited references.

FIGURE 1.2: Number of documents per year



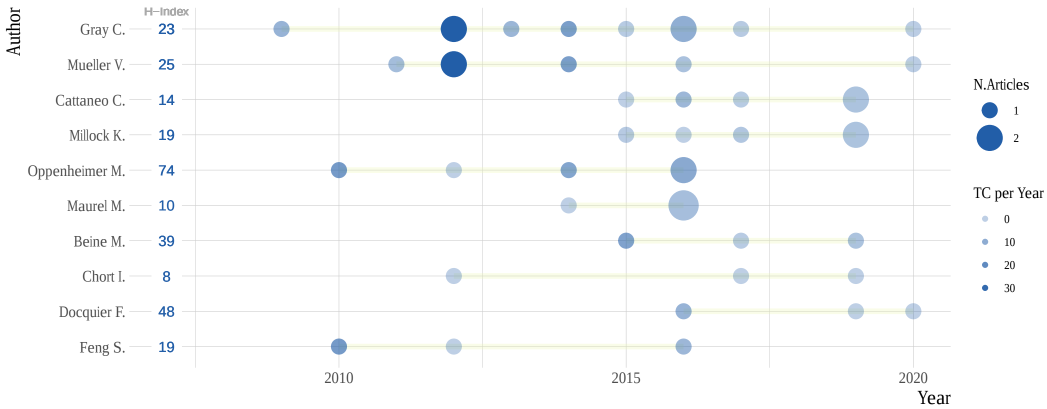
Note: Sample of academic contributions about migration and environmental factors from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021) collected, merged, screened and included by the authors.

had already gained some relevance in global debate decades before. Figure 1.2 shows that the scientific production on the specific field covers a period that goes from 2003 to 2020, with a peak of 20 contributions in 2016 and an annual growth rate for the overall period at 18.5 percent. Taking a closer look at the cited references, it is possible to trace back an article published before 2003 (Findley, 1994) that provides a qualitative analysis of drought-induced mobility in Mali (finding no evidence of any role of 1983-85 droughts on migration).

Authors. By extracting the author field from the database of all contributions, it is possible to observe the frequency of most productive authors and their citations per year (Figure 1.3). Geographer Clark Gray is by far the most productive in our sample, authoring 10 articles spanning an entire decade, followed by his co-author, economist Valerie Mueller, authoring 6 articles and appearing together in 5 of them. Interestingly, their articles have the highest total citations per year of all most productive authors, especially for the two articles published in 2012 (Gray and Mueller, 2012a; Gray and Mueller, 2012b).

Other relevant contributors are Cristina Cattaneo, Katrin Millock and Michael Oppenheimer with 5 documents each. The figure shows also the *h-index* of the authors, a bibliometric measure introduced by Jorge Hirsch in 2005 (Hirsch, 2005) and now widely used in infometrics (Bar-Ilan, 2008; Harzing and Alakangas, 2016). An author has an index h if h of his/her N papers have at least h citations each, and the

FIGURE 1.3: Top-Authors' Production over time and *h-index*



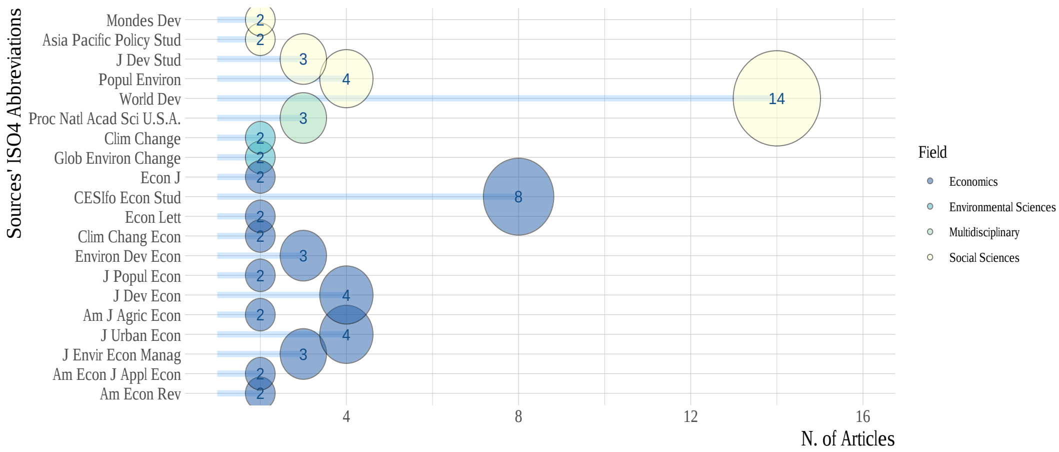
Note: Sample of academic contributions about migration and environmental factors from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021) collected, merged, screened and included by the authors.

other $(N-h)$ papers have no more than h citations each (Hirsch, 2005). The measure can be retrieved from either of the source databases used, Scopus and Web of Science, and Google Scholar, but the values would result very differently. Although each of the source databases has its limitations in terms of the preciseness of the measure, from time to publication coverage, the indices reported rely on Google Scholar measures,[10] which provides the most comprehensive and interdisciplinary coverage of the literature (Harzing and Alakangas, 2016). Among the top authors included in the environmental migration literature, Professor Michael Oppenheimer scores the highest *h-index* and at least 5 contributions, being globally considered one of the pioneers to warn about the climate emergency both in academic research and international organisations.[11] Michel Beine and Fréderic Docquier, as two prominent economists specialised in migration, appear in the top 10 authors with 3 contributions each, denoting a growing interest in environmental issues within migration literature. Overall 288 authors have contributed to this literature, with 372 appearances. On average, considering the sample entirely, thus including the 34 single-authored documents, the number of authors per document is 1.88; when considering exclusively multi-authored documents, the number of co-authors per document rises to 2.16, with a maximum of co-authors of 9.

[10] Whenever the *h-index* of an author was not available on Google Scholar, I included the value extracted from Web of Science. Infometric literature has argued that Scopus shows consistently lower scores of *h-indices*, compared to Web of Science (Harzing and Alakangas, 2016).

[11] https://www.reuters.com/investigates/special-report/climate-change-scientists-oppenheimer.

FIGURE 1.4: The 20 most relevant publication sources by field



Note: Sample of academic contributions about migration and environmental factors from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021) collected, merged, screened and included by the authors.

Sources. The sample is composed of published and unpublished documents coming from 80 different sources (respectively peer-reviewed articles, book chapters and working and discussion papers, conference proceedings). Overall, 119 documents are published in a journal or a book, while the remaining 32 are still unpublished or correspond to the last available draft of an unpublished document. Figure 1.4 shows the most relevant journals having published an article on the effect of climate or hazards on migration from an economic perspective or using an econometric approach. Various disciplines have put the attention on the topic: even if journals specialised in economics and econometrics represent the majority of the sources of publication, the literature includes also other disciplines. Specifically, economic environmental migration is the object of publication in journals specialised in environmental sciences, geography, and social sciences such as urban studies, agriculture, demography, political studies. A special mention has to be done of development studies: many reviews and journals specialised in development have issued contributions to the topic, highlighting the trend of observing the topic through development lenses. As an example, 14 documents in our sample are published in *World Development*, a multi-disciplinary journal of development studies.

Citations. Table 1.3 shows preliminary measures of citations concerning the documents included in our sample. A further investigation on the links among papers based on citations will be discussed and analysed in the next section. However, a

TABLE 1.3: Most cited documents: global and local citations

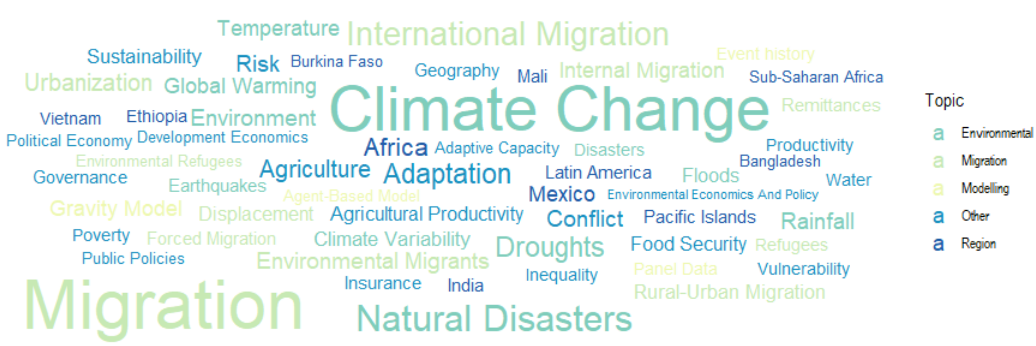
Author (year)	Global Citations	Author (year)	Local Citations
Gray and Mueller (2012b)	216	Marchiori et al. (2012)	48
Barrios et al. (2006)	203	Gray and Mueller (2012b)	46
Feng et al. (2010)	203	Barrios et al. (2006)	45
Henry et al. (2004)	198	Beine and Parsons (2015)	42
Gray and Mueller (2012a)	154	Feng et al. (2010)	37
Hornbeck (2012)	140	Henry et al. (2004)	36
Mueller et al. (2014)	130	Gray and Mueller (2012a)	36
Gray (2009)	115	Bohra-Mishra et al. (2014)	36
Henry et al. (2003)	112	Halliday (2006)	32
Bohra-Mishra et al. (2014)	111	Mueller et al. (2014)	29

Note: Sample of academic contributions about migration and environmental factors from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021) collected, merged, screened and included by the authors.
* Global citations: actual number of citations in Scopus
* Local citations: number of citations within the sample of 151 contributions

picture of the most relevant documents included in the sample is provided by simple measures, such as the number of global citations as reported in Scopus (at the moment of bulk download of all sources), and the number of local citations, which shows how many times a document has been cited by other papers included in the sample. The difference between global and local citations scores (almost four times higher) reveals that the documents have been cited by papers not included in our sample. It means that environmental migration has attracted the interest of different disciplines or they became part of the two main strands of literature, climate change, and migration, separately. There are 58 papers that have not been cited in the sample, while 52 have zero citations globally. A part of it can be explained by the 18 papers that have been published recently in 2020, which could not have been cited yet because of timing[12] (except for some contributions published in early 2020 such as Mueller et al., 2020 and Rao et al., 2020). Position and number of citations confirm the central role of papers published by Clark Gray and Valerie Mueller (Gray and Mueller, 2012b; Gray and Mueller, 2012a; Mueller et al., 2014), receiving high citations both globally and internally. Some papers seem to be more relevant locally than globally: Marchiori et al. (2012) and Beine and Parsons (2015) had a bigger influence on our sample of economic environmental migration literature rather than globally, scoring the highest number of local citations. At the same time, Hornbeck (2012) seems to be cited more in literature outside the specific literature of environmental migration.

[12] The issue of timing will be addressed in the network analysis, choosing a specific type of citation-based network, the bibliographic coupling network, to minimise the risk of missing connections between papers.

FIGURE 1.5: Word cloud of most common keywords



Note: Sample of academic contributions about migration and environmental factors from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021) collected, merged, screened and included by the authors.

Keywords. Figure 1.5 shows the cloud of most common authors' keywords in the sample. The cloud contains only words or phrases repeated more than once. As our research of documents is based on keywords, naturally the three most repeated are those put as search key ("migration", "climate change" and "natural disasters").[13] As far as migration is concerned, it seems that international mobility has been treated more than internal migration; however, internal migration may include also urbanisation or rural-urban migration which, aggregated together, are as recurrent as international migration (counting 21 repetitions per group). Environmental migration is also present as a form of *forced migration*, originating refugees, or specifically environmental refugees. Keywords regarding environmental topics show a special focus on slow-onset events (*rainfall, temperature, global warming* and *climate variability*) more than specific rapid-onset events. Although, some of the latter are more recurrent than others, such as *drought, floods* and ultimately *earthquakes*. The cloud gives also a picture of the geographical scope of the analyses, with Africa being the top region in keywords (15 repetitions) as a continent (*Africa*), as specific regions (*Sub-Saharan Africa*) and specific countries within the area (i.e. *Mali, Ethiopia, Burkina Faso*). It is followed by *Mexico* (being a keyword 5 times alone) and *Latin America* in general. Asian countries mostly appear separately instead of as a region, with *Bangladesh, India* and *Vietnam* on top, being the object of specific case studies. Some phrases related to the specific economic model or estimation method used to analyse the data enter the cloud, giving a picture of the direction of empirical studies. Gravity models are

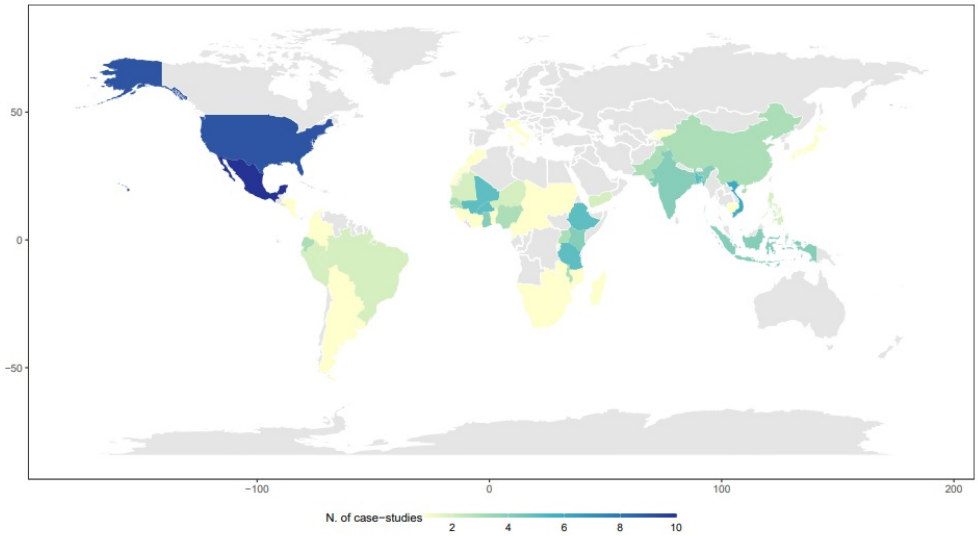
[13] Variants of words or concepts have been aggregated in a unique item i.e. *climate change* and *climatic change* or *environmental migrants* and *environmental migration*.

most used, mainly for international migration modelling, while event history models are mainly used for micro-econometric analyses at the household or individual level. As already mentioned, environmental migration is often studied looking at potential mechanisms channelling the effect of climate or disasters on human mobility. Some of these channels appear clearly in the cloud, forecasting the main topics the literature treated to analyse the complexity of the phenomenon. Agriculture is a prominent channel explored in environmental literature and it appears in keywords as *agriculture* and *agricultural productivity* representing together the most recurrent words. Agriculture is closely followed by *conflict* which is often investigated in literature as a link between environment and migration. Other important concepts emerging from the cloud and characterising the literature are *adaptation* and *risk*, as a way of conceiving migration as an adaptive strategy, and the adverse environmental conditions as a source of risk for human lives, assets, and livelihoods.

1.2.5 Review of the results

The literature on the effects of climate and natural disasters on migration is characterised by a rich variety of studies both in micro- and macro-economic analyses. Country-level analyses tend to find evidence of a direct or indirect impact of environmental factors on migration patterns, either internally or internationally. Barrios et al. (2006) and Marchiori et al. (2012) find evidence of an increase in internal migration, especially towards urban areas in the case of Sub-Saharan Africa, according to many specific historical and development-related factors. Both contributions highlight how worsening climatic conditions correspond to a faster urbanisation process. Marchiori et al. (2012) add also that this climate-driven urbanisation process results also in higher international migration rates, acting as a channel of transmission of the effect of climate. The macro literature, in line with most validated theoretical models of migration, also investigates whether the effect is conditioned to income levels of the country of origins of potential migrants (Marchiori et al., 2012; Beine and Parsons, 2015; Beine and Parsons, 2017). The role of income in a specific origin country experiencing the effects of environmental events is found to be crucial to determine the sign and the magnitude of the impact. Cattaneo and Peri (2016) support from one side the active role of those events on fostering migration, but show how this effect is conditioned to middle-income countries. The effect is opposite when conditioning the analysis to poor countries, highlighting the existence of certain *constraints* to mobility. Worsened environmental conditions may in fact exacerbate liquidity constraints or lack of access to credit aimed at financing the migratory project, which leads to what has been called *poverty trap*. Furthermore, these

FIGURE 1.6: Number of case studies covered by the micro-level sub-sample per country



Note: Sub-sample of micro-level studies about migration and environmental factors from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021) collected, merged, screened and included by the authors.

conditioned results seem to be robust even when another important channel is controlled, agricultural productivity. Climatic conditions and disruptive hazards may constitute major drawbacks for agricultural productivity, leading the agriculture-dependent part of the population to move out from rural areas: Cai et al. (2016) and Coniglio and Pesce (2015) provide evidence of an indirect link between worsened temperature and precipitation conditions and migration, mediated by the level of agricultural dependency of the country of origin. Sudden and fast-onset hazards, on the other side, are not found contributing significantly to human mobility, except in the case of highly-educated population, more mobile than other groups after the disruption of a natural disaster (Drabo and Mbaye, 2015).

Micro-level literature provides a vast variety of case studies on the different potential impacts of environmental factors on mobility. In the sample, they count almost the double of macro-level contribution (86 contributions against 47) and provide different scenarios. Firstly, while macro-level studies mostly provide analyses at the global level or for some group of countries or macro-regions, micro-level analyses tend to observe a specific phenomenon hitting a specific area or to study differences in the impact of a common phenomenon in different areas. Figure 1.6 shows the coverage of literature of case studies or specific analysis per country. The most covered region as a whole is Sub-Saharan Africa, with 65 case studies included in the contributions (note that some contributions are not single-case studies). When the level of analysis is less aggregated than the national or sub-national level, and individuals or households' behaviour is observed through the use of surveys, the picture gains complexity and less generalised conclusions. This seems clear in Gray and Wise (2016) who analyse a series of comparable surveys across five Sub-Saharan countries, which have consistent differences. The heterogeneity of responses to climatic variations across those countries is strictly linked to the characteristics of the area and of the specific households. Poorer countries (such as Burkina Faso) mainly experience internal and temporary migration, often on a rural-rural channel as a way to diversify risk (Henry et al., 2003; Henry et al., 2004). Long-distance migration seems to be constrained by liquidity and access to credit to finance those expensive journeys. Migratory trends of Nigerian households are pushed in times of favourable climatic conditions, while the effect of adverse conditions interacts with a negative effect on income and traps populations at origin (Cattaneo and Massetti, 2019). Overall, micro-level studies focused on the African continent highlight the importance of considering the interplay of a variety of factors when it comes to the analysis of the role of environmental factors, defining the new path towards hybrid literature.

The single countries that receive alone the most attention are Mexico, with 10 case studies, and the U.S., with 9 case studies. This should not be a surprise because of two reasons: firstly, the stock of Mexican emigrates has been constantly the highest in the world (in absolute terms) as well as the migratory flow between Mexico and the U.S. But there might also be a publication-related reason based on the fact that the vast majority of journals in our sample are U.S. based. Major findings support the relevance of environmental drivers (mainly precipitation shortage) on push factors from Mexico (Feng et al. (2010) estimates that a 10% reduction of agricultural productivity driven by scarce rainfall corresponds to the rise of 2% of emigrants).

Southern and Eastern Asia, representing by far the most disaster-prone area in the world[14] also provide a variety of heterogeneous scenarios. The case of Vietnam (Koubi et al., 2016a; Berlemann and Tran, 2020) shows how the Vietnamese population chooses different coping strategies in response to different kinds of environmental stressors. While gradual climatic variations lead to mechanisms of adaptation *in loco* to new climatic conditions, sudden shocks drive the decision to migrate elsewhere. However, mobility responses to different types of hazards might be different

[14] In 2019 the 40% of all natural hazards occurred in the Planet happened in a Southern-Eastern Asian country

according to their specific consequences and duration (Berlemann and Tran, 2020). On the contrary, the case of Bangladesh supports the hypothesis that the existence of previous barriers of access to migration is worsened by the occurrence of disasters, specifically in the face of recurrent and intense flooding (Gray and Mueller, 2012b).

The specific case of earthquakes across the world (El Salvador in Halliday, 2006, Japan in Kawawaki, 2018, and Indonesia in Gignoux and Menéndez, 2016, for instance) shows a common trend of outcomes: highly disruptive disasters such as earthquakes tend to decrease mobility from the hit area. An interesting mechanism to explain this common trend found in three very different contexts is given by, not only the already mentioned financial constraints, but also the possibility of higher local employment opportunities due to post-disaster reconstruction (Gignoux and Menéndez, 2016; Halliday, 2006). Moreover, households are found to respond to hazards by using labour force as a buffer to the damages and redistributing labour within the household, with female mobility drastically dropping more than males and being substituted with increased hours of domestic labour (Halliday, 2012).

Analyses on South American countries also contribute to give a hint of the complexity of the phenomenon. Thiede et al. (2016) show how internal migration is indeed impacted by rising temperature when considering the general effect; however, it hides an extreme heterogeneity of outcomes when specific characteristics of the areas and individuals are taken into account, resulting in a non-uniform effect.

An evident gap in the literature emerges in Figure 1.6: European countries have rarely been the object of study of the impact of environmental factors on mobility. This might be motivated by the fact that the European continent is mostly seen as a destination for migrants than an origin. It should not surprise that the two articles covering European countries, namely Italy (Spitzer et al., 2020) and the Netherlands (Jennings and Gray, 2015) analyse historical data of mobility at the beginning of the 20th century (respectively earthquake in Sicily and Calabria and climate variability associated with riverine flooding in the Netherlands). Nevertheless, figures show that Europe is not unrelated to the occurrence and frequency of hazards as well as to sizeable internal mobility.

1.3 The inter-connectivity of papers

Science mapping has been used in many disciplines for many purposes. Investigating the existence of some kind of partitioning in scientific production is made possible through the analysis of the links that generate among articles according to their different attributes. Partitions (or clusters) of the literature are a useful tool to analyse the topology of the network formed by the documents and to identify potential similar patterns in characteristics, authorship, final results, and other potential forces aggregating them together. The aim of the quantitative approach proposed in this chapter is to map the target literature, analyse the connectivity that exists among papers according to a citation-based approach and detect the existence of communities or groups of articles that can be aggregated together according to certain characteristics. Since the literature under study is characterised by a high heterogeneity of results, both in the direction and magnitude of the impact, the investigation will now turn on the existence of potential specific patterns that lead to a certain type of analysis, methodology, or results. To do so, I draw from scientometric literature and social network analysis (SNA) to build and describe a citation-based network of documents linked by the attribute of cited references.

1.3.1 Bibliographic coupling and citation-based approaches

The citation-based approach chosen is called bibliographic coupling, it has been used as a strategy to map scientific production and introduced by Kessler (1963a) and Kessler (1963b). Two scientific papers "bear a meaningful relation to each other when they have one or more references in common". Thus, the fundamentals of the link between two papers are represented by the number of shared papers they both include in their references, which constitute the strength of the connectivity they have. In other words, a reference cited by two papers constitutes a "unit of coupling between them" (Kessler, 1963b). Two articles are then said bibliographically coupled if at least one cited source appears in both articles (Aria and Cuccurullo, 2017). Bibliographic coupling belongs to the broader class of citation-based approaches to science mapping. Other common approaches are co-citation analysis (Small, 1973) and direct citation (Boyack and Klavans, 2010). The co-citation approach is based on the relationship established by citing authors of a paper: two papers are linked whenever they jointly appear in the cited references of at least a third paper. This approach was first introduced by Small (1973) to establish a measure of "the degree of relationship or association between papers as perceived by the population of citing authors". Co-citation analysis has been prominently adopted since the 1970s, especially for its ability to capture shifts in paradigms and schools of thought over time. To do so, the sample of paper analysed through the co-citation should have a period long enough to let the literature evolve and change direction. Direct citation is the most intuitive approach, linking two papers if one has cited a precedent one. As well as co-citation, direct citation performs better for long time windows to visualise historical connections (Klavans and Boyack, 2017). In terms of accuracy, it has been established that direct citation provides a more accurate representation of the taxonomy of scientific production (Klavans and Boyack, 2017), but for the specific requirements the methodology imposes, it has not gained much success (Boyack and Klavans, 2010). On the other hand, the bibliographic coupling is increasingly becoming widely used in citation analysis, thanks to some specific advantages (and despite some disadvantages). Conceptually, through the linkages established, it gives a representation of the basic literature of reference of papers and, incidentally, implies a relation between two papers that reveals a potential common intellectual or methodological approach (Weinberg, 1974). Another advantage consists in the constancy of the links between the papers over time, being based on cited references which, once published and indexed, do not change (Thijs et al., 2015). The most relevant advantage of the bibliographic-coupling approach is that it is more suitable for recent literature than any other citation-based approach. As in our case, in fact, the sampled literature starts in 2003 and ends at the moment the research has been done (November 2020). No paper preceding 2003 has been found nor included in the sample, highlighting the recent interest of economic literature on the topic. For reasons of timing and extension of the time window, using any other citation-based approach would have resulted in a very sparse matrix and created many isolated observations which would not be inter-connected for reasons other than conceptual, but just for the fact that they could not have been cited yet (there are 18 papers contained in the sample that has been published in 2020). Not only do the characteristics of our sample motivate the choice of the approach: keeping in mind that this stage of the analysis aims to investigate and map current research fronts in the target literature, rather than to look at historical links or the evolution of school of thoughts, bibliographic coupling seems to be the best tool to capture them (Klavans and Boyack, 2017).

To obtain the network of bibliographically coupled papers, it is primarily necessary to extract the cited references from the dataset of articles' information downloaded from each source database or manually inserted in the residual .bibtex files. The field of references appears as a long string of paper identifiers separated by a semicolon[15]. After the extraction, a bipartite network is obtained, a rectangular binary matrix **A** linking each paper in the sample to their reference (Aria and Cuccurullo, 2017).

$$\mathbf{A} = Paper \times References \tag{1.1}$$

[15] Most of the references in each cell of the database came already with the same format and matched automatically, nonetheless some errors and not corresponding formats were also present. Thus, polishing of the list of cited references has been made by aggregating any duplicates to guarantee the coherence of the results.

The matrix **A** is composed of 151 rows i representing the papers belonging to the sample and 5.433 columns j representing the ensemble of references cited by each paper in the sample. Each element a_{ij} of the matrix equals 1 when paper i cites paper j in its bibliography; a_{ij} is equal to 0 otherwise. As mentioned, two papers are bibliographically coupled when at least one source appears in the references of both articles. In other words, paper i is bibliographically coupled with paper j when they share the citation of at least one paper in their respective references. A matrix that corresponds to bibliographic coupling can be derived from the bipartite matrix **A** defined above. A bibliographic coupling network **B** can be expressed as:

$$\mathbf{B} = \mathbf{A} \times \mathbf{A}^{\mathbf{T}} \tag{1.2}$$

where **A** is the cited reference bipartite network and $\mathbf{A}^{\mathbf{T}}$ is its transpose[16]. **B** is a symmetrical square matrix 151 × 151, where rows and columns are papers included in the sample. Element b_{ij} of the matrix **B** contains the number of cited articles that paper i and paper j have in common. By construction, the main diagonal will contain the number of references included in each paper (as element a_{ii} defines the number of references that a paper has in common with itself).

1.3.2 Describing the network

The resulting matrix displays an undirected weighted network in which the 151 vertices are the set of papers included in our sample and the edges represent the citation ties between them. An existing tie implies that common reference literature exists between i and j, identifying a connection of a certain type between them. When two nodes are not linked, the corresponding value of their tie is zero, as they do not share any common reference. Therefore, the network is weighted, the strength of the connections between papers i and j is measured by the weights associated with each tie. To avoid loops, which would be meaningless for our investigation as it is trivial to observe the value of ties that link a paper with itself (naturally corresponding to the number of listed references), the main diagonal is set to zero. Few ties exceed 20 shared cited references, with a maximum value of 48: this number seems very high, but at a closer look, the two papers that register the highest value are two consecutive papers published by the same author (Naudé, 2008; Naudé, 2010). It can be argued that the number of references included in an article is not neutral to the resulting tie with any other article. Measuring the correct relatedness of nodes is of

[16] Conversely, a co-citation network, as defined in the previous section, would be defined as $\mathbf{C} = \mathbf{A}^{\mathbf{T}} \times \mathbf{A}$, as it establishes ties between two papers that are contemporary cited by at least a third paper (Aria and Cuccurullo, 2017).

primary importance to produce an accurate mapping of literature (Klavans and Boyack, 2006). Citation behaviours of authors may interfere with the observation of core reference literature at the basis of coupled nodes. An author may opt for an extensive approach of citations and include a consistent number of references to display some particular links or details of a paper; authors may also decide for a less inclusive approach and include just essential cited references in the list. In other words, the number of included references in one article may dissolve meaningful information about the ties. Furthermore, specific formats or types of articles lead to broader or narrower bibliographies: for example, a survey of the literature is expected to include a large number of citations, corresponding to the extent of reviewed contributions. Not surprisingly, the highest number of cited references can be found in reviews such as Berlemann and Steinhardt (2017), Bardsley (2014), Castells-Quintana et al. (2018), Auffhammer and Kahn (2018), and Millock (2015), including more than a hundred cited references each. On the contrary, articles published in journals in the format of *letters* (i.e. *Economics Letters*, *Applied Economic Letters*) tend to have an extremely limited number of cited references (for example Ouattara and Strobl (2014) and Khamis and Li (2020) include only 8 and 13 references respectively). To address these concerns, a process of normalisation is needed so that data can be corrected for differences in the total number of references. Bibliometric literature has dealt with this issue through the calculation of different *similarity measures*. An accurate overview of the possible measures of similarity is provided in Eck and Waltman (2009). Overall, such indices aim to determine the similarity between two units according to their co-occurrence (value of association between them, which in our case, is the number of common references in the bibliography) adjusted in different ways for the number of total occurrences of the single units. However, despite the need to correct data for many purposes in citation-based networks and obtain a size-independent measure of association, there is no consensus on which measure is the most appropriate (Eck and Waltman, 2009): tests of accuracy and coverage proposed by different authors have reached different conclusions (Klavans and Boyack, 2006; Eck and Waltman, 2009; Sternitzke and Bergmann, 2009). Thus, I will apply a simple ratio between the observed number of commonly shared references and the product of the number of cited references in each of the two coupled papers. It has been defined as a measure of *association strength* (Eck and Waltman, 2009) and it can be expressed as:

$$b^n_{ij} = \frac{b_{ij}}{b_{ii} b_{jj}} \tag{1.3}$$

where b_{ij} corresponds to the weights of ties in the original bibliographic coupling network between paper i and paper j and b_{ii} and b_{jj} are respectively the number of cited references included in paper i's bibliography and in paper j's bibliography,

TABLE 1.4: Bibliographic coupling network descriptive statistics

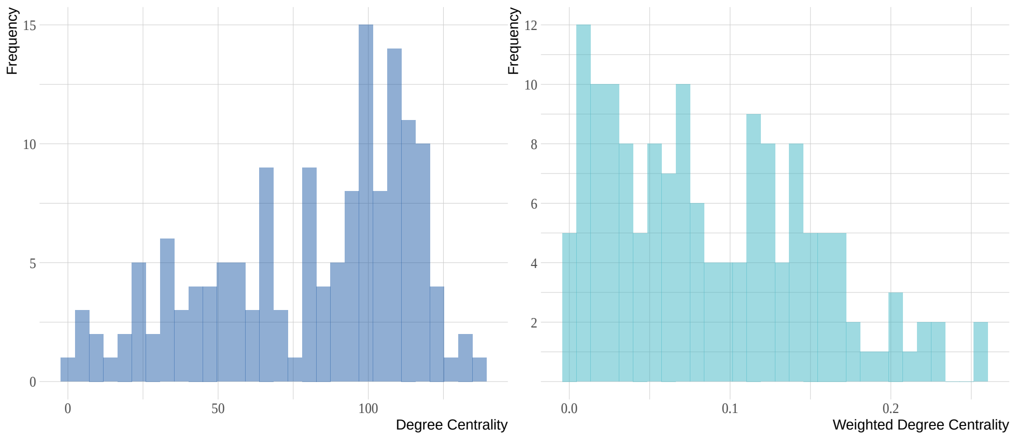
Network structure		
No. Vertices (papers)		151
No. Edges (ties)		6063
No. missing ties		5262
Topological network measures		
Density		0.54
Clustering coefficient		0.78
Longest Path Length		3.00
Average Path Length		1.47
Network node centralisation		
Degree	Maximum	139
	Minimum	2
	Average	80.3
Weighted degree	Maximum	0.258
	Minimum	0.002
	Average	0.088
Closeness	Maximum	27.447
	Minimum	5.672
	Average	17.611
Betweenness	Maximum	2251
	Minimum	0
	Average	110.05

Note: Bibliographic coupling network of 151 documents included in the sample obtained from Scopus, Web of Science, Google Scholar, IDEAS RePEc and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021).

which corresponds to the original value on the diagonal. The obtained weighted network will serve to detect communities of papers through their common references, and investigate if referring to a certain (group of) paper(s) creates meaningful clusters of items aggregating around certain common characteristics.

Table 1.4 reports the main descriptive statistics about the network. Network density, which represents the proportion of actual links overall potential links, is 54%, highlighting, in general, a quite dense network. Furthermore, the value of the average clustering coefficient shows that 74% of triples of vertices are fully connected (in other words, the 74% of triples form closed triangles), which means that almost three quarters of all triangles close. No isolated node is found (the value of minimum degree centrality is 2, which means that the least connected node, Pismennaya et al. (2015), has two edges), while the maximum degree is 139, scored by a literature review (Millock, 2015). These figures correspond to the non-normalised network, which, as already discussed, may misrepresent links between nodes due to the size of reference lists (not surprisingly in figure 1.8, the highest values of simple degree centrality are mainly scored by literature reviews). The weighted degree helps to capture the degree centrality taking into account actual weights related to every edge. Beine and Parsons (2017) is the most central node of the entire network,

FIGURE 1.7: Frenquency by degree and weighted degree centrality



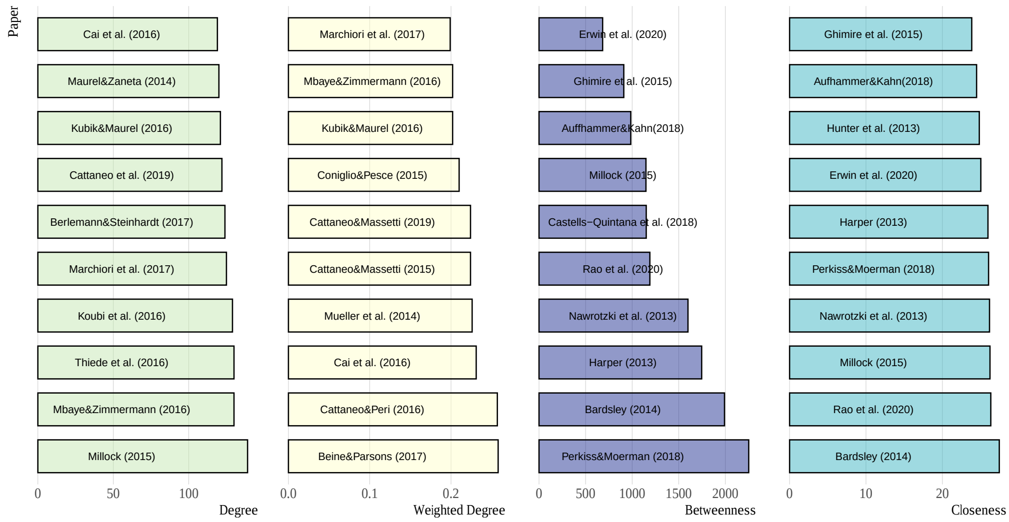
Note: Bibliographic coupling network of 151 documents included in the sample obtained from Scopus, Web of Science, Google Scholar, IDEAS RePEc and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021).

followed by Cattaneo and Peri (2016), Cai et al. (2016), Mueller et al. (2014). In terms of betweenness, more central nodes are those located at the shortest geodesic distance between any other nodes in the network, which makes them serve as bridges connecting sub-graphs. The strong betweenness is found mainly in qualitative or theoretical modelling papers (Perkiss and Moerman, 2018; Harper, 2013; Nawrotzki et al., 2013), as well as literature reviews (Bardsley, 2014; Millock, 2015). Their positioning relative to the distance between any other node identifies pathways between different potential sub-graphs of different kinds of approaches to the analysis; these papers do not belong indeed to the densest groups, but just relate between them.

1.4 Community Detection

The main intent is to identify the existence of communities within citation-based networks. The assumption is that papers citing the same references aggregate into a group that shares certain features, which could be methodological approach, level of analysis, specific sub-topics of the literature, but also outcomes. The extreme heterogeneity of outcomes in this specific literature may be motivated partially by the heterogeneity of the events themselves (type of environmental factor, type of mobility, pre-existing conditions in the specific area) or the theoretical and empirical modelling; it may also be motivated by other factors, that can be traced in some patterns linked to the characteristics of single publications. The procedure of community detection is aimed at investigating which are the "forces" that aggregate or disperse papers with each other, primarily through the direct observation of main

FIGURE 1.8: Centrality measures of bibliographic coupling network

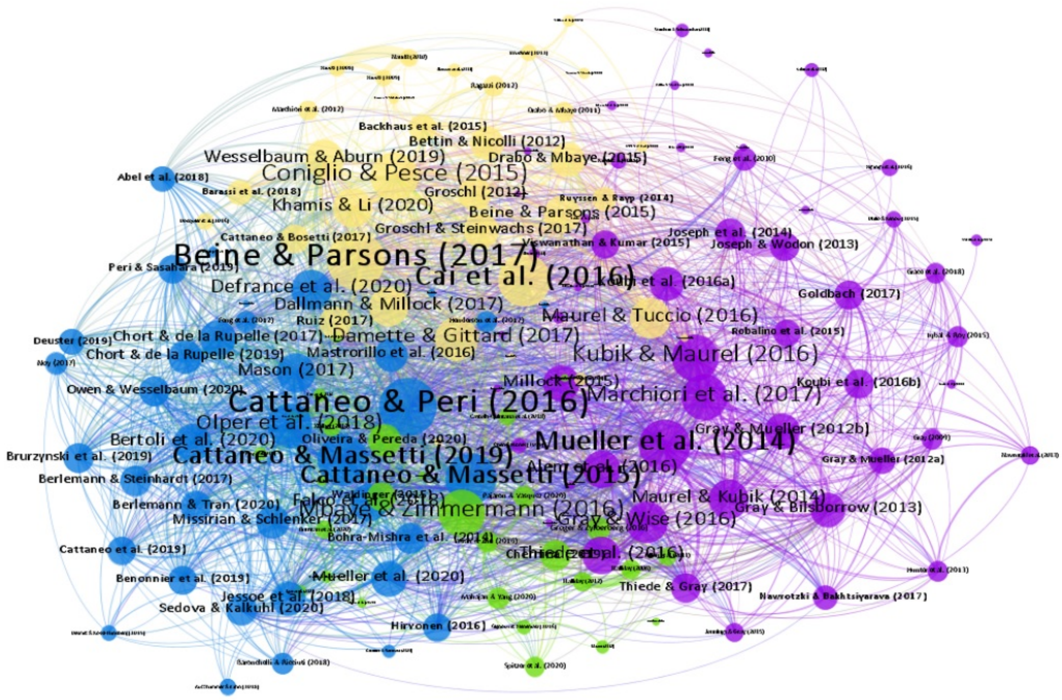


Note: Sample of academic contributions about migration and environmental factors from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021) collected, merged, screened and included by the authors.

characteristics, and then running separate MAs on each cluster. Community detection in the bibliographic network is often made through the Louvain community detection algorithm (Blondel et al., 2008). In this analysis, a community is thought of as a group of contributions that share common references and form strong common ties with each other, while others have less shared characteristics and structure. The algorithm is able to detect clusters of contributions with dense interaction with each other and sparse connections with the rest of the network.

The procedure identifies four main clusters in the network. The network being relatively small allows to analyse the main characteristics of each cluster. Following the full-text screening made in the first step, I summarised some meaningful indicators about the analysis (such as type - quantitative, qualitative, theoretical, policy, literature review -, level - macro or micro for quantitative and qualitative studies -, unit - country, household, individual, territorial units), the object of the analysis (concerning the type of migration and environmental factors studied and the area) and theoretical and empirical approach (empirical approach and whether it is theory-based, estimation strategy and potential channel investigated). Finally, a synthetic indicator of the concluding effect of environmental factors on migration patterns is recorded: each paper is assigned to a value “positive”, “negative”, “not significant” or a combination of the three (in case a paper contains multiple analysis of different migration or environmental factors that lead to different outcomes). Thanks to these

FIGURE 1.9: Bibliographic coupling network



Note: Bibliographic coupling network of 151 documents included in the sample obtained from Scopus, Web of Science, Google Scholar, IDEAS RePEc and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021). Each node represents a paper included in our sample and its size corresponds to its weighted degree. Nodes are tied by links whenever two nodes share at least one common reference. The thickness of links is given by the association strength of the tie between two nodes (to provide a clear visualization, only nodes with weights higher than the mean are displayed). Colors correspond to communities of belonging of each paper: Cluster 1 is represented in violet, Cluster 2 in green, Cluster 3 in blue, and Cluster 4 in yellow. The description of each Cluster is presented below.

indicators a picture of the main common characteristics of the papers included in a cluster emerges, which will then be tested and eventually confirmed in the meta-analysis.

Cluster One The first cluster is the most populated, counting 51 papers spanning for the entire period considered (from 2003 to 2020). In terms of type of analysis, it contains the largest variety of different types: as in all clusters, quantitative studies represents the majority (as they are the 76% of the full sample), but this cluster contains also most of the qualitative analyses (10 out of 13) and policy papers (5 out of 7) of the full sample. Published papers are predominant (47 out of 50). Except for

TABLE 1.5: Comparative information about clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Size	51	28	37	35
included in MA	27	17	21	32
Published	47	24	21	27
Time-span	2003-20	2006-20	2011-20	2006-20
Average citations per document	34.84	18.96	10.89	24.91
Type of paper				
Policy	5	0	0	2
Qualitative	10	1	1	1
Quantitative	32	22	30	32
Review	2	5	4	0
Theoretical	2	0	2	0
Level of analysis				
Macro	4	1	12	30
Micro	39	22	21	4
Not Applicable	8	5	4	1
Unit of analysis				
Country	4	1	12	30
Household	12	5	5	0
Individual	20	7	9	0
Territorial	7	10	7	4
Not applicable	8	5	4	1
included in other MAs				
in Hoffmann et al. (2020)	2	1	4	23
in Beine and Jeusette (2021)	21	5	6	18
Migration				
Both	25	8	18	7
Cross-country	8	7	9	22
Internal (urbanization included)	18	13	10	6
Environmental Factors				
Both	12	2	7	13
Slow-onset events	32	6	26	11
Fast-onset events	7	19	4	11

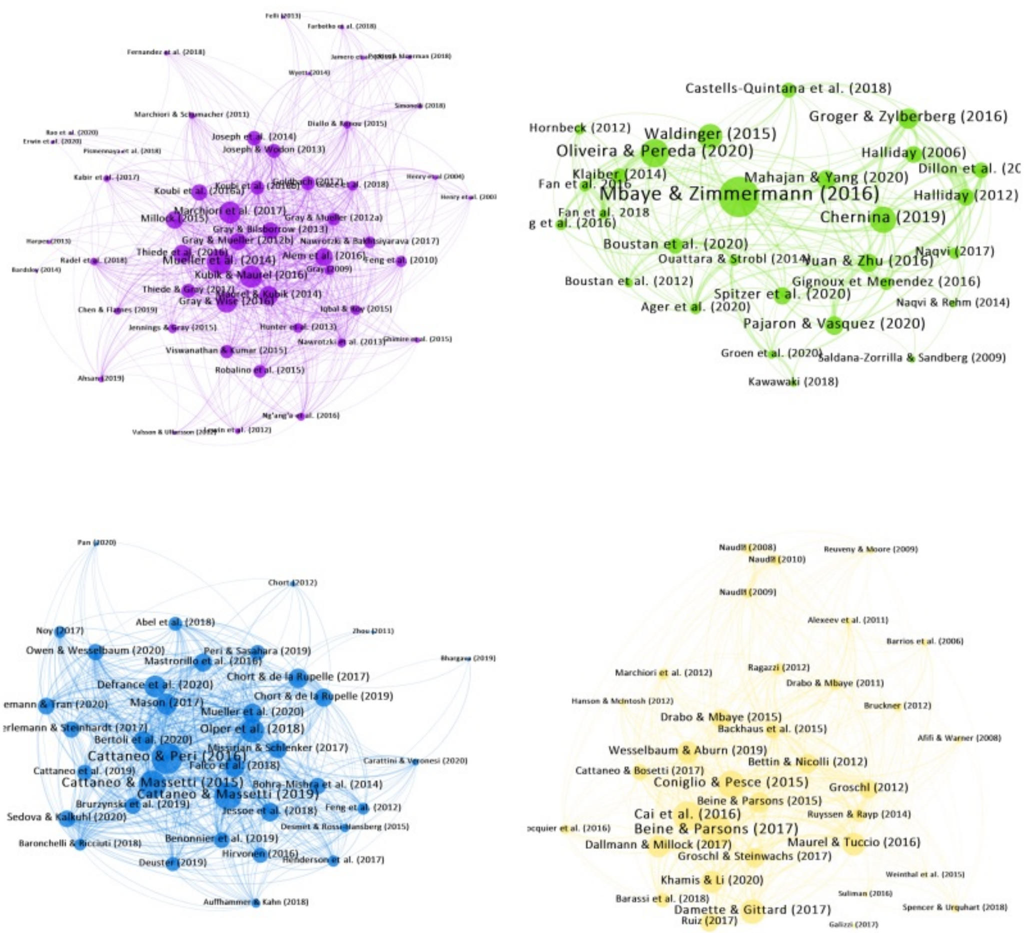
Note: Sample of academic contributions about migration and environmental factors from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021) collected, merged, screened and included by the authors.

few papers, the analysis is mainly carried from a micro perspective, with mainly individuals as unit of analysis, based on surveys. Interestingly, most of the micro-level studies included in (Beine and Jeusette, 2021) can be found in this cluster. Authorship is very concentrated around two main authors, Clark Gray, (co-)authoring 9 papers, and Valerie Mueller, (co-)authoring 4 papers. Many of their co-authors appear in this community, which indeed scores the highest collaboration index of all communities (2.86), much higher than the full sample (2.16). Another important feature is that Cluster one includes the micro-level papers with the highest global citations (see Table 1.3): (Gray and Mueller, 2012b), (Feng et al., 2010), (Gray and Mueller, 2012a), (Mueller et al., 2014), (Henry et al., 2004), (Henry et al., 2003) and (Gray, 2009). This is also shown by the fact that the number of average citations per document is the highest among all clusters (34.84). Journals are also quite concentrated around few of them, World Development and Population and Environment mainly. The content of analysis is mainly focused on climatic change exclusively (precipitation and temperature), while few studies include also analysis on natural disasters. All corridors of migration are investigated, with no specific predominance of internal or international migration (which is a characteristic of individual-level studies, mainly based on surveys). Even though the majority of outcomes show a positive coefficient, that can be translated in finding an active role of environmental factors in pushing migrants out of their origin areas, it is not consensual: variation among results is high compared to other clusters, most papers finding complex relations between the two phenomena and different directions according to different dimension. Empirical strategies are often based on discrete-time event history models estimated through multinomial logit. This reflects the approach of the main authors included in this community. A strong accent is put on the importance of the agricultural channel and the thematic of adaptation to the change in environmental conditions.

Cluster two The second community counts 28 papers, mostly published (only 4 of them are not). It is composed of mostly quantitative papers, which are accompanied by 5 literature reviews. As in the previous cluster, most studies are at a micro level, with all kinds of units of analysis and aggregations, and considering both patterns of migration, but with special attention to urbanisation and internal mobility. Contrarily, it seems to put a stronger accent on natural disasters rather than on slow-onset events. The majority of papers in Cluster 2 seems to have been excluded from (Beine and Jeusette, 2021) (only 5, compared to the 21 in cluster 1) and (Hoffmann et al., 2020) (only 1). All papers analysing the impact of different kinds of natural disasters in the U.S. are included in this cluster. Empirical approaches such as the differences-in-difference model and instrumental variable are often used. The papers explore a large variety of potential channels and mechanisms of transmission of the impact of environmental factors on migration (income, agriculture, employment, liquidity constraints), and only in few cases, a negative direction is found.

Cluster three The third cluster includes the most recent papers: only one paper dates 2011, all other ones are published or issued after 2015. This is part of the reasons why the average citations per document in this cluster is the lowest (10.89) compared to any other cluster. Half of the overall unpublished papers are included in this cluster. In terms of kind of analysis, this cluster appears to be very heterogeneous: even if micro-level analyses are the majority, 12 papers apply a macro-level analysis on countries. Both cross-country and internal migration are considered, but

FIGURE 1.10: Sub-graphs by clusters of the bibliographic coupling network



Note: Sub-graphs of communities issued from bibliographic coupling network of 151 documents included in the sample obtained from Scopus, Web of Science, Google Scholar, IDEAS RePEc and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2021). Each node represents a paper included in our sample and its size corresponds to its weighted degree. Nodes are tied by links whenever two nodes shares at least one common reference. The thickness of links is given by the association strength of the tie between two nodes (to provide a clear visualization, only nodes with weights higher than the mean are displayed). Colors correspond to communities of belonging of each paper: Cluster 1 is represented in violet, Cluster 2 in green, Cluster 3 in blue and Cluster 4 in yellow. The description of each Cluster is presented below.

the majority of them investigate the impact of slow-onset events rather than fast-onset. Many of the analyses are theory-based, especially on classic economic migration theories (Roy-Borjas model, New Economics of Labour Migration), or general or partial equilibrium models. This cluster is also peculiar for the heterogeneity of empirical outcomes, which are often multiple for a single paper: outcomes vary according to the different channels explored, i.e. different levels of agricultural dependency, presence of international aids, level of income. In many cases, environmental factors have been found an obstacle to the decision to migrate from an area, or completely neutral. Comparatively, outcomes from this cluster tend more to show a complex picture and highlight the many dimensions that may intervene in determining the direction of the impact.

Cluster four Contrarily to the previous one, Cluster 4 is extremely homogeneous. It contains almost exclusively quantitative (32 out of 35) macro-level studies (30 out of 35). It covers equally slow- and fast-onset events and their impact on mobility. Most importantly, it aggregates 23 of the 30 papers reviewed in Hoffmann et al. (2020), making this cluster very representative and comparable to Hoffmann et al. (2020)'s meta-analysis. Additionally, this community appears to be solid also in terms of theoretical and empirical approach, as micro-founded gravity or pseudo-gravity models are widely used in it (more than half of them use such models). None of the studies find a negative impact of environmental factors on migration, they mainly estimate positive and significant outcomes, with few not-significant results for specific cases. The most locally cited macro papers are included in this cluster (see Table 1.3), which also receive high global citations with an average of citations per document of 24.91 (even though lower than cluster one).

1.5 Concluding remarks

This description of cluster composition serves as a preliminary investigation of the main characteristics linking papers together through their citation behaviour. It emerges that stronger links are given by diverse indicators varying across clusters. The analysis offered in this chapter sheds some light on the very heterogeneous results of the relationship between the two phenomena reported by an extended sample of contributions of various kinds. The sample collected through a systematic review of the literature, the bibliometric analysis and, the community detection on the citation-based network of essays, highlights the absence of a uniform and cohesive literature. To test further explore the sources of heterogeneity between clusters that aggregate papers within a cluster and their impact on the estimated effect size, in the next section the partitioning will be used to run four separate MAs and compare the conclusions.

Chapter 2

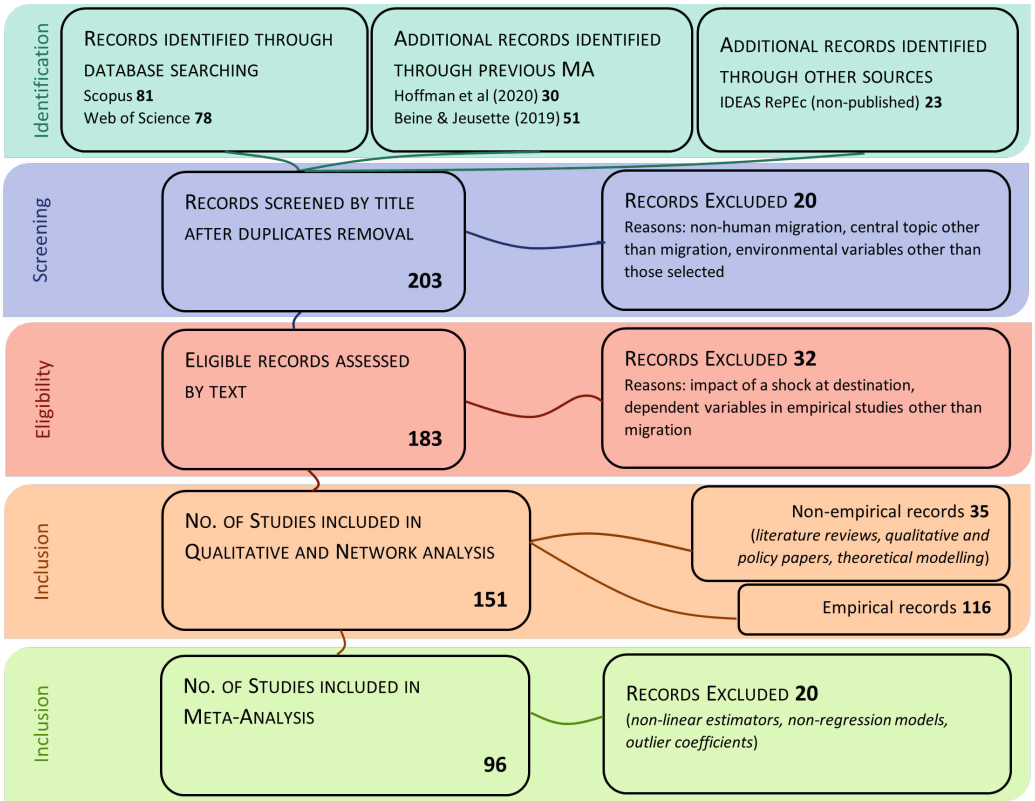
Meta-Analysis

The literature on environmental migration has produced over time heterogeneous findings on the impact, direction, and strength of the factors linking mobility to slow- and fast-onset environmental events. The picture of the literature that emerged from the systematic review in Chapter 1 shows a quite recent production of contributions, during the last 17 years. Micro-economic literature prevails on macro, with some areas and events more studied than others and some evident gaps on analysis. Results lead to very different conclusions according to many different factors. The additional community detection on the bibliographic coupling network manifested the existence of clusters of contributions that aggregate together on specific dimensions.

In this chapter, I draw from the results obtained in the previous chapter to run a meta-analysis on the estimated effects reported in empirical contributions included in the sample. Among 151 papers included, 96 of them are empirical studies reporting coefficients eligible for the meta-analysis. I build a unique dataset that synthesises the estimated coefficients concerning the effect of slow-onset (e.g. climate change) and fast-onset natural events (e.g. catastrophes) on different corridors of human mobility (international, domestic, and with a clear pro-urban directionality), accounting for the main potential sources of heterogeneity (scope, level, unit and area of analysis, theoretical and empirical approaches, publication biases). Additionally, the clustered structure that emerged from the network analysis is included. This offers the possibility to condense the results of all contributions in a single representative result. A highly significant result can be potentially considered as a consensual indication of the external validity of the correlation, or even the causal link, of the phenomena under scrutiny.

Prof. Maria Cipollina and Prof. Luca De Benedictis contributed to the design and implementation of the research and the analysis of the results.

FIGURE 2.1: PRISMA Diagram



Note: PRISMA Diagram (Liberati et al., 2009) of identification, screening, eligibility and inclusion stages of academic contributions. The resulting sample is obtained through search on Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2019).

Overall, the meta-analytic average effect estimates a small impact of slow- and rapid-onset variables on migration, however positive and significant. When the communities of papers are accounted for, however, a significant heterogeneity emerges among the four clusters of papers, giving rise to new evidence on limits of a consensual effect of climatic shocks on permanent human displacement and the formation of club-like convergence of literature outcomes.

2.1 Coding the dataset

2.1.1 Description of the sample

Prisma Diagram adds a second level of inclusion compared to the process presented in Chapter 1. As already mentioned, the first level identifies the sample of contributions included in network analysis, while the second level is restricted to quantitative analyses suitable for the meta-analysis. The motivation behind this choice can be found in the purpose of the two different stages. To conduct a meta-analysis it is crucial to select only comparable papers that provide complete information (mainly on estimated coefficients and standard errors) that can then be used to recover the average effect size. This implies the exclusion of papers that do not comply with the requirements of a meta-analysis. However, those excluded papers can be of interest in building the taxonomy of the whole concerned literature, as they may play a role in building links between different contributions (see section 3). Similarly, non-quantitative (policy, qualitative or theoretical) papers may participate as well in the development of research fronts or to give a direction to a certain thread of contributions and incidentally affect the detection of clusters. These reasons led us to build the citation-based network and perform the network analysis and the community detection on the whole sample, while only the sample for the MA is restricted only to quantitative contributions that meet the coding requirements. Overall, 20 out of the 116 empirical papers are excluded from the MA sample because of the use of non-linear estimators, non-regression modelling or the presence of outlier coefficients.

2.1.2 Codebook of moderators

After the selection of suitable papers to perform the MA, the following step consists of the codification of information about the regressions. I coded each relevant coefficient estimated in each regression included in the 96 papers included in the sample to build a unique dataset of 5.969 observations. In order to highlight potential sources of heterogeneity, several variables are detailed in the dataset and are described in Table 2.1.

TABLE 2.1: Dataset Description

Paper Characteristics

Paper ID	Unique identifier of each paper
Year of publication	Year of publication of the paper
Cluster	Identifier of the cluster obtained in community detection
Publication flag	Equal to 1 if paper is published

Publication Impact	Value of the impact factor of the publishing journal in 2019 (latest value available)
First Author	Name of the first author
Author 2	Name of second author
Author 3	Name of third author
Author n	Name of the n-th author
Corresponding Author	Name of the corresponding author (if included)
	Regression characteristics
Regression ID	Reference of table and column in original paper
Preferred	Equal to 1 if the regression is identified as the preferred specification
Robustness	Equal to 1 if the regression is identified as a robustness check
Panel	Equal to 1 if data are panel
Estimator	
Poisson	Equal to 1 if the estimation is done with Poisson, Pseudo-Poisson or Negative Binomial
OLS and ML	Equal to 1 if the estimation is done with OLS or Maximum Likelihood
Logit	Equal to 1 if the estimation is done with logit or multinomial logit
IV	Equal to 1 if estimation strategy controls for endogeneity through Instrumental Variable techniques or GMM
Other	Equal to 1 if estimation strategy is different from Poisson, OLS, logit and IV categories
	Sample characteristics
Time span	Number of years considered in the data
Data source	
Census	Equal to 1 if data are taken from national censuses
Official statistics	Equal to 1 if data are taken from official statistics
Survey	Equal to 1 if data are taken from surveys
Unit of analysis	
Household	Equal to 1 if household is the unit of analysis
Individual	Equal to 1 if individuals are the unit of analysis
Country level	Equal to 1 if countries are the unit of analysis
Territorial unit	Equal to 1 if other territorial units are taken as unit of analysis (municipality, district, province, state, grid cell)
	Dependent variable - Migration
Corridor	
Internal	Equal to 1 if the dependent variable captures internal migration
International	Equal to 1 if the dependent variable captures international migration
Urbanisation	Equal to 1 if the dependent variable captures urbanisation process (rural-urban migration)
Undefined	Equal to 1 if the dependent variable do not specify any of the corridors listed above (internal, international, urbanisation)
Measurement	
Flows	Equal to 1 if migration is measured by flows or rate
Stock	Equal to 1 if migration is measured by stock of migrants
Direct	Equal to 1 if migration is measured by a dummy that takes value 1 when migration occurs
Origin areas	
Africa	Equal to 1 if the origin area is an Sub-Saharan African country
Asia	Equal to 1 if the origin area is a Asian country
Europe	Equal to 1 if the origin area is a European country
LAC	Equal to 1 if the origin area is a Latin American or Caribbean country

MENA	Equal to 1 if the origin country is a Middle Eastern or North African country
North America	Equal to 1 if the origin area is a Northern American country
World	Equal to 1 for multi-country analysis
Destination areas	
High income	Equal to 1 if destination area is an high-income country (World Bank)
Upper-middle income	Equal to 1 if destination area is a upper-middle income country (World Bank)
Lower-middle income	Equal to 1 if destination area is a lower-middle income country (World Bank)
Low income	Equal to 1 if destination area is a low-income country (World Bank)
Undefined	Equal to 1 if destination area is not specified
Independent variable - Slow-onset events	
Slow	Equal to one if the coefficient refers to a type of slow-onset event: temperature, precipitation or soil degradation
Temperature	
Temperature	Equal to 1 if the coefficient refers to a measure of temperature
Levels	Equal to 1 if temperature is measured in levels
Variation	Equal to 1 if temperature is measured as a variation or deviation from the average (difference between level and long-run average)
Anomaly	Equal to 1 if temperature is measured by anomalies (difference between level and average over standard deviation)
Time Lag	Lag of the measure of temperature
Precipitation	
Precipitation	Equal to 1 if the coefficient refers to a measure of precipitation
Level	Equal to 1 if precipitation is measured in levels
Variation	Equal to 1 if precipitation is measured as a variation or deviation from the average (difference between level and long-run average)
Anomaly	Equal to to 1 if precipitation is measured by anomalies (difference between level and average over standard deviation)
Time lag	Lag of measure of precipitation
Soil degradation	
Soil degradation	Equal to 1 if the coefficient refers to a measure of soil degradation (desertification, soil salinity, erosion)
Independent variable - Fast-onset events	
Fast	Equal to 1 if the coefficient refers to a fast-onset event: geophysical, hydrological, climatological, meteorological, others
Type of hazard	
Geophysical	Equal to 1 for geophysical disasters: earthquake, tsunami, mass movement, volcanic eruption
Earthquake	Equal to 1 for earthquakes and tsunamis
Mass movement	Equal to 1 for dry mass movements
Volcano	Equal to 1 for volcanic eruptions
Meteorological	Equal to 1 for meteorological disasters: extreme temperature and storms
Extreme temperature	Equal to 1 for episodes of hot or cold extreme temperature
Storm	Equal to 1 for cyclone, tornado, hurricane and tropical storm
Hydrological	Equal to 1 for hydrological disasters: floods and landslides
Floods	Equal to 1 for floods
Landslide	Equal to 1 for wet landslides
Climatological	Equal to 1 for climotological disasters: droughts and wildfire
Droughts	Equal to 1 for droughts
Wildfire	Equal to 1 for wildfire

Other disasters	Equal to 1 for other disasters, such as epidemics, insect infection and miscellaneous
Measurement	
Frequency	Equal to 1 if disasters are measured as the count of events
Intensity	Equal to 1 if disasters are measured according to its scale of intensity (i.e. Richter scale for earthquakes, wind speed for tornadoes, etc.)
Duration	Equal to 1 if disasters are measured by the length of the event
Occurrence	Equal to 1 if disasters is measured by a dummy that capture if any event has occurred
Losses	Equal to 1 if disasters are measured according to affected population, deaths, injured people, destroyed houses, damages
Control variables	
Slow and fast	Equal to 1 when the regression contains both a measure of fast-onset events and a measure of slow-onset events
Income	Equal to 1 if the regression includes controls for income (GDP per capita, households' or individuals' income)
Conflict	Equal to 1 if the regression includes controls for conflicts (war, civil war, conflict)
Political	Equal to 1 if the regression includes controls for political system or situation (state fragility index, democracy, institutional trust, institutional quality, corruption, political stability, polity index)
Population	Equal to 1 if the regression includes controls for population characteristics (count or density)
Diaspora	Equal to 1 if the regression includes controls for diaspora or presence at destination of migrants of the same origin (diaspora, network)
Past migration	Equal to 1 if the regression includes controls for migratory history or trends from the same area (regardless of destination)
Poverty	Equal to 1 if the regression includes controls for poverty or development of the area
Cultural	Equal to 1 if the regression includes controls for societal or cultural characteristics of the area (ethnic composition, language, colonial past)
Geography	Equal to 1 if the regression includes controls for geography (distance, shared borders, distance from the equator, landlocked vs island)
Agriculture	Equal to 1 if the regression includes controls for agriculture and farming (agricultural dependency, share of agricultural activity, farming activities, livestock, arable land)
Employment	Equal to 1 if the regression includes controls for labour or employment (unemployment, sector of employment, business ownership, employment rate, labour force participation rate)
Urban	Equal to 1 if the regression includes controls for urban or rural areas (urbanisation rate, rural vs urban origin)
Aid	Equal to 1 if the regression includes controls for financial aids to the area (international aids, public funding, financial aids for reconstruction)
Education	Equal to 1 if the regression includes controls for educational level (illiteracy rate, level of education, primary/secondary education share)
Interaction terms	
Income	Equal to 1 if the environmental variable is interacted with income (GDP per capita, households' or individuals' income)
Conflict	Equal to 1 if the environmental variable is interacted with conflicts (war, civil war, conflict)

Political	Equal to 1 if the environmental variable is interacted with political system or situation (state fragility index, democracy, institutional trust, institutional quality, corruption, political stability, polity index)
Population	Equal to 1 if the environmental variable is interacted with population characteristics (count or density)
Diaspora	Equal to 1 if the environmental variable is interacted with diaspora or presence at destination of migrants of the same origin (diaspora, network)
Past migration	Equal to 1 if the environmental variable is interacted with migratory history or trends from the same area (regardless of destination)
Poverty	Equal to 1 if the environmental variable is interacted with poverty or development of the area
Cultural	Equal to 1 if the environmental variable is interacted with societal or cultural characteristics of the area (ethnic composition, language, colonial past)
Geography	Equal to 1 if the environmental variable is interacted with geography (distance, shared borders, distance from the equator, landlocked vs island)
Agriculture	Equal to 1 if the environmental variable is interacted with agriculture and farming (agricultural dependency, share of agricultural activity, farming activities, livestock, arable land)
Employment	Equal to 1 if the environmental variable is interacted with labour or employment (unemployment, sector of employment, business ownership, employment rate, labour force participation rate)
Urban	Equal to 1 if the environmental variable is interacted with urban or rural areas (urbanisation rate, rural vs urban origin)
Aid	Equal to 1 if the environmental variable is interacted with financial aids to the area (international aids, public funding, financial aids for reconstruction)
Education	Equal to 1 if the environmental variable is interacted with educational level (illiteracy rate, level of education, primary/secondary education share)

2.1.3 Coefficients and Standard Errors

To collect all necessary information for the MA, dealing with some missing information about coefficients and standard errors is needed. I chose an inclusive strategy against the option of just excluding those observations for which certain details were lacking or incomplete. Despite a potential concern of inaccuracy of the approximations or derivations, a check on the results including only original coefficients and standard errors has been run which shows robust results. Furthermore, those missing or incomplete information represents a small share of the total number of observations.

Coefficients. Coefficients are usually shown and can be directly reported in the dataset. In few cases, odds ratios are reported, especially in logistic models. In this case, they are correctly translated into coefficients by taking their logarithm ($\beta = ln(OR)$). The correct coefficient for interacted terms is more challenging to recover. In the case of controls interacted with dummy variables both the main effect, capturing the unconditional effect on the entire population and the combined effect is included, when the dummy takes value 1, normally referring to a sub-sample of the population (origin areas, i.e. Sub-Saharan Africa in Barrios et al., 2006) or a specific characteristic (dummies for agricultural dependency as in Marchiori et al., 2012 or poor countries as in Cattaneo and Peri, 2016). Therefore, for environmental variables interacted with a dummy, the coefficient non-interacted (β) and the combination of β and the combined effect δ ($\beta + \delta$) is reported and flagged with the appropriate channel or sub-sample. When the interacted term is a continuous variable, the simple addition cannot be made, as the term does not take only the [0, 1] values. In order to recover the effect of the environmental factors and a continuous interacted variable (capturing one of the different features listed in Table 2.1), following Hoffmann et al. (2020), the average effect at the mean of the interaction variable is recovered and the coefficient obtains as $\beta + \delta * \bar{I}$. However, this calculation has been possible only when summary statistics of interaction variables were included in the paper, otherwise not included. Overall, more than 80% of observations are original coefficients and odds ratios, while the rest accounts for interacted terms.

Standard Errors. The most compelling issue comes from missing standard errors. Although the majority of regression tables reports either standard errors or t-statistics (from which standard errors can be easily derived), in some cases none of this information is reported. Following the conservative strategy used in Hoffmann et al. (2020), I impute an upper bound standard error at the level of significance indicated (i.e. for a significance level of 5%, the standard error equals $\beta/1.96$). Not significant coefficients (more than 10%) are assigned with a standard error equal to the value of the coefficient. To recover the standard errors of the combined effect of interacted terms, a formula introduced in Hoffmann et al. (2020) ($\sqrt{SE_\beta^2 + SE_\delta^2 + 2Cov(\beta, \delta)}$) is used, assuming that the covariance between coefficients is zero when the information is not available.

2.2 Methodology

A meta-analysis (MA) is a quantitative-statistical technique, which allows to assemble the results of multiple trials of the same treatment into a single cumulative result. The main purpose is to summarise data from different primary research tools, integrate the results and obtain a single quantitative index of estimation that allows stronger conclusions to be drawn than those drawn based on each individual study. The analysis poses three questions to the coded estimates: do econometric results of the same phenomenon converge in a meta-media that we might see as the truth?

Do they suffer from distortions that should be corrected? Can we identify the main features of analyses relevant to convergence? Theories can change and develop to become much more complex, but they must be reduced to an econometric model that can be estimated. Such models tend to be quite similar formally (Paldam, 2015), however, estimated coefficients can differ because the studies in the literature greatly vary in terms of the dataset, sample sizes, estimation methods, independent variables and so on. The purpose of the MA is to summarise the results of collected studies and, at the same time, highlight the possible sources of heterogeneity. The analysis is based on four assumptions: (i) the parameter of interest, β, is the effect of environmental factors on migration; (ii) most researchers believe that β is greater than zero; (iii) the sign is not enough for decision-makers; (iv) this has attracted a large literature that has obtained a large number of estimates $\hat{b}$ of β.

All selected papers contain one or more equations that estimate the migration effect due to slow- or fast-onset events. Since comparability among studies, and more specifically among estimated β, is a crucial issue for the MA, collected estimates are grouped according to the two different kinds of event conducting two separate analyses:

- Climate-change related phenomena, including gradual or slow-onset events, such as the progressive variations in temperatures and rainfall or the desertification of the soil, which concern a longer-term perspective and specific adaptation processes;

- Hazard-related events, i.e. natural disasters, more or less linked to climatic variations, such as hurricanes and floods or even earthquakes and volcanic eruptions, which instead occur as destructive shocks of limited duration and for which the capacity forecast is reduced.

The final sample includes 96 papers released between 2003 and 2020, published in academic journals, working papers series or unpublished studies, providing 3,904 point estimates of the effect of slow-onset events and 2,065 point estimates of the effect of fast-onset events. All selected papers contain one or more equations that estimate the impact of these two kinds of events on different left-hand side variables, used as a proxy of migration. To compare the estimates and correctly interpret the synthetic results, standardisation of all collected effect sizes β in a common metric is needed. In this MA the estimates from separate, but similar studies, are converted in partial correlation coefficients (*pcc*), commonly used in meta-analytic literature (Doucouliagos, 2005; Stanley and Doucouliagos, 2012; Doucouliagos and Ulubasoglu, 2006; Brada et al., 2021), allowing to analyse within a single framework all available studies on the effects of the environment on migration regardless to the specification or measure of migration used. Letting t_i and df_i be the t-value and the degrees of freedom of the i-th estimate β_i, the pcc of the i-th estimate, r_i, is calculated as:

$$r_i = \frac{t_i}{\sqrt{t_i^2 + df_i}}, \tag{2.1}$$

with the standard error, se_i, calculated as:

$$se_i = \sqrt{\frac{(1 - r_i^2)}{df_i}}. \tag{2.2}$$

Summarising all the different estimates together in a single coefficient raises the question of heterogeneity within the same study and between studies. To take this into account, two models are distinguished: a fixed-effects model (FEM) and a random-effects model (REM). The FEM is based on the assumption that the collected effect sizes are homogeneous (the differences observed among the studies are likely due to chance). The estimate of each study is weighted by the inverse of its variance ($1/se_i^2$), which, in turn, is a function of the sample size so that studies with smaller standard errors carry more weight than studies with larger standard errors (Higgins and Thompson, 2002). The REM takes into account the heterogeneity among studies. It assumes that each study has its own effect size and that there is a random distribution of the estimates of the effect of the different studies around the mean value (Sutton et al., 2000). Individual studies are not assumed to be estimating true single effect size, but the true effects in each study are assumed to have been sampled from a distribution of effects in a normal distribution with mean zero and variance τ^2. In REM, weights incorporate a "between-study heterogeneity", $\hat{\tau}^2$, which is equal to $(1/(se_i^2 + \hat{\tau}^2))$. The summary effect is calculated as follow:

$$\hat{\beta} = \frac{\sum_i^N \hat{b}_i w_i}{\sum_i^N w_i}, \tag{2.3}$$

where $\hat{b}_i$ are the individual estimate of the effect and weights, w_i, are equal to $(1/se_i^2)$ or $(1/(se_i^2 + \hat{\tau}^2))$ according to the FEM or REM, respectively. In presence of homogeneity between the different studies, the two models likely find very similar results. In the presence of heterogeneity, it may not be appropriate to combine results. To verify the presence of heterogeneity it is necessary to statistically test the degree of

The major criticism of the use of the partial correlation is that its distribution is truncated at +1 and -1 and, in some cases, such truncation might cause an asymmetry. (Stanley et al., 2018) suggest as an alternative measure the Fisher's z-transformed correlation effect size. It is computed and used for a robustness check, results do not change sensitively. They are available from the authors upon request.

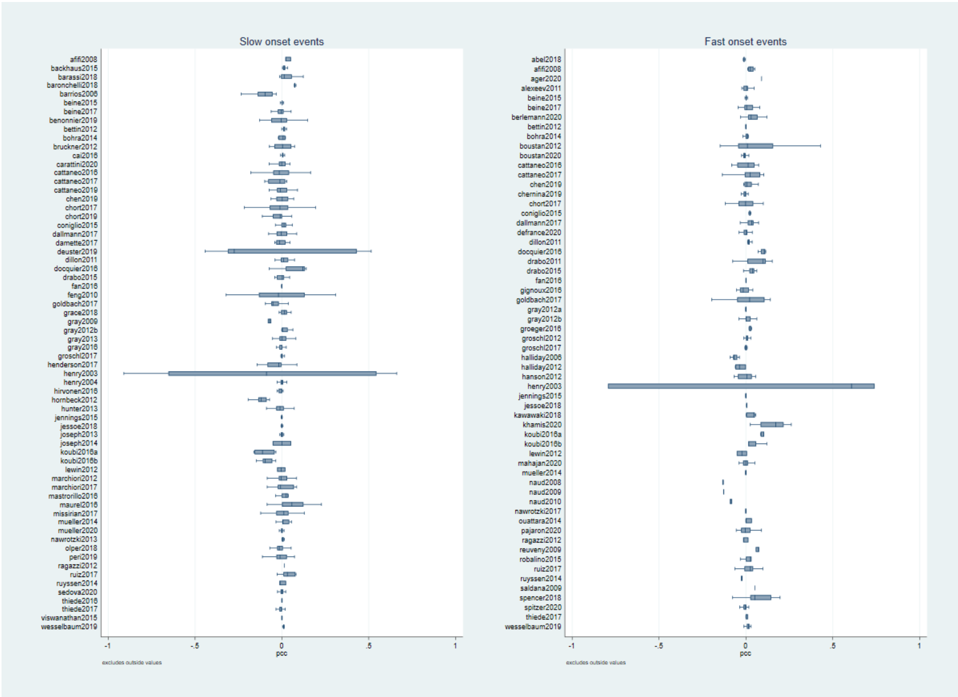
similarity of the results of the various studies. The test for heterogeneity measures whether the differences between the results of individual studies are greater than what would be expected if: (i) all studies measured the same effect and (ii) the observed differences are purely random. A test of homogeneity of the β_i is provided by referring the statistic Q to a χ^2-distribution with n - 1 degrees of freedom (Higgins and Thompson, 2002): if the test is higher than the degrees of freedom, the null hypothesis is rejected (there is heterogeneity). Another test commonly used is the I^2 inconsistency index by Higgins and Thompson (2002) describing the percentage of the variability of the estimated effect that is referable to heterogeneity rather than to chance (sample variability). It is interpreted as the proportion of variability due to heterogeneity between studies rather than sampling error. Values range from 0 per cent to 100 per cent where zero indicates no observed heterogeneity. The results of meta-synthesis of the collected estimates (Table 2.2) are statistically significant, except for findings of the slow onset effect of paper included in Cluster 2, in which both FEM and REM give statistically insignificant averages. Considering the high heterogeneity in our sample of estimates (see columns 5-6), REM results should be looked at as the most appropriate models.

TABLE 2.2: Basic meta-analysis (Fixed and Random effect MA)

	(1) Model	(2) Averages	(3) Lower bound 95% CI	(4) Upper bound 95% CI	(5) I^2	(6) Q-test p-value	(7) N. of Obs. (N. of studies)
Slow onset effect	FEM	0.0001***	0.0001	0.0001	86.78	0.00	3897
	REM	0.0006	−0.0010	0.0022	99.93	0.00	(66)
- Cluster 1	FEM	0.0001***	0.0000	0.0001	83.15	0.00	932
	REM	−0.0025 **	−0.0048	−0.0002	99.97	0.00	(23)
- Cluster 2	FEM	0.0003	−0.0001	0.0008	95.32	0.00	100
	REM	0.0068	−0.0051	0.0186	99.84	0.00	(3)
- Cluster 3	FEM	−0.0037***	−0.0042	−0.0032	77.58	0.00	1814
	REM	−0.0039***	−0.0063	−0.0014	93.58	0.00	(18)
- Cluster 4	FEM	0.0060***	0.0057	0.0064	88.44	0.00	1051
	REM	0.0082***	0.0064	0.0101	94.96	0.00	(22)
Fast onset effect	FEM	0.0021***	0.0018	0.0024	91.42	0.00	2032
	REM	0.0085***	0.0062	0.0107	97.76	0.00	(60)
- Cluster 1	FEM	0.0022***	0.0013	0.0032	86.50	0.00	176
	REM	0.0140***	0.0037	0.0243	98.98	0.00	(13)
- Cluster 2	FEM	−0.0021***	−0.0027	−0.0014	85.84	0.00	789
	REM	−0.0033	−0.0095	0.0029	98.77	0.00	(16)
- Cluster 3	FEM	−0.0004	−0.0009	0.0002	80.19	0.00	409
	REM	0.0028***	0.0008	0.0049	89.04	0.00	(7)
- Cluster 4	FEM	0.0071***	0.0066	0.0077	96.11	0.00	688
	REM	0.0224***	0.0170	0.0278	98.94	0.00	(24)

Note: Basic meta-analysis of collected estimates. Fixed Effect Model and Random Effect Model are reported for overall slow- and fast-onset samples and sub-samples defined by clusters. Averages (2), lower (3) and upper (4) bound of 95% confidence interval. I^2 and Q-test for heterogeneity reported in Columns (4-5); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 2.2: Box plot of Partial Correlation Coefficients



Note: Box plot of partial correlation coefficients. Panel (1) reports PCC for slow-onset events by study. Panel (2) reports PCC for fast-onset events. PCCs are calculated on coefficients reported in each study included in the sample obtained from Scopus, Web of Science, Google Scholar, IDEAS RePEc, and previous meta-analyses (Hoffmann et al., 2020; Beine and Jeusette, 2019) and coded by the authors.

The preliminary result of the basic MA is that environmental factors seem to influence migration positively, even if the magnitude is very small and the REM mean is statistically significant only in the case of the fast-onset events. The mean effect by cluster becomes negative in the case of estimates of slow-onset events in Clusters 1 and 3 and for the estimates of fast-onset events in Cluster 2. For a graphical inspection, Figure 2.2 shows a box plot of the estimates reported in the primary studies; the heterogeneity both between and within studies is substantial.

2.2.1 Meta-Regression tests of publication selection bias

Different findings of the same phenomenon can be explained in terms of heterogeneity of studies' features, however, the literature also tends to follow the direction consistent with the theoretical predictions causing the so-called publication bias.

The publication bias occurs when (i) researchers, referees, or editors prefer statistically significant results and (ii) it is easier to publish results that are consistent with a given theory. However, the consequences of the peer-review process refer more to a general "publication impact" rather than a "bias" (Cipollina and Salvatici, 2010).

TABLE 2.3: Descriptive Statistics of the Partial Correlation Coefficients

	(1) Mean	(2) Median	(3) Min	(4) Max	(5) N. Obs	(6) N. Studies
Slow onset effect	−0.0002	0.0000	−0.9101	0.8566	3897	66
- Cluster 1	−0.0048	0.0000	−0.9101	0.6613	899	22
- Cluster 2	0.0075	−0.0017	−0.4618	0.8566	332	9
- Cluster 3	−0.0036	−0.0028	−0.4422	0.5138	1727	16
- Cluster 4	0.0080	0.0038	−0.2349	0.6073	939	19
Fast onset effect	0.0105	0.0011	−0.9768	0.9481	2062	60
- Cluster 1	0.0147	0.0002	−0.7943	0.7410	170	13
- Cluster 2	0.0009	−0.0041	−0.9768	0.9297	376	14
- Cluster 3	0.0053	0.0000	−0.1185	0.2737	939	12
- Cluster 4	0.0238	0.0106	−0.1355	0.9481	577	21

Meta-regression tests, as the funnel asymmetry test (FAT), allows for an objective assessment of publication bias:

$$pcc_i = \beta_0 + \beta_1 se_i + \epsilon_i \tag{2.4}$$

Weighted least squares (WLS) corrects the previous equation for heteroskedasticity (Stanley and Doucouliagos, 2017) and it can be obtained dividing by the standard errors:

$$t_i = \frac{pcc_i}{se_i} = \beta_1 + \beta_0 \frac{1}{se_i} + \epsilon_i \tag{2.5}$$

Results are used to test for the presence of publication selection ($H_0 : \beta_1 = 0$) or a genuine effect beyond publication selection bias ($H_0 : \beta_0 = 0$). According to the funnel asymmetry–precision estimate test (FAT-PET), in the absence of publication selection the magnitude of the reported effect will vary randomly around the "true" value, β_1, independently of its standard error (Stanley and Doucouliagos, 2012). The use of the variance se_i^2, instead of the standard error, as the precision of the estimate, gives a better estimate of the size of the genuine effect corrected for publication bias (Stanley and Doucouliagos, 2014). This model is called "precision-effect estimate with standard error" (PEESE) and the WLS version is :

$$t_i = \frac{ppc_i}{se_i} = \beta_1 se_i + \beta_0 \frac{1}{se_i} + \xi_i \tag{2.6}$$

To take into account the issue of the dependence of study results, when multiple estimates are collected in the same study, the errors of meta-regressions are corrected with the "robust with cluster" option, which adjusts the standard errors for intra-study correlation. Table 2.4 shows the FAT-PET and PEESE results. Publication bias can be detected by implementing a full comparison of the FAT-PET and PEESE, through multiple methods for sensitivity analysis and to ensure the robustness of findings. Column (1) of table 2.4 presents the FAT-PET coefficients, column (2) shows the results of the WLS model to deal with heteroskedasticity, columns (3) and (4) present the results of the panel-random effect model (REM) and multilevel mixed-effect model that treats the dataset as a panel or a multilevel structure.

TABLE 2.4: FAT-PET MR model and PEESE correction of publication selection

		(1) WLS	(2) REM	(3) Multilevel Mixed Effect	(4) N. of Obs.
Slow-onset events	Standard Error (FAT): $\hat{\beta}_1$	0.108 (0.144)	0.268 (0.204)	0.260 (0.208)	3897
	Constant (PET): $\hat{\beta}_0$	0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	
	PEESE: $\hat{\beta}_0$	0.000** [0.000,0.000]	-0.005 [-0.013,0.003]	-0.004 [-0.011,0.003]	
- Cluster 1	Standard Error (FAT): $\hat{\beta}_1$	-0.337 (0.248)	-0.208 (0.417)	-0.213 (0.407)	932
	Constant (PET): $\hat{\beta}_0$	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	
	PEESE: $\hat{\beta}_0$	0.000** [0.000,0.000]	-0.001 [-0.020,0.019]	0.004 [-0.017,0.025]	
- Cluster 2	Standard Error (FAT): $\hat{\beta}_1$	0.412 (0.446)	0.042 (0.482)	0.123 (0.488)	100
	Constant (PET): $\hat{\beta}_0$	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	
	PEESE: $\hat{\beta}_0$	0.000** [-0.001,0.002]	-0.001 [-0.019,0.017]	0.006 [-0.010,0.023]	
- Cluster 3	Standard Error (FAT): $\hat{\beta}_1$	0.001 (0.117)	0.825* (0.469)	0.797** (0.357)	1814
	Constant (PET): $\hat{\beta}_0$	-0.004 (0.003)	-0.011** (0.005)	-0.011*** (0.001)	
	PEESE: $\hat{\beta}_0$	-0.004 [-0.009,0.001]	-0.011** [-0.023,0.000]	0.010** [-0.018,-0.002]	
- Cluster 4	Standard Error (FAT): $\hat{\beta}_1$	0.439 (0.379)	0.461 (0.347)	0.460 (0.443)	1051
	Constant (PET): $\hat{\beta}_0$	0.004** (0.001)	0.005** (0.002)	0.005*** (0.002)	
	PEESE: $\hat{\beta}_0$	0.006**	-0.002	-0.002	

TABLE 2.4: FAT-PET MR model and PEESE correction of publication selection

		(1) WLS	(2) REM	(3) Multilevel Mixed Effect	(4) N. of Obs.
		[0.003,0.009]	[-0.021,0.016]	[-0.022,0.018]	
Fast-onset events	Standard Error (FAT): $\hat{\beta}_1$	0.532*	0.755**	0.755**	2062
		(0.274)	(0.334)	(0.309)	
	Constant (PET): $\hat{\beta}_0$	-0.001	0.001	0.001	
		(0.002)	(0.002)	(0.001)	
	PEESE: $\hat{\beta}_0$	0.001	0.012*	0.012*	
		[-0.002,0.005]	[-0.001,0.025]	[-0.000,0.025]	
- Cluster 1	Standard Error (FAT): $\hat{\beta}_1$	0.942**	1.314**	1.329**	176
		(0.366)	(0.618)	(0.670)	
	Constant (PET): $\hat{\beta}_0$	-0.002	-0.001	-0.001	
		(0.002)	(0.001)	(0.003)	
	PEESE: $\hat{\beta}_0$	0.002	-0.012*	0.011	
		[-0.001,0.004]	[-0.000,0.024]	[-0.007,0.030]	
- Cluster 2	Standard Error (FAT): $\hat{\beta}_1$	-0.381	0.095	0.151	789
		(0.332)	(0.410)	(0.431)	
	Constant (PET): $\hat{\beta}_0$	-0.000	0.001	0.001	
		(0.002)	(0.001)	(0.002)	
	PEESE: $\hat{\beta}_0$	-0.002	-0.004	-0.004	
		[-0.007,0.003]	[-0.011,0.003]	[-0.014,0.005]	
- Cluster 3	Standard Error (FAT): $\hat{\beta}_1$	0.283	0.293	0.294	409
		(0.394)	(0.715)	(0.372)	
	Constant (PET): $\hat{\beta}_0$	-0.002	0.001	0.001	
		(0.004)	(0.007)	(0.002)	
	PEESE: $\hat{\beta}_0$	-0.001	0.012**	0.012*	
		[-0.007,0.005]	[0.002,0.023]	[-0.001,0.025]	
- Cluster 4	Standard Error (FAT): $\hat{\beta}_1$	1.877**	1.134**	1.072	688
		(0.703)	(0.480)	(0.774)	
	Constant (PET): $\hat{\beta}_0$	-0.003	0.003	0.003	
		(0.004)	(0.005)	(0.004)	
	PEESE: $\hat{\beta}_0$	0.006**	0.046	0.047**	
		[0.001,0.010]	[-0.028,0.121]	[0.013,0.080]	

Note: FAT, PET and PEESE correction coefficients estimated with Weighted Least Squares (1), Random Effect Model (2) and Multilevel mixed effect model. Overall effect of slow- and fast-onset events reported, along with sub-samples defined by clusters. PCC precision square weights ($1/se_i^2$); robust standard errors clustered by study in parentheses; 95% confidence intervals in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Looking at the estimates of the effect of climate change on migration, the FAT coefficients ($\hat{\beta}_1$) are not statistically significant, implying that there is no evidence of publication bias, while the positive and statistically significant PET coefficient ($\hat{\beta}_0$) indicates a genuinely positive slow-onset effect exists, in particular in the case of Cluster 4. Conversely, in the case of Cluster 3 the REM and multilevel mixed-effect model find that, even if in presence of publication bias, the impact on migration is negative. Table 2.4 provides evidence of publication bias in the literature focusing on the effect of natural disasters on migration. The estimated FAT coefficient is statistically significant in the overall sample, especially due to papers in clusters 1 and 3, and there is insufficient evidence of a genuinely positive effect (accept $H_0 : \hat{\beta}_0$). The PEESE results, however, suggest a significant and positive slow- and fast-onset effect on migration after correcting for publication bias. Preliminary results between migration and slow- and fast-onset events are positive and significant (though very small in magnitude).

2.2.2 Multiple Meta-Regression Analysis: econometric results e discussion

The multiple meta-regression analysis (MRA) includes an encompassing set of controls for factors that can integrate and explain the diverse findings in the literature. Coded variables (summarised in table 2.1) are meant to capture differences in the features of various studies and regressions and to be included as a set of dummies to control for them. Specifically, left- and right-hand side characteristics of regressions estimated in the collected papers generate a set of dummies for paper features, dependent variables, independent variables, sample characteristics, regression characteristics.

The overall sample includes both unpublished and published papers, so some moderators variables describing different features of the studies that are published are added. In particular, a dummy for *Published articles* controls for the quality of the journal in which the study is published by adding the variable *Publication Impact-factor*. In reporting the main results, some authors emphasise a benchmark regression that produces a preferred estimate, which in the MRA is controlled for by adding the dummy *preferred specification* equal to 1 when the reported effect size is obtained from the main specification. Concerning the measure of migration, the dependent variable in the left-hand side of the regression, original studies mainly distinguish migration by *corridor*, which are mainly two, internal and international migration. In this context, it distinguishes also a special internal corridor, the one characterised by rural-urban mobility, to investigate the potential impact of an environmental variable on the urbanisation process. Whenever the corridor is not specified, the variable is categorised as undefined (which will be the reference category in the estimation). Dependent variables differ also in terms of *measurement* of the phenomenon: specifically, they are separated into measures that express flows from those expressing stocks. The first category includes both studies that use flows (or an estimation of flows) and rates of migration. The second category captures those cases in which migration is measured as stock of migrants at the destination. The reference category is direct measures, which mainly captures whether migration has occurred or not (typically dummy variables used on survey-based samples equal to 1 when the individual migrates and 0 otherwise). Information about countries of origin and the destination of migrants are also included. *Origins* are categorised by macro-regions: Africa, Asia, Europe, Latin America and Caribbean, Middle East and North Africa and North America. The reference category is "world", identified whenever origin countries are not specified (typically in multi-country settings). *Destinations* are categorised by level of income. The choice of this categorisation is led by the aim to identify differences in the possibility to choose a destination. Categories are divided into high, higher-middle, lower-middle and low income.

The specific objective of the study is the impact of environmental variables on migration, thus on the right-hand side of the regression, a proxy of the environmental change is included. Slow-onset events are typically defined as gradual modifications of temperature, precipitation and soil quality. Respectively, three dummies *temperature, precipitation* and *soil degradation* are created. Each of these phenomena is measured in different ways, and the use of a specific kind of measurement is relevant for the outcome. Both temperature and precipitation have been measured in levels (simple level or trend of temperature/precipitation); deviation, as the difference between levels and long-run averages; and anomalies, mostly calculated as the ratio of the difference between the level and the long-run mean and its standard deviation. Soil degradation includes events such as desertification, soil salinity, or erosion. Additionally, the time lag considered is included concerning the time units of the dependent variable: whenever the period considered corresponds to the same time-span as the dependent variable the lag is zero, while it takes values more than zero for any additional period before the dependent variable time-span. The second battery of coded variables refers to fast-onset events, which can be also defined as natural hazards or extreme events. The main classification of fast-onset events reflects the one reported in table C.1: *geophysical* (earthquakes, mass movements, volcanic eruptions), *meteorological* (extreme temperature, storms - cyclones, typhoons, hurricanes, tropical storms, tornadoes), *hydrological* (floods and landslides) and *climatological* (droughts or wildfires). Fast-onset events also differ in the way they are measured. Possible measures are: occurrence (when the measure is a dummy capturing if the disaster happened or not), frequency (the count of events that occurred in the area), intensity (i.e. Richter scale for earthquakes, wind speed for tornadoes, etc.), duration (length of the occurrence of the event) and losses (when the disaster is measured in terms of the affected population, number of deaths or injured people, number of destroyed houses or financial value of the damaged goods). As for slow-onset events, a continuous variable capturing the time lag of the event concerning the dependent variable is added. A dummy capturing whether the coefficient refers to multiple disasters is also included.

Characteristics of the sample are one of the main sources of heterogeneity. The level of the analysis varies considerably from paper to paper, including both micro-and macro-level studies. Typically micro-level studies uses data coming from *censuses* or *surveys* where *households* or *individuals* are the units of analysis. *Country-level* studies usually take the source of their data from *official statistics*. Other kinds of sampling are included in the reference group (for example small territorial aggregates such as districts, provinces, or grid cells). The set of coded variables also includes a variable capturing the time span of the analysis, subtracting the last year of observation from the first one. The role of econometric approaches may have an impact on resulting outcomes. Beine and Jeusette (2019) and Beine and Jeusette (2021) emphasised in their work the importance of methodological choices, with differentiated results depending on estimation techniques. First of all, a *panel* dummy to capture whether the structure of data and related estimation techniques has an impact. Furthermore, estimation strategies are distinguished by *Poisson*, which includes the Pseudo Poisson Maximum Likelihood (PPML) estimator and Negative Binomial Models; *linear* estimators, both Ordinary Least Squares (OLS), linear probability models and maximum likelihood models; conventional *Instrumental Variables* (IV) estimators, two-stage least squares (2SLS), and other cases of estimators as Generalised Method of Moments (GMM) used to control for endogeneity; and finally, *logit* which comprises multinomial logit models. Any other estimator (i.e. Tobit, panel VAR) are less frequent and grouped in a category *other estimators* used as the reference group.

Theoretically, the impact of environmental variables on migration may be mediated, channelled, or transmitted through other phenomena that can be controlled for or interacted with. Most models investigating general migration determinants usually controls for several possible determinants to recover the effect of the specific objective variable, with all potential other factors being controlled for. The majority of these additional controls are suggested by theoretical models and then introduced in the empirical model. Furthermore, methodological approaches in our sample are found to often include interaction terms to specifically address the combined effect of an environmental variable with other potential factors. In the dataset they are introduced in two groups of variables, *controls* and *interacted terms*, categorised both to capture factors or channels such as income, agriculture, conflicts, political stability, cultural or geographical factors, (a full description of the categories can be found in the Supplementary materials). The list of controls also includes a dummy that captures whether both slow- and fast-onset events are included in the regression.

Table 2.5 shows the results of the multiple MRA on the literature in slow-onset events (precipitation, temperature and soil quality) in which potential biases are filtered out sequentially by the addition, in a step-wise manner, of statistically significant controls. Column (1) presents results for the whole sample of studies estimating the impact of climatic variations on migration, columns (2) to (5) show the results of papers grouped by clusters to highlight how specific features characterising the cluster influence the magnitude of the estimated effect. The results are unfolded below.

TABLE 2.5: MRA Results for slow-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
Constant (PET): $\hat{\beta}_0$	-0.011^{***}	-1.040^{***}	0.959^{***}	-0.031^{***}	0.102^{***}
	(0.003)	(0.264)	(0.010)	(0.008)	(0.009)
Standard Error (FAT): $\hat{\beta}_1$	-0.205^{*}	-4.939^{**}	-29.959^{***}	0.099	-0.671^{***}
	(0.119)	(1.894)	(0.264)	(0.273)	(0.190)
Paper features					
- Preferred specification		-0.001^{**}			
		(0.000)			
- Published article					-0.008^{***}
					(0.002)
- Publication Impact-factor		0.024^{**}			
		(0.009)			
Corridor					
- Internal	0.002^{***}	0.002^{***}		-0.009^{***}	0.012^{**}
	(0.001)	(0.000)		(0.002)	(0.005)
- International				-0.010^{***}	
				(0.001)	
- Urbanisation	0.002^{***}	0.002^{***}			
	(0.001)	(0.000)			
Measurement					
- Flows	-0.016^{***}	1.565^{***}			
	(0.004)	(0.481)			
Region of origin					
- Asia	0.008^{**}				
	(0.003)				
- Europe	0.033^{***}	-0.332^{***}			0.010^{***}
	(0.004)	(0.083)			(0.002)
- LAC				0.096^{***}	-0.012^{***}
				(0.017)	(0.002)
- North America	-0.021^{***}				
	(0.004)				
Destination					
- High income		-0.000^{*}		-0.049^{***}	
		(0.000)		(0.012)	

Results of specifications that control for all moderator variables are reported in Appendix B

TABLE 2.5: MRA Results for slow-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
- Upper-middle income		-0.000^{***} (0.000)		-0.049^{***} (0.012)	
- Lower-middle income		0.000^{***} (0.000)		0.004^{***} (0.001)	
Precipitation measures					
- levels	-0.000^{**} (0.000)	0.000^{***} (0.000)	-0.924^{***} (0.009)	-0.007^{***} (0.002)	-0.002^{*} (0.001)
- deviation		0.000^{***} (0.000)		-0.008^{**} (0.004)	
- anomaly		0.002^{**} (0.001)			
Time lag	-0.000^{***} (0.000)	-0.000^{***} (0.000)			
Temperature measures					
- levels		0.000^{***} (0.000)	-0.924^{***} (0.009)		
- deviation	0.000^{***} (0.000)	0.000^{***} (0.000)	-0.410^{***} (0.005)		
- anomaly		-0.005^{***} (0.001)		-0.012^{***} (0.001)	
Time lag	-0.000^{***} (0.000)	-0.000^{***} (0.000)	0.021^{***} (0.000)		
Soil Degradation		0.011^{***} (0.003)		-0.055^{***} (0.002)	
Sample features					
Time span	-0.000^{***} (0.000)			-0.002^{***} (0.000)	
Source of data					
- Census	0.016^{***} (0.002)	-0.331^{**} (0.140)		0.076^{***} (0.012)	-0.089^{***} (0.005)
- Official statistics		0.397^{***} (0.096)			
- Research data	-0.007^{**} (0.003)	0.257^{**} (0.103)			
Unit of analysis					
- Household		1.256^{***} (0.362)		0.052^{***} (0.005)	
- Individual	-0.015^{***} (0.004)	1.051^{***} (0.287)			
- Country level	0.014^{***} (0.004)	-0.856^{**} (0.311)		0.079^{***} (0.019)	-0.098^{***} (0.009)
Estimation:					
- Panel	0.019^{***} (0.004)	0.066^{**} (0.024)		0.042^{***} (0.006)	
- Poisson		-0.514^{**} (0.219)			
- OLS and ML	0.010^{***} (0.003)		-0.017^{***} (0.000)		0.011^{***} (0.002)
- IV	0.041^{***} (0.011)				0.044^{***} (0.011)
Controls:					
- Slow and fast included				-0.032^{***}	

TABLE 2.5: MRA Results for slow-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
				(0.008)	
- Income	0.004***	0.170**	0.004***		
	(0.001)	(0.065)	(0.000)		
- Conflict		0.249***			
		(0.063)			
- Political stability		−0.130***			0.012***
		(0.040)			(0.002)
- Population	0.005**			0.031***	0.009***
	(0.002)			(0.008)	(0.002)
- Diaspora		−0.156**			
		(0.074)			
- Past migration		−0.090**	0.007***		
		(0.042)	(0.000)		
- Poverty		0.096**			−0.011***
		(0.039)			(0.002)
- Culture		0.436**			
		(0.173)			
- Agriculture	0.004***	−0.461**			
	(0.001)	(0.193)			
- Labour					
- Urban	−0.013***	0.265**		−0.016***	
	(0.002)	(0.111)		(0.004)	
- International aids	−0.025***			−0.036***	
	(0.008)			(0.003)	
Interacted terms (channels):					
- Agriculture			−0.055***		0.003*
			(0.000)		(0.001)
- International aid	0.023*			0.034***	
	(0.013)			(0.000)	
- Culture	−0.006***				−0.006***
	(0.001)				(0.002)
- Destination	0.012***				
	(0.002)				
- Poverty				−0.058***	
				(0.011)	
- Income and agriculture	0.029***			0.024***	
	(0.005)			(0.004)	
- Education	−0.000***	−0.000***			
	(0.000)	(0.000)			
- Environment	−0.000***	−0.000***		0.003*	
	(0.000)	(0.000)		(0.001)	
- Income		−0.003**		−0.018***	
		(0.001)		(0.004)	
- Origin	−0.000***	−0.000***		−0.046***	
	(0.000)	(0.000)		(0.005)	
- Past migration	−0.013***	−0.007***			
	(0.003)	(0.000)			
- Political stability	−0.037***				−0.047***
	(0.008)				(0.002)
- Population	−0.019***			−0.028***	
	(0.006)			(0.008)	
- Urban	0.011***			0.021***	

TABLE 2.5: MRA Results for slow-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
	(0.004)			(0.001	
PEESE Correction: β_0	-0.012^{***}	-0.783^{***}	0.655^{***}	-0.030^{***}	0.079^{***}
N. of Obs.	3897	932	100	1814	1051
N. of Studies	66	23	3	18	22

Note: Stepwise regression of overall sample (1) and sub-samples defined by clusters (2-5) for slow-onset events. Estimates shown represent significant coefficients obtained through a stepwise procedure (not reported when not significant). Controls are grouped by paper features, dependent variable, independent variable, sample and regression characteristics. PCC precision square weights ($1/se_i^2$); robust standard errors clustered by study in parentheses; 95% confidence intervals in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (1) refers to the overall sample and shows a coefficient of the main variable of interest ($\hat{\beta}_0$) negative and statistically significant, implying that climatic variations may decrease incentives for migration by exacerbating credit constraints of potential migrants. Looking at results for different clusters (columns 2-5) such negative effect is generated by studies that are included in clusters 1 and 3. The MRA of papers in clusters 2 and 4, instead, gives positive and statistically significant PET coefficients ($\hat{\beta}_0$) implying that climate changes induce people to migrate. Concerning the FAT-test, the intercept ($\hat{\beta}_1$) might deviate from zero confirming the presence of publication bias: the peer-review process seems to particularly affect the magnitude of the estimated effect of studies in all clusters except for Cluster 3.

Most of the papers included in the MRA for slow-onset events are published (52 articles out of 66), indeed the estimated coefficients of controls for published articles are useful to evaluate if the peer-review process exerts some influence on reported results in the collected studies. In Cluster 3 estimates obtained by the *Preferred specification* tend to be slightly lower while articles published in journals with higher impact factors report lower estimates of the impact of slow-onset events on migration. In Cluster 4, instead, results of *Published articles* are lower, even if the mean effect of this group of studies remains positive.

From the other sets of controls emerges that specific features of studies included in the MRA differently explain the diversity in the results within clusters. The positive coefficients of controls for corridors such as *Internal* and *Urbanisation* state that people respond to adverse climatic change with increased internal migration. The only exception is for studies included in Cluster 3, this is the most heterogeneous cluster of most recent papers, where heterogeneous approaches (micro-and macro-level and type of migration) lead to a large heterogeneity in outcomes, varying according to different channels explored. Findings obtained when mobility is measured by *Flows* seem to be lower in the overall sample. In macroeconomic literature, usually, the measurement of migration is a stock variable, since it is generally easier to find and measure the number of foreign citizens born or resident in a country at any given time. Data on flow variables and migration rates, or the number of people who have moved from an origin to a destination in a specific period, are less available, and analyses often rely on estimates and computations of this data. Therefore, the opposite sign of the coefficient of the variable *Flows* in Cluster 1 is not surprising since this cluster collects all micro-level studies (where the migration variable refers to movements of individuals as a unit, based on surveys).

Controls for how the climatic phenomenon is measured, *Precipitation measures* and *Temperature measures*, seem to differently affect the heterogeneity of results and, in many cases, the estimated coefficients are statistically significant but very close to zero. The estimated coefficients of dummies for country groups included in the multiple MRA indicate how results from analyses focusing on specific regions of origin differ. In particular, positive coefficients of controls *Asia* and *Europe* support the idea that the results of analyses that focus on the migration from these regions are likely to be positive (with exception of Cluster 1), while if the people move from a country in the region of *North America* the impact of climate changes on migration is lower and can be negative. The climate impact on migration from *LAC* (Latin America and the Caribbean) countries are higher in Cluster 3 (where the PET coefficient is negative) and lower in Cluster 4 (where the PET coefficient is positive).

Dummies are included to control for the heterogeneity produced by the fact that studies use different sources of data for migration. All estimated coefficients of this set of controls are statistically significant in Cluster 1: the use of different databases might influence the wide variety of findings. Effect sizes in Cluster 2, instead, are not affected by the source of data used.

Since it is natural to expect the adjustment of migratory flows in response to climate change is not instantaneous, especially in the case of gradual phenomena, most of the studies use a panel structure with macroeconomic focus and attempt to assess the impact of changes in climatic conditions on human migratory flows in the medium-long term. Microeconomic analyses mostly use cross-section data to explain causal relationships between specific features of individuals, collected through surveys and censuses, and various factors determining the migration by isolating the net effect of the environment. Analyses at *Individual* level tend to capture a more negative impact of climate changes on migration, whereas analyses at *Country* level tend to find a more positive effect. As already said, for micro-level analyses in Cluster 1 controls related to sample characteristics have opposite signs. Looking at dummies for the estimation techniques, evidence suggests that the diversity in the effects sizes is in part explained by differences in techniques. In particular positive and significant coefficients are found for controls as *OLS and ML* estimators for cross-section analyses, same for panel studies that use *Panel* estimation techniques, and Instrumental Variables (*IV*) or GMM estimators to correct for endogeneity. Micro-economic analyses (Cluster 1) use more disaggregated data, while the high presence of zeros in the dependent variable is treated with a *Poisson* estimator, which tends to produce lower estimates.

Many authors highlight the importance of variables of political, economic, social and historical nature, in influencing the impact of climatic anomalies on migration processes, emphasising the role of important channels of transmission of the environmental effect to migrations. The multiple MRA includes a set of dummies for *Controls* included in the estimation of the model of migration and dummies for *Channels* through which the climatic event determines migration. The idea is that studies based on the same theoretical framework tend to include the same set of control variables or interacted terms and these controls may positively and negatively affect the effect size of climate changes on migration.

Table 2.6 shows the results of the MRA for fast-onset events, or rather natural disasters, more or less related to climate change, which appear as destructive shocks of limited duration and for which the ability to predict is reduced.

TABLE 2.6: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
Constant (PET): $\hat{\beta}_0$	0.044^{**}	-0.127^{***}	3.147^{***}	-0.508^{***}	0.419^{***}
	(0.021)	(0.032)	(0.091)	(0.038)	(0.030)
Standard Error (FAT): $\hat{\beta}_1$	0.997^{***}	-1.506	-0.097	6.410^{***}	1.070
	(0.279)	(1.399)	(0.116)	(0.961)	(0.783)
Paper features					
- Preferred specification				0.001^{***}	
				(0.000)	
- Published articles		0.145^{***}	0.936^{***}		
		(0.004)	(0.056)		
- Publication Impact-factor	0.002^{**}	0.015^{***}	-0.475^{***}		0.048^{*}
	(0.001)	(0.004)	(0.007)		(0.026)

TABLE 2.6: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
Corridor					
- Internal				0.043*** (0.005)	−0.021** (0.008)
- International			0.004*** (0.001)	0.041*** (0.005)	
- Urbanisation			0.003*** (0.000)		
Measurement					
- Flows		0.322*** (0.027)	−3.199*** (0.296)	−0.240*** (0.042)	−0.355*** (0.072)
- Stock			−0.087*** (0.012)		−0.357*** (0.071)
Region of Origin					
- Africa	−0.015** (0.007)	−0.003** (0.001)	0.346*** (0.106)	0.212*** (0.044)	
- Asia			−0.773*** (0.145)		
- Europe		−0.340** (0.156)	2.114*** (0.313)		
- LAC		−0.034*** (0.002)	0.974** (0.380)	0.030*** (0.001)	
- North America	−0.023** (0.009)		1.827*** (0.332)		
Destination					
- High income			−4.148*** (0.181)		−0.003* (0.002)
- Upper-middle income				−0.003* (0.001)	
- Lower-middle income		−0.002*** (0.000)	−0.002*** (0.000)	0.021*** (0.000)	−0.020*** (0.004)
Type of event					
- Geophysical			−0.054*** (0.002)	−0.107*** (0.006)	
- Meteorological	0.004** (0.002)		−0.063*** (0.006)	−0.146*** (0.006)	
- Hydrogeological	0.005** (0.002)	0.006** (0.002)	−0.054*** (0.002)	−0.109*** (0.006)	0.006** (0.003)
- Climatological			−0.065*** (0.006)	−0.077*** (0.006)	
Time lag			0.002*** (0.000)		
Measurement					
- Frequency		0.031*** (0.000)	−0.023*** (0.000)	0.556*** (0.026)	
- Intensity			1.137*** (0.265)	0.493*** (0.026)	
- Occurrence			0.024*** (0.000)	0.474*** (0.009)	
- Duration		0.368*** (0.057)		0.584*** (0.029)	
Sample					
Time span	0.000* (0.000)	0.014*** (0.003)	0.030*** (0.005)	−0.001* (0.000)	

TABLE 2.6: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
Source of data					
- Census			-0.005^{***}		
			(0.000)		
- Official statistics		-0.127^{**}	0.002^{***}		0.152^{*}
		(0.044)	(0.000)		(0.085)
- Research data					
- Survey			-3.360^{***}		
			(0.052)		
Unit of analysis					
- Household		-0.197^{***}	-0.910^{***}	0.757^{***}	
		(0.064)	(0.027)	(0.067)	
- Individual			0.121^{***}		
			(0.032)		
- Country level					-0.230^{*}
					(0.116)
Estimation					
- Panel	-0.034^{***}	-0.621^{***}	0.788^{***}		-0.116^{*}
	(0.011)	(0.103)	(0.059)		(0.059)
- Poisson				-0.003^{***}	0.058^{***}
				(0.000)	(0.010)
- OLS and ML	-0.027^{**}	-0.037^{***}			0.036^{***}
	(0.012)	(0.003)			(0.011)
- IV	-0.066^{***}	-0.037^{***}	0.830^{***}		0.058^{*}
	(0.019)	(0.003)	(0.043)		(0.031)
- Logit	-0.023^{*}				
	(0.012)				
Controls					
- Slow and fast included	-0.016^{*}				
	(0.009)				
- Income			0.008^{***}	-0.009^{***}	0.094^{*}
			(0.000)	(0.000)	(0.049)
- Conflict	0.018^{***}				-0.061^{*}
	(0.005)				(0.033)
- Political stability	0.017^{***}	0.029^{***}	0.002^{***}		0.097^{*}
	(0.005)	(0.001)	(0.000)		(0.048)
- Population		0.394^{***}	0.001^{*}	0.008^{***}	-0.036^{**}
		(0.076)	(0.001)	(0.000)	(0.017)
- Diaspora	-0.028^{***}	-0.296^{***}	-0.043^{***}		
	(0.010)	(0.024)	(0.001)		
- Past migration					-0.127^{***}
					(0.037)
- Poverty	-0.015^{**}	-0.032^{**}	-0.001^{***}		
	(0.006)	(0.014)	(0.000)		
- Geography		-0.095^{***}	-0.006^{***}		
		(0.021)	(0.000)		
- Agriculture			0.002^{*}	0.008^{***}	
			(0.001)	(0.001)	
- Labour					-0.084^{*}
					(0.047)
- Urban				-0.016^{***}	
				(0.000)	
- International aids			-0.001^{***}	-0.030^{***}	0.107^{**}

TABLE 2.6: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
			(0.000)	(0.004)	(0.047)
Interacted terms (channels)					
- Agriculture	0.005**		0.007***	−0.005***	−0.027***
	(0.002)		(0.002)	(0.001)	(0.004)
- International aid	−0.031***				−0.039***
	(0.005)				(0.001)
- Culture	0.019**	0.015***			0.026***
	(0.008)	(0.001)			(0.004)
- Destination		−0.023*			
		(0.011)			
- Diaspora			0.004**		
			(0.001)		
- Poverty			0.004***	0.008***	
			(0.001)	(0.000)	
- Education		0.034***			
		(0.001)			
- Environment				0.015***	
				(0.000)	
- Geography			0.025***		
			(0.001)		
- Income		−0.005***	0.010***		−0.014***
		(0.000)	(0.001)		(0.001)
- Past migration	0.016***	0.014***	0.020***		
	(0.006)	(0.001)	(0.000)		
- Political stability	−0.013***		−0.000***		
	(0.004)		(0.000)		
- Urban				0.038***	−0.342***
				(0.000)	(0.026)
PEESE Correction: β_0	0.047**	−0.138***	2.938***	−0.464***	0.443***
N. of Obs	2062	176	789	409	688
N. of Studies	60	13	16	7	24

Note: Stepwise regression of overall sample (1) and sub-samples defined by clusters (2-5) for fast-onset events. Estimates shown represent significant coefficients obtained through a stepwise procedure (not reported when not significant). Controls are grouped by paper features, dependent variable, independent variable, sample and regression characteristics. PCC precision square weights ($1/se_i^2$); robust standard errors clustered by study in parentheses; 95% confidence intervals in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The coefficient of $\hat{\beta}_0$, is positive and statistically significant in the overall sample and in clusters 2 and 4, providing evidence of an increase of migration due to sudden natural hazards. It is worth noting that papers in Cluster 2 (column 3) mainly focus on fast-onset events and the summarised effect size is positive and very high. On the other side, the summarised effect of papers in clusters 1 and 3 is negative and statistically significant.

Results show evidence of publication bias for the overall sample and in Cluster 3, with $\hat{\beta}_1$ statistically significant signalling that the reported effect is not independent of its standard error. The significant and positive coefficient found for the published dummy confirms that there is a general *Publication Impact*, so the peer-review process seems to affect the magnitude of the estimated effect, especially in clusters 1 and 2. Articles published in journals with higher *Impact-factor* get higher estimates of the effects of natural disasters on migration, with exception of published articles in Cluster 2, suggesting that editors prefer to publish results that have a positive but more limited effect. Natural disasters affect domestic and international migration flows. The positive coefficients of the group of controls related to the type of migration, in clusters 2 and 3 confirm that people respond to natural disasters with any kind of mobility. Specifically in Cluster 2 natural disasters increase both *Internal* and *Urbanisation* migration, while studies in Cluster 3 find a greater effect on *Internal* and *International* movements of people. In Cluster 4, instead, estimates of the impact of natural disasters are lower in the case of *Internal* migration. *Hydrological* events have a greater impact on migration, the estimated coefficient is statistically significant in all clusters; if the fast-onset event refers to *Geophysical*, *Meteorological* and *Climatological* disasters the effect on migration is lower.

The severity of natural disasters, such as hurricanes, landslides, or floods, affects regional agricultural production and it also has direct effects on employment and income in the agricultural sectors of the affected regions pushing people to migrate. However, if on the one hand natural disasters, such as droughts, floods, and storms, push individuals to move to find new sources of income or livelihood, on the other hand, natural disasters such as earthquakes, tsunamis, or hurricanes cause losses to populations that might lead people into a poverty trap, with potential migrants not having the resources to finance the trip. These effects, already highlighted by the literature, seems to be confirmed. Also in this literature, indeed, various controls and transmission channels analysed in the original empirical models have a role in determining heterogeneity in results.

Finally, table 2.7 shows estimates of the sample when, one by one, each cluster is excluded from the overall sample. In the case of slow-onset events, not including papers of Cluster 1 and 4 results in a loss of significance of the estimate, while Cluster 2 do not change consistently the final estimate. Excluding Cluster 3, conversely results in a higher negative average effect. This highlight the fact that, with the only exception of papers included in Cluster 2, the selection of papers entails a consistent loss of information and different conclusions on the average effect of climatic variations on migration patterns. In the case of fast-onset events, the major change in estimates occurs when Cluster 2 is excluded, which is very significant when taking into account the fact that it is the most focused on natural disasters. Excluding Cluster 3, conversely, results in higher estimates of the average effect of these events on

TABLE 2.7: MRA Results for slow-onset events - Exclusion cluster by cluster

	(1) All	(2) Cluster 1 excluded	(3) Cluster 2 excluded	(4) Cluster 3 excluded	(5) Cluster 4 excluded
Panel A: Slow-onset events					
Constant (PET): $\hat{\beta}_0$	-0.011^{***}	-0.006	-0.012^{***}	-0.384^{***}	0.021
	(0.003)	(0.009)	(0.003)	(0.014)	(0.022)
Standard Error (FAT): $\hat{\beta}_1$	-0.205^{*}	-0.335^{**}	-0.194^{*}	-0.605^{***}	0.073
	(0.119)	(0.137)	(0.113)	(0.178)	(0.203)
PEESE Correction: β_0	-0.012^{***}	-0.143^{***}	-0.000	0.009	-0.013^{***}
	(0.003)	(0.015)	(0.000)	(0.009)	(0.003)
N	3897	176	3797	2083	2846
Panel B: Fast-onset events					
Constant (PET): $\hat{\beta}_0$	0.044^{**}	0.042^{**}	0.005	0.272^{**}	0.028^{***}
	(0.021)	(0.019)	(0.004)	(0.127)	(0.005)
Standard Error (FAT): $\hat{\beta}_1$	0.997^{***}	0.920^{***}	1.128^{***}	0.288	-0.011
	(0.279)	(0.268)	(0.325)	(0.486)	(0.120)
PEESE Correction: β_0	0.047^{**}	-0.138^{***}	2.938^{***}	-0.464^{***}	0.443^{***}
	(0.022)	(0.028)	(0.141)	(0.002)	(0.025)
N	2062	176	789	409	688

Note: FAT-PET and PEESE coefficients of overall sample (1) and sub-samples created by the exclusion of one cluster at a time (2-5) for slow-onset events (Panel A) and fast-onset events (Panel B). The entire list of controls is included in the estimation but not reported. PCC precision square weights ($1/se_i^2$); robust standard errors clustered by study in parentheses; 95% confidence intervals in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

mobility.

Estimates shown in tables 2.5 - 2.7 show consistency on the initial assumption of the existence of a bias created by the convergence of certain papers on communities that show a high level of heterogeneity in average estimated effects and determine consistent differences in overall results when accounted for or excluded.

2.3 Concluding remarks

The analysis offered in the chapter, combined with the results of the systematic review of the literature, the bibliometric analysis, and the community detection on the citation-based network of essays, finds evidence of the absence of a uniform and cohesive literature. The too many different characteristics in terms of object of analysis, methodology and mediating covariates renders the meta-analytic average effect estimates just a first approximation of the quantitative evidence of the literature. The small, positive, and significant effect of slow- and rapid-onset variables on migration, can barely be considered a consensual outcome. The high level of heterogeneity in the four clusters of papers that compose the economic literature on environmental migration tells us that the contributions in each cluster are conditionally converging towards a different average effect, indicating that the estimates obtained by the meta-analysis on the entire sample must be examined taking into account the specificities of every group of studies. All this calls for a group-by-group analysis of the link between environmental change and migration, and a greater effort by scholars and institutions in validating existing studies.

Chapter 3

Network Analysis of World Migration Flows

3.1 Background

This chapter focuses on a descriptive analysis of international migration flows and their evolution across the last 30 years. To meet the purpose, the analysis will use social network analysis (SNA) tools, to identify the connectivity of the world international migration network, capitalising on the idea that human mobility configures itself as a complex structure of connections between nodes (in this setting, countries) through the size of migrants flows. The use of a network perspective adds to traditional studies on migration a view on characteristics of connectivity, topology and clustering of the network. I will hereby try to analyse the migration network and combine it with the thematic of environmental hazards.

SNA has been used in different applications, including migration, although relatively recently. The study of migration from a network perspective consists of few applications, however, it is rapidly expanding. This might be mainly due to the unavailability of suitable dyadic and directional data until very recently. For their shared characteristics, these applications have been often compared and related to gravity models applied to migration (Fagiolo and Mastrorillo, 2013; Leone Sciabolazza, 2018; Tranos et al., 2015). SNA revealed to be a useful tool to test the validity of most influential gravity modelling assumptions (mainly on economic, geographic, cultural and historical distances and other specific factors), capitalising on the shared dyadic observation of the phenomenon and focusing on spatial interactions. Employing the World Bank's bilateral data on migration stocks (Özden et al., 2011), Fagiolo and Mastrorillo (2013) provide a comprehensive study on the entire matrix of countries, exploring the systemic structure of migration stocks from 1960 until 2000. They find evidence of a disassortative structure of linkages between differently central nodes and high clustering with a decreasing number of clusters, as well as relative stability in migration patterns throughout decades included (Fagiolo and Mastrorillo, 2013). Davis et al. (2013), using the same data within the same period, found a trend of strengthening of what is called the "small-world" behaviour of the migration network, accompanied by an overall homogenisation of the migration network. Through a set of measures of centrality, Aleskerov et al. (2016) focuses on determining which are the most influential actors in the network for a selected number of countries and considering the year 2013. Similarly, Cappart and Thonet (2015) provide a ranking of central nodes according to different centralities. Gravity modelling techniques are blended with network analysis tools in Tranos et al. (2015), in the attempt to bridge the gap between descriptive and econometric approaches. More recently, Plotnikova and Ulceluse (2021) highlight the complexity of patterns linking migration and inequality, suggesting a bi-modal system of low-to-high inequality countries direction of migration as well as a high-to-high direction. Overall, the concept of dynamic stability has been proven by most of these contributions: Abel et al. (2021) draws from new techniques of community detection in migration flow networks, providing additional evidence by showing how the size and composition of international migration communities have been stable over time, raising the idea of the existence of multiple international migration networks, instead of a single one. This idea is supported by observing the complexity of migration networks and internal communities: within the overall system, in fact, different features emerged. Notably, spatial fragmentation of migration can be captured by observing the co-existence of regional centralisation and global interconnectedness (Danchev and Porter, 2018).

Adding the most recent wave of migration flows available (2015-2020), this analysis will try to map the topology and evolution of migration flows in the last 30 years and introduce a simple descriptive method not yet used in SNA applications to migration to visualise hierarchical structures of the network and compare it with canonical community detection strategies. To introduce the next chapter, a specific focus on the potential impact of natural disasters on migration networks will be provided.

3.2 The World Migration Network

3.2.1 Methodology and Data

The analysis uses methods issued from SNA to sample the network, measure connectivity and characteristics of nodes and links and visualise the network. Additionally, it will provide a visualisation of the hierarchical structure of the network and detect communities. The world migration network (WMN) is intended as the system that connects nodes through linkages of different strengths generated by human mobility. The analysis uses a macro perspective on international migration, considering countries as nodes from and to which links start or end. Linkages between nodes are made through human mobility so that a connection between two countries exists whenever a number of people originating from a node decide to move to a different destination node within the time frame considered. The number of migrants that moved from one node to another in a specific period represents the weight of the links, which is stronger for numerous and structured corridors of migrants.

The network can then be formalised as $\mathscr{N} = (\mathscr{V}, \mathscr{L}, \mathscr{W}, \mathscr{P})$, where the first part represents a simple graph, with $\mathscr{V}$ as the set of vertices and $\mathscr{L}$ the set of linkages. Additional features to the two graph elements are weights $\mathscr{W}$, which are associated with each link, and $\mathscr{P}$, which includes a set of characteristics of each node. Each edge has a specific direction, that goes from the node that originates it to a target node. The network is then *directed*. Furthermore, the network is also *weighted* by the size of flows.

To describe and represent graphically the WMN, I will use a recently published data estimation of migration flows taken from Abel and Cohen (2019b). This dataset offers an overview of different estimation methods for migration flows derived from International Migrant Stock data inputs by the United Nations (UNDESA, 2019). The estimation strategy chosen to represent the network hereby comes from Abel (2018) and it contains six waves: 1990-95, 1995-2000, 2000-05, 2005-2010, 2010-2015, 2015-2020. It is important to point out that, unlike several previous analyses, the data hereby used contain measures of flows of migration. Due to data unavailability, data on stocks have often been used in studies requiring dyadic observations, with the non-negligible difference that stocks of migrants describe the cumulative presence of foreign-born in a country, while flows are able to capture the number of people moving from a place to another in the specific time window considered (actual *e*migration and *im*migration). Furthermore, this work adds on previous by including a new wave of migration flows, the most recent time window 2015-2020.

The final section of the analysis will also try to give a picture of the relationship between migration and environmental factors. To do so, migration data have been

Version 6, Posted on 06.02.2021
A more detailed description of the dataset is provided in Chapter 4 and Appendix D, section **??**
The same estimation strategy to flows has been used in Leone Sciabolazza (2018)

FIGURE 3.1: World Migration Network by 5-year period

TABLE 3.1: Global summary statistics of world migration network

Period	Flows (in mln)	Nodes (countries)	Links	Mean edge weight
1990-95	33.1	163	9012	3564
1995-00	33.0	185	11 394	2837
2000-05	40.4	185	11 553	3326
2005-10	47.4	186	11 667	3896
2010-15	44.8	186	11 394	3795
2015-20	40.7	186	11 109	3522

	Density	Clustering coefficient	Longest Path Length	Average Path Length	Reciprocity	Assortativity (by degree)	Assortativity (by strength)
1990-95	0.34	0.76	5	1.80	0.19	-0.28	-0.12
1995-00	0.33	0.76	5	1.72	0.21	-0.28	-0.14
2000-05	0.34	0.77	4	1.70	0.23	-0.33	-0.16
2005-10	0.34	0.77	6	1.74	0.21	-0.33	-0.14
2010-15	0.33	0.78	5	1.73	0.20	-0.33	-0.15
2015-20	0.32	0.78	5	1.73	0.26	-0.33	-0.18

Note: Summary statistics of WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018).

merged with data on natural disasters. The most reliable and complete dataset for natural disasters is the Emergency Events Database EM-DAT, compiled by the Centre for Research on the Epidemiology of Disasters (CRED), which contains 22,000 mass disasters from 1900 to present day. Observations have been grouped to match time windows in Abel and Cohen's dataset, aggregating the number of disasters by type and by the total number. In this way, I obtained a measure of the frequency of hazards by country for each 5-year period. Occurrence and frequency of natural hazards are the most common tools used by the literature to relate disasters on migration determinants (cf. Chapter 1-2). However, the simple fact that they occur and hit a specific area might not be enough to determine a causal relation with migration, because of their interaction with many aspects of human lives. This concern will be addressed in the next chapter, in which a novel index of risk connected to natural hazards will be introduced.

3.2.2 Descriptive Analysis

Global network topology The analysis starts from global metrics of the migration flow network. Since the first period of observation (1990-95), it is possible to observe an increase in the number of migrants in the world, from 33 to almost 41 million for the last round of observation. A peak is detected in the five years going from 2005

CRED is part of the School of Public Health of the Université Catholique de Louvain (UCL). CRED launched the EM-DAT in 1988, with the support of the World Health Organization and the Belgian government. EM-DAT is compiled from various sources, according to their rank in terms of reliability: UN agencies (OCHA, WHO, WMO, FAO, etc.), national governments, US agencies (NOAA, USGS, etc.), inter-governmental organisations (World Bank) and insurance companies. www.emdat.be

Details on different types of natural disasters are reported in table C.1 Appendix C

Unfortunately, data are available for a restricted and very recent period (2012-2020).

and 2010 when global flows reached more than 47 million. This figure is reflected also in the overall number of links: while the number of nodes reflects the number of countries included in the sample, meaning that every node has at least a connection to another (in other words, every country is either - or both - a sender or a receiver of migrants), the number of links increases from 1990-95 to 1995-2000 (more 2000 than additional links are created) with a peak in the number of links in the period corresponding to the peak of flows (2005-2010). While the first increase can be explained by the creation of new nations (with countries splitting and gaining independence by the end of the millennium), *de facto* creating new nodes in the network (and jumping from 163 to 185), the peak in 2005-2010 (with a stable number of countries) testifies a process of formation of new connections. Although the following two periods show a decreasing amount of links between nodes, the overall process of formation and deletion of links, despite some fluctuations, proves stability in the inter-connectivity of nodes and persistence of links (Fagiolo and Mastrorillo, 2013, found the same persistence of links also in migrants stocks for antecedent decades 1960-2000). The stability of network linkages can also be seen in values of network density, which represents the proportion of connected links over the entire amount of potential links in the network: overall, a third of potential links connect in each period considered. This figure is lower than the density calculated on networks defined by stocks of migrants (Fagiolo and Mastrorillo, 2013), consistently with the different measuring of migration employed. The coefficient of reciprocity shows that each network is mainly unidirectional: in fact, it represents the probability that an edge going from node i to node j corresponds with another edge going from j to i. In each period, this probability is around 20 percent, meaning that the majority of edges are unidirectional (keeping in mind that a probability of 0 corresponds to purely unidirectional networks), although a fifth of links configures as reciprocal. A jump in reciprocity can be seen in the last wave of observations, in which more than a fourth of edges are found to be reciprocal. To describe the directionality of links it is also interesting to look at assortativity coefficients. These metrics can provide information about how nodes with similar or opposite characteristics connect with each other: the two metrics reported in table 3.1 describe assortativity coefficients by degree and by strength. The first captures the presence or absence of *homophily* among vertices of the same or opposite degree. Assortativity by degree shows if vertices showing high degree (high number of edges connected to a node) tend to connect to other high-degree vertices (positive coefficient, the case of *homophily*) or else they tend to connect more with low-degree vertices (negative coefficient). The constant negative values reported show a persistent disassortative mixing, a trend

i.e. nations created after the dissolution of Soviet Union that is consistent also when weights (strength) of the connections is taken into account. Countries with few connections or less intense flows have the tendency to connect with countries with a consistent number of (weighted) connections. The disassortative behaviour of migration networks is not new to the literature (Fagiolo and Mastrorillo, 2013; Leone Sciabolazza, 2018) and can be at the basis of hierarchical structures and star-like structures. This aspect will be investigated in section 3.3

Local measures This section summarises some of local measures of centrality of each network and provide some rankings of most central nodes according to different features. Starting by *in-* and *out-degree*, measures simply capturing the number of links reaching or starting from a node and are calculated as $c_d^{in}(i) = \sum_{j \neq i}^{N} \mathscr{L}_{ij}$ for *in-degree* and $c_d^{out}(i) = \sum_{j \neq i}^{N} \mathscr{L}_{ji}$ in the case of *out-degree*. Centrality according to *degree* gives a picture of central nodes without taking into consideration the size (weights) of links reaching or starting from them. World migration configures as a weighted network, thus it is interesting to observe how the size of flows (weights of edges) determines the centrality of a node: *in-* and *out-strength* (or weighted in- and out-degree) are calculated aggregating over the total of weights linked to the node and, similarly to *degree*, are computed both for weights of edges directed to node i (*in-strength*) as $c_s^{in}(i) = \sum_{i \neq j}^{N} \mathscr{W}_{ij}$ and for those originating from node i (*out-strength*) as $c_s^{out}(i) = \sum_{i \neq j}^{N} \mathscr{W}_{ji}$. Table 3.2 shows normalised measures of degree and strength of both directions (in- and out-). The highest *out*-strength scores show a constancy of some of the biggest players (India, Bangladesh, China), along with contextual nodes emerging, that can be explained by the current major crisis at the time of observation (i.e. Rwanda for 1990-95 period or Syria for 2010-2015). The difference in ranking between strength and degree centrality highlight the potential existence of strongly preferential migration streams toward a specific destination instead of various nodes. This difference is higher in initial waves (until 2000), where a high score of out-strength centrality corresponds to a low ranking in-degree centrality and manifests the existence of flows mainly directed toward a few other nodes. Except for Syria and Venezuela, in the last rounds, this trend changes, equalising high ranking in strength to high ranking in degree, which displays a tendency of such central nodes to "diversify" their linkages towards new destinations.

The importance of a node in the network can also be captured not only because of the high number of connections it has but also because of its crucial positioning in the network. For this purpose, *betweenness* centrality describes the centrality of a node in terms of how its position serves as a hub between different nodes, by computing the number of paths between other pairs that pass through the node. Defining $\sigma(s,t)$ as the number of shortest path between node s and node t, the betweenness

TABLE 3.2: Ranking by degree and strength centrality

Out				In			
Country	Strength	Degree	Outflows in mln	Country	Strength	Degree	Inflows in mln
1990-1995							
Mexico	6.76 (1)	0.87 (27)	2.17 (1)	United States	17.07 (1)	1.45 (8)	5.48 (1)
Pakistan	6.11 (2)	0.47 (55)	1.96 (2)	Afghanistan	9.49 (1)	0.50 (61)	3.05 (2)
India	4.77 (3)	1.13 (11)	1.53 (3)	Ethiopia	4.49 (1)	0.68 (47)	1.44 (3)
Rwanda	4.58 (4)	0.22 (74)	1.47 (4)	Germany	4.29 (1)	1.41 (11)	1.38 (4)
United States	3.72 (5)	1.26 (5)	1.19 (5)	Congo - Kinshasa	4.20 (1)	0.65 (4)	1.35 (5)
1995-2000							
Mexico	7.59 (1)	0.50 (55)	2.45 (1)	United States	27.77 (1)	1.53 (1)	8.98 (1)
Kazakhstan	4.03 (2)	0.68 (37)	1.30 (2)	Russia	7.49 (1)	0.91 (32)	2.42 (2)
India	3.73 (3)	1.18 (2)	1.21 (3)	Germany	4.12 (1)	1.22 (14)	1.33 (3)
Philippines	3.16 (4)	0.78 (28)	1.02 (4)	Rwanda	3.88 (1)	0.04 (101)	1.26 (4)
Congo - Kinshasa	3.05 (5)	0.50 (55)	0.99 (5)	Canada	3.32 (1)	1.45 (5)	1.07 (5)
2000-2005							
India	7.31 (1)	1.01 (9)	2.81 (1)	United States	18.15 (1)	1.29 (18)	6.98 (1)
Mexico	6.16 (2)	0.92 (15)	2.37 (2)	Spain	7.59 (1)	1.45 (5)	2.92 (2)
China	5.02 (3)	0.89 (18)	1.93 (3)	Russia	4.67 (1)	1.38 (11)	1.79 (3)
United States	4.30 (4)	1.12 (4)	1.65 (4)	Italy	4.49 (1)	1.54 (1)	1.73 (4)
Bangladesh	4.03 (5)	1.06 (7)	1.55 (5)	United Kingdom	4.15 (1)	1.49 (3)	1.60 (5)
2005-2010							
India	8.61 (1)	0.91 (17)	3.92 (1)	United States	14.95 (1)	1.33 (13)	6.79 (1)
Bangladesh	7.49 (2)	1.05 (7)	3.40 (2)	United Arab Emirates	8.08 (1)	0.93 (34)	3.67 (2)
China	4.32 (3)	0.82 (24)	1.96 (3)	United Kingdom	5.21 (1)	1.41 (7)	2.37 (3)
Philippines	3.46 (4)	1.05 (7)	1.57 (4)	Russia	5.15 (1)	1.37 (11)	2.34 (4)
United States	2.96 (5)	0.97 (12)	1.34 (5)	Spain	5.08 (1)	1.48 (2)	2.31 (5)
2010-2015							
Syria	12.71 (1)	0.47 (56)	5.50 (1)	United States	14.20 (1)	1.47 (5)	6.14 (1)
India	7.80 (2)	1.07 (8)	3.37 (2)	Turkey	6.22 (1)	0.97 (28)	2.69 (2)
Bangladesh	5.38 (3)	1.02 (11)	2.33 (3)	Germany	5.18 (1)	1.37 (13)	2.24 (3)
Nepal	4.72 (4)	0.97 (15)	2.04 (4)	Saudi Arabia	4.80 (1)	0.59 (51)	2.08 (4)
China	3.59 (5)	0.72 (31)	1.55 (5)	Russia	4.16 (1)	1.41 (11)	1.80 (5)
2015-2020							
Venezuela	9.61 (1)	0.26 (77)	3.76 (1)	United States	14.45 (1)	1.53 (3)	5.65 (1)
India	7.98 (2)	1.36 (1)	3.12 (2)	Germany	9.42 (1)	1.49 (6)	3.68 (2)
Bangladesh	6.10 (3)	1.22 (4)	2.39 (3)	United Kingdom	4.59 (1)	1.40 (9)	1.80 (3)
Syria	5.52 (4)	0.62 (41)	2.16 (4)	Turkey	4.49 (1)	1.27 (20)	1.76 (4)
China	4.16 (5)	1.19 (5)	1.63 (5)	Colombia	4.07 (1)	0.76 (40)	1.59 (5)

Note: Centrality measures of WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018).

TABLE 3.3: Betweenness centralities

Country	Score	Country	Score	Country	Score
1990-95		*1995-00*		*2000-05*	
Italy	0.073	Uganda	0.073	Costa Rica	0.067
Greece	0.069	South Africa	0.062	Thailand	0.062
Bolivia	0.053	Bolivia	0.052	Malta	0.051
Bahrain	0.051	Slovenia	0.048	New Zealand	0.049
Kuwait	0.050	Argentina	0.045	Panama	0.043
2005-10		*2010-15*		*2015-20*	
Bolivia	0.082	Egypt	0.081	Argentina	0.077
Mali	0.067	Latvia	0.081	Lithuania	0.069
Thailand	0.063	Bolivia	0.070	Chile	0.062
Philippines	0.056	Guinea	0.068	Qatar	0.051
Greece	0.041	Mexico	0.054	Guinea	0.051

Note: Centrality measures of WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018).

TABLE 3.4: Closeness centralities

Country	Score	Country	Score	Country	Score
1990-95		*1995-00*		*2000-05*	
Bolivia	0.526	South Africa	0.530	Costa Rica	0.530
Iceland	0.523	Uganda	0.526	Thailand	0.527
Bahrain	0.518	Bolivia	0.526	Panama	0.526
Bulgaria	0.518	Costa Rica	0.524	Malta	0.524
Costa Rica	0.513	Bahamas	0.523	Namibia	0.521
2005-10		*2010-15*		*2015-20*	
Bolivia	0.533	Latvia	0.541	Argentina	0.508
New Caledonia	0.517	Bolivia	0.526	Iceland	0.505
Costa Rica	0.510	Lithuania	0.517	Guinea	0.504
Ghana	0.508	Thailand	0.514	New Zealand	0.499
Slovenia	0.508	Mexico	0.511	Lithuania	0.495

Note: Centrality measures of WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018).

centrality of node i is calculated as $c_b(i) = \sum_{i \neq s \neq t}^{N} \frac{\sigma(s,t|i)}{\sigma(s,t)}$ or the total number of shortest paths between s and t passing through i over the total number of shortest paths between s and t (Kolaczyk and Csárdi, 2014). In table 3.3, it emerges how centrality intended in terms of betweenness changes the importance of specific countries. On the other hand, closeness centrality defines the centrality of a node according to how close it is to many other nodes (Kolaczyk and Csárdi, 2014), taking into account short paths between nodes and weights. In the world migration network closeness centralities are calculated on the undirected graph weighted by the size flows. It is useful to identify potential migration flows for countries close to nodes counting for intense migration flows (Aleskerov et al., 2016). It is calculated as $c_c(i) = \frac{1}{\sum_{i \neq j}^{N} dist(i,j)}$. Ranking of countries by closeness centrality is reported in table 3.4.

3.3 Hierarchical structure of the WMN

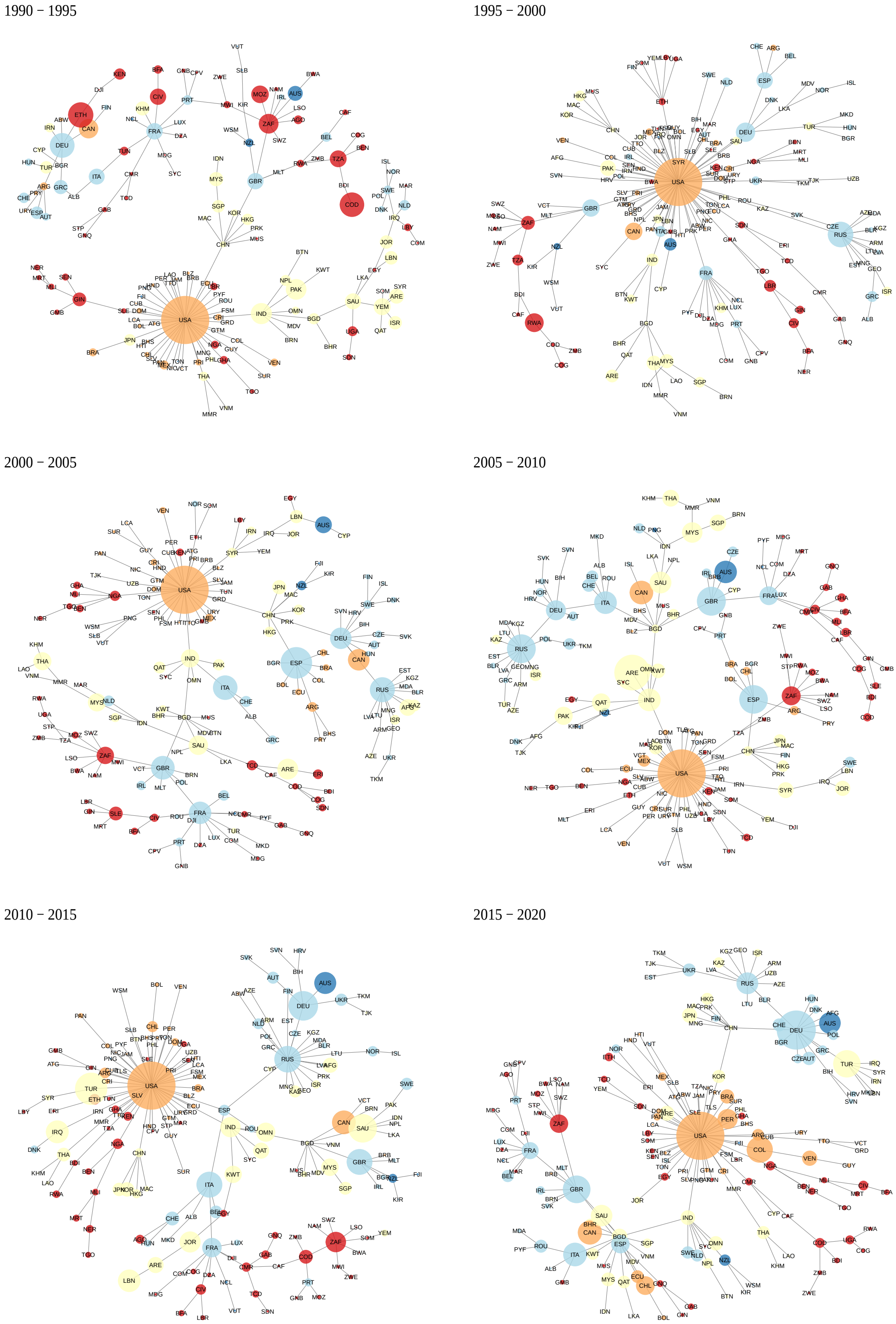
The minimal spanning tree. Global measures in table 3.1 and local centralities described in tables 3.2-3.4 provide some information about the connectivity, topology and characteristics of main nodes in each of the WMN by 5-year period. Visualisations of flows (figure 3.1) give a picture of flows of human mobility, although quite messy. However, they also show the extremely high dimensionality of linkages between nodes, making it difficult to observe hierarchical structures or node positioning. Although informative, visualising the entire system of elements and interactions might result unclear. For densely connected networks, such is also the case of trade, the *minimal spanning tree* (MST) has been used as a technique of reduction of dimensionality, able to provide a representation of a sort of *backbone* of the network. It is based on an algorithm introduced by Kruskal (1956) to give a practical solution method for constructing a subgraph that spans throughout all vertices of the main graph and minimises the distances between them. Examples of applications for densely connected networks can be found in the complex network such as international trade networks, which are closely comparable to the case of migration. To identify important trading partners of countries Maeng et al. (2012) extracts the *skeleton* network in the international trade network, by keeping the most important importing link of a country by using Kruskal's algorithm. Thanks to this technique, they were able to identify the dominant interacting trading partner among countries and the existence of hub nodes. For time series, MSTs are particularly useful to visually observe shifts in the hierarchical structure and dominant positions of the network (Lee and Nobi, 2018; Cepeda-López et al., 2019).

Methodology. Formally, a *minimal spanning tree* is a subgraph of the main graph that connects all vertices in such a way that the cost of connections is reduced at its minimum. In graph theory, a *tree* is an undirected graph in which for two given nodes only one connection exists, so that no cycles or triangles are formed. The MST *spans* throughout all nodes included in the original graph. It is *minimal* because it consists of a subset of edges such that the total weight of all edges is minimised, selecting the shortest edge between two nodes. Kruskal's algorithm allows extracting the MST from an undirected weighted network, resulting in especially useful to reduce the dimensionality of densely connected networks and create a subset of edges connecting all nodes without any loop and with minimum possible edge weight. The graph must then be undirected and weighted. The WMNs analysed here are weighted by the size of flows between two nodes and directed so that for each node they both include *im*migration and *e*migration patterns. However, as highlighted by reciprocity measures in table 3.1, all the networks are not reciprocal, meaning that flows are almost completely unidirectional. To obtain a symmetrical undirected version of the networks is then possible to consider exclusively one directionality (outward) of the weighted matrix, without entailing loss of information. Additionally, the strength of links is set as the inverse of the obtained bilateral flow weights $g_{ij} = 1/m_{ij}$, to correctly take into account the concept of distance between nodes in a migration network. In fact, minimising distance in this context can be translated as maximising the undirected weights of each migration network. For each 5-year period of observation an MST graph is extracted: each of them counts of N nodes, the same number of nodes included in the original graph, and $N-1$ edges, exclusively one per each node, without any loop, representing the shortest distances between countries. The resulting graph is a "filtered" version of the original system (Cepeda-López et al., 2019), manifesting as a *skeleton* of relations between countries.

Results. MSTs for each period included in the sample (1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20) are represented in figure 3.2. Each node is a country code with the corresponding ISO3 system. Links between each node are unique and are the edges that minimise the distance between two nodes; in other words, only the edge with the shortest distance between two nodes is displayed. The size of nodes captures the in-strength score of each country. The colours of each node are set by continent, to capture intra- and inter-regional structures. Across every period, a star-like structure emerges and evolves over the years. The central positioning of the United States is persistent and counting the maximum number of edges (degree) in every period. The U.S. are constantly the centre of a group of countries and the biggest node in size by weighted degree centrality. However, its positioning compared to every other subgroup changes over time. While the first wave shows flows connected one another more through linkages between them, in a sort of chain of connectivity, during the period going from 1995 to 2000 the U.S. configure as the centre of a star, connecting each regional subgroup. The composition of countries belonging to the U.S.-led group highlight the dimension of global inter-connectivity that goes beyond regional geography. A trend in regionalisation in flows can be detected by comparing the first wave with the others. During the period 1990-95, flows do not seem particularly driven by geographical proximity by continent (with some exceptions) as much as linguistic and colonial linkages (the case of nodes connected to France, United Kingdom, Belgium and Portugal for example). The dissolution of

Literature on trade (Maeng et al., 2012; Cepeda-López et al., 2019) uses the undirected version of a directed network by symmetrising the flow-weighted adjacency matrix $\mathbf{M}$ as $M_{ij} = (M_{ij} + M_{ji})/2$. This is mainly motivated by the consistent difference between trade and migration flow networks, with the former characterised by high reciprocity.

FIGURE 3.2: Minimum spanning tree of WMNs



Note: Minimal spanning tree of the undirected weighted migration network. Each continent is assigned to a colour: red (Africa), orange (Americas), yellow (Asia), light blue (Europe) and darker blue (Oceania). Each node has only one edge. Node size is proportional to weighted in-degree centrality of each node. Fruchterman-Reingold algorithm used for forced layout.

the Soviet Union creates starting from 1995-00 a Russia-led group, constantly having neighbouring and former-soviet countries orbiting around its node. Western and Central African countries create a more spread tree of strongly regionalised connections between them, resulting to be strictly connected mostly according to the contiguity of borders between countries constantly over time, with some exception due to past colonial linkages. In the last ten years, however, their distance to the most central node (U.S.) has shortened considerably and attracted in a direct way (the case of Nigeria, Kenya). The force of attraction of the central node seems to go increasingly beyond the negative effect that distance would exert on long-distance migration. However, this might raise evidence to the role played by pull factors such as income (cf. figure C.1 in Appendix C, where per capita GDP-weighted nodes around the US show a consistent difference in size compared to its satellites). The role of European countries, evolving during the time considered, generate a shift in the U.S.-led star-like structure starting from the beginning of 2000. A competing pole of a group of Europe-centred nodes starts to emerge, creating independent sub-groups. France leads for the entire period a subgroup of ties with countries sharing same language (in the case of European countries, Belgium and Luxembourg) and, most importantly, past colonial domination (Algeria, Tunisia, Morocco in the Maghreb area, Senegal and Cameroon for Sub-Saharan Africa and New Caledonia in the Pacific). Linguistic proximity and colonial links drives also the most important links to Portugal and Spain. A central node by in-strength emerging from table 3.2 is the United Kingdom, which compared to the U.S. shows less direct links connected to it, whereas generates a stream of connections to other subgroups. Many of its links are driven by linguistic and past colonial relations, as well as consistent intercontinental flows. Overall, it is possible to see that geographic proximity mainly drive inter-regional migration within the African continent, often between neighbouring countries. Exceptions, as already pointed out, can be made with respect to past colonial links (and consequent language proximity). This trend starts to change in the last 10 years, with countries becoming closer to third countries. Starting from the early 2000s, and consequently, to crucial historical events, Russia becomes the hub of former soviet or satellite countries, starting to share this role with Germany in the last 2 waves. The position of Italy shows a prevalence of geographical proximity until the early 2000s, mostly exclusively linked with Mediterranean countries (Albania, Greece, North Macedonia) which shift more recently. The leading role of Germany might have more mixed explanations: its position evolves from geographically close tied countries (linking Scandinavian countries) to a more mixed scenario shown in last waves, in which Germany leads a new group of countries: this new hub seems led by geographical proximity, with third European countries and corridors mainly driven by countries with ongoing conflicts (Syria, Afghanistan). The central role of India, which exhibit high outward centrality scores, is quite stable all along the 30 years, linking together different leaders of groups and subgroups: United States, United Kingdom and a new emerging group orbiting around Gulf countries (starting from 2005-10) and the Central as well as Southern Asian subgroup.

The evolution of WMNs starting from the first wave compared to the last round can be summarised in the persistence of certain regional patterns: however, earlier flows performed sorts of “chains” of connections between one another, with a big player identified by the United States, while the last round shows a less concentrated tree, with at least three multiple groups of countries generating independent subgroups (even after removing links with the leading node). The visual inspection hereby summarised highlights some interesting points. From one side, it validates some of the traditional gravity model assumptions. The majority of patterns are strongly linked to geographical proximity, with subgroups strongly based on neighbouring countries. Regional flows remain prevalent for African countries and, later on for Central and Southern Asia. Geographical proximity is increasingly determining main linkages with European countries: even if cultural ties such as colonial past and linguistic proximity have played and still play an important role in reducing “distance” between countries, the last two waves show the biggest European players involved in inter-regional migration, gathering them together (except the United Kingdom and Russia). Canonical bilateral covariates included in gravity model (Beine et al., 2016, for an overview of the gravity model applied to migration) are found consistent with the hierarchical structure displayed by the six MSTs shown in figure 3.2.

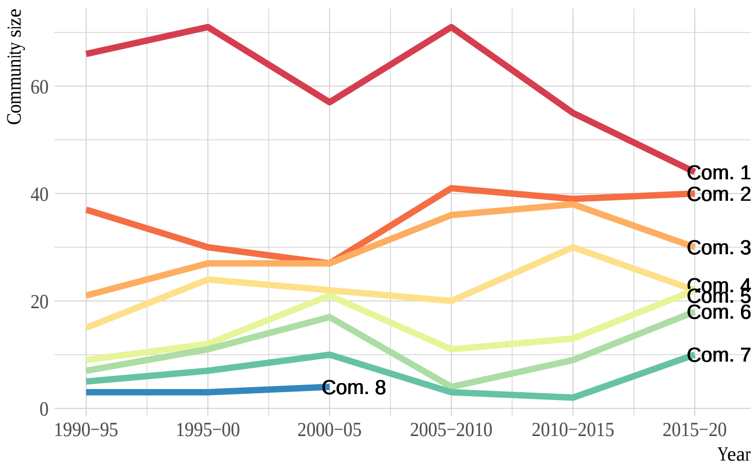
The results provide additional evidence to two coexisting phenomena, persisting regional concentration of migration, showing how flows occur mainly within the same macro-area, and, at the same time, global interconnectedness among countries belonging to different regions through some specific hub node. In the next section, a community detection will be run to identify how countries cluster together beyond the mere geographical locations.

3.4 Community detection of the WMN

To obtain communities, a version of modularity maximisation algorithm (Newman and Girvan, 2004) for directed weighted networks (Leicht and Newman, 2008) is

This point has already been highlighted in literature (Danchev and Porter, 2018).

FIGURE 3.3: Size of communities ordered by numerosity

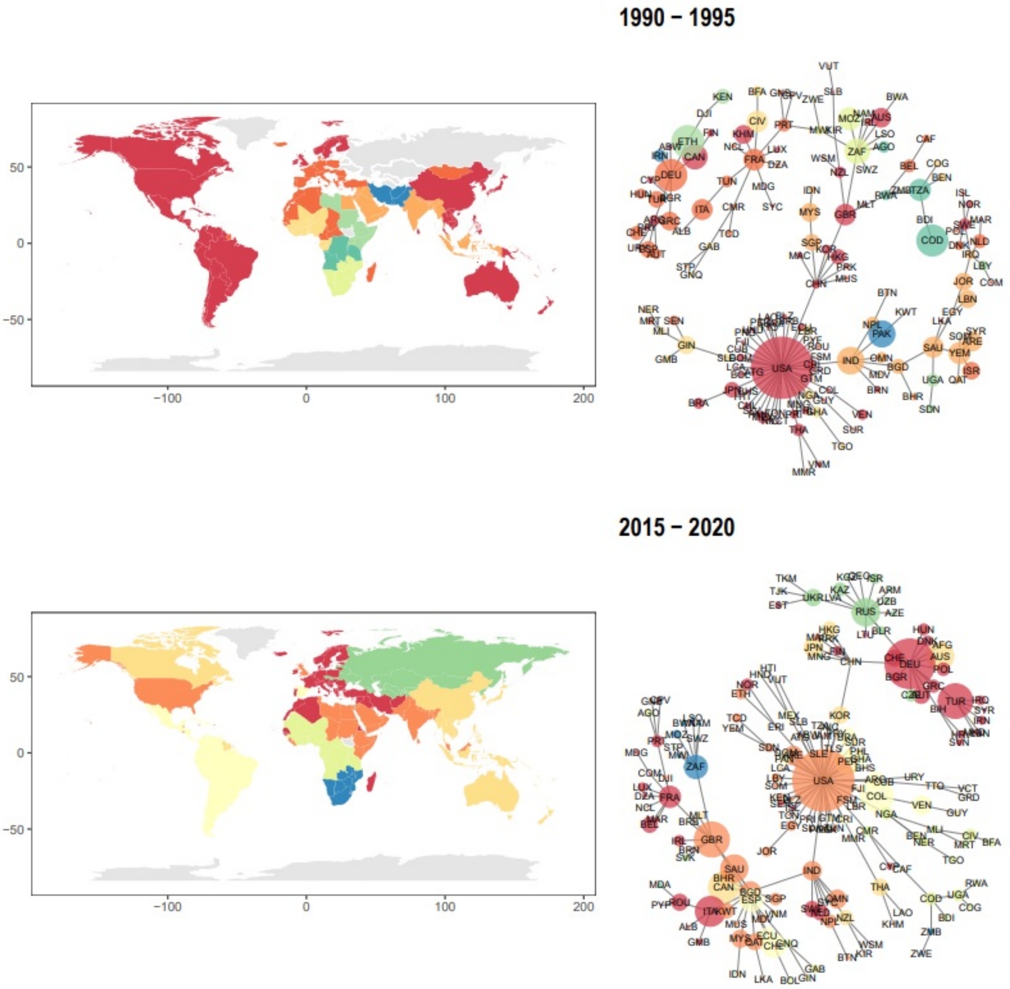


Note: Community sizes obtained from WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018).

used, a method already widely employed in previous applications of community detection to migration networks (Danchev and Porter, 2018; Fagiolo and Mastrorillo, 2013). For every 5 years resulting communities vary between 8 (for the first 3 waves) and 7 (for the last three). What changes consistently is the size of each community. Figure 3.3 shows the size of communities ordered from the most populated (by number of countries) to the least. It is possible to observe in the first place that the smallest in size communities disappear (the eighth community disappearing in 2005, and community 7 reaching a size of 10 by the end of the period). At the same time, the largest community (Com. 1) consistently decreases in number of included countries, from a maximum value of 71 to around 40. Reduction in size and number of communities has been pointed out in earlier studies: figure 3.3 adds the evidence of a persisting trend of a shrinking number of communities accompanied by the larger size of each of them. These figures show increasing connectivity between countries, which aggregates to largest communities of closer nodes and separate more distantly connected nodes. Figure 3.4 shows graphically a comparative partitioning of countries. The first column reports the geographical mapping of cluster partitioning all over world countries; each country is coloured according to the community of belonging. The same scheme of colours associated with each

These two applications are run on a different data source, which contains data on migrant stocks. The dataset hereby used, instead, uses an estimation of migration flows

FIGURE 3.4: Community detection on WMNs 1990-95 and 2015-20



Note: Community obtained from WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018).

TABLE 3.5: Assortativity coefficients by cluster and frequency of natural disasters

	1990-95	*1995-00*	*2000-05*	*2005-10*	*2010-15*	*2015-20*
Assortativity by degree	−0.277	−0.284	−0.330	−0.334	−0.331	−0.333
Assortativity by strength	−0.119	−0.140	−0.156	−0.143	−0.154	−0.178
Assortativity by frequency attribute						
Overall	*-0.011*	*-0.027*	*-0.022*	*-0.015*	*-0.003*	*-0.015*
Community 1	−0.043	−0.046	−0.030	−0.022	−0.033	−0.037
Community 2	−0.027	−0.064	−0.053	**0.0002**	−0.042	−0.105
Community 3	−0.018	−0.037	−0.063	−0.070	−0.044	−0.001
Community 4	−0.014	−0.137	−0.101	−0.146	−0.044	−0.074
Community 5	−0.094	−0.144	−0.110	**0.016**	−0.104	**0.097**
Community 6	−0.059	−0.065	−0.066	−0.798	−0.140	−0.014
Community 7	−0.271	−0.162	**0.017**	−0.577	−1	−0.089
Community 8	−0.389	**0.500**	−0.428			

Note: Community obtained from WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018).

community is then reported in *minimal spanning trees* for each 5 years. A visible evolution, also highlighted by the visualisation of MSTs is the stronger centralising role of the cluster led by the United States evolving in different composition of the cluster. Clustering according to the community detection algorithm is mirrored in the hierarchical structure displayed by the MSTs.

This new visualisation gives some insights on the geographical distribution of communities around world countries and through which main channels are they strongly connected. The highly fragmented picture portrayed in the first wave, with a big U.S.-led community and other small communities composed of few countries, evolves in a progressively more homogeneous partitioning.

3.5 The WMN and Natural Hazards

To introduce the next chapter, this section puts together findings from previous sections (hierarchical structure and community detection) and combine them with the role of environmental hazards in human migration. I will consider in this section a specific vertex value function $\mathscr{P}$ describing the frequency of environmental disasters. Figure C.5 in Appendix C reproduce the visualisation of *minimum spanning trees* by weighting the size of nodes, this time, by the frequency of occurrence of natural hazards within the corresponding time windows. In order to explore the role of natural disasters on international migration, table 3.5 shows indices of assortativity by attribute. Assortativity by attribute is a way to evaluate the *homophily* of nodes concerning a specific attribute. In this case, the occurrence of natural disasters in a country is taken as an attribute for each vertex. Disassortative mixing has already been established to be a characteristic of migration networks when considering degree or strength as an attribute. For each wave, the coefficients are always negative. When the frequency of natural disasters attribute is taken into account, each wave still shows the absence of any assortative mixing. Countries differently exposed to the occurrence of natural disasters of various kinds tend to connect more than countries with more similar countries. However, a different picture emerges when (dis)assortativity is calculated on single detected communities. In turn, the presence of (slightly) assortative mixing is observed in some communities across the waves. In 2000-05, the cluster composed of countries located in the Middle East and North Africa show a positive coefficient of flows directed to countries with comparable levels of occurrence of disasters. The same happens during the next wave for the Russian-led cluster and neighbouring countries as well as for the cluster composed of Southern and Western Europe and Western Africa. In the last wave, the regional cluster composed of Sub-Saharan countries show a trend of assortativity mixing. All this calls for a thorough exploration of the role of the environment on determinants of migration. Furthermore, the frequency and occurrence of natural disasters might not explain the complexity of the role played by the environment on human mobility.

3.6 Concluding remarks

The tools used in this chapter add to the analysis and visualisation of international migration networks throughout the last 30 years. The overall stability in topological and centralisation characteristics of the network pairs two opposite trends toward regional and global connectivity.

Chapter 4

Hazard-related Risk and Migration. A Gravity Approach

4.1 Background

Previous chapters provided a map of the discussion and the investigation around the phenomenon of environmentally-driven migration, as well as a description of migratory flows in general. This chapter provides a further investigation on the thematic, attempting to suggest a broader point of view of the complex interrelations between environment and human mobility. Migration decisions take their origins from a vast set of potential determinants that jointly or alternatively pushes individuals to move from an origin area to a potential destination. Drivers can be of different orders, social, political, economic, and, among others linked to environmental conditions. What has emerged in the overview of the literature is the evidence that the relationship between hazards and mobility may not be straightforward, and reducing the observation to the immediate direct effect of a shock might not be the only factor to take into account. Climatic variations and hazards are a generalised issue all over the world (although at different extents and manifestations) and occur in areas regardless of their preexisting condition, such as wealth, development or governance. Nevertheless, some areas are more affected than others. In other words, their occurrence does not depend on the situation before the event, while contrarily the impact of those events depends on the situation before their occurrence. A striking example can be found when two countries, such as the Philippines and Japan are taken into account: they both show very high levels of natural-hazard related risk, mainly driven by being both a seismic area, but very different socio-economic conditions. This might result in different responses when, for example, an earthquake of similar intensity disrupts in each of them.

According to the framework elaborated by the United Nations Office for Disaster Risk Reduction (UNDRR), the impact of disasters is given by the risk connected to them. The occurrence of disasters and their intensity are just one component of the risk: the susceptibility of individuals to their impact depends also on physical, social, economic and environmental characteristics of the area. Livelihoods are affected by an interplay of dimensions connected to natural hazards, which has been categorised as exposure, vulnerability and lack of coping strategy, which might play different roles also in promoting or constraining human mobility.

In this chapter, I will make use of a composed index derived from each dimension participating in the definition of a certain level of risk for each area and provide a study of the role of each component among migration drivers. The aim will be achieved by including risk measures in a gravitation model of migration. The chapter is structured as follows: section 4.2 provides a description of the tool used to measure hazard-related risk, drawing from the INFORM framework; section 4.3 describes data on migration used in the model, reviews the literature on gravity models and details the theoretical model; section 4.4 describes the empirical strategy and section 4.5 presents and discussed the results obtained through the estimation, while section 4.6 concludes.

4.2 Understanding risk

Natural hazards are not just a matter of occurrence, frequency or intensity. Their impact depends on many different aspects that have been studied separately by literature. Hazards might not directly displace people, but produce effects that indirectly entail migration. The impact of disasters on population occurs in a complex interplay of factors that may, among other impacts, drive mobility. The risk of the impact of hazards comes with their occurrence combined with the extent of exposure and vulnerability and to the lack of institutional coping capacity related to the area. Those elements compose a complex framework that identifies the broader concept of risk as the interface of reciprocal interactions linking humans to nature. An interesting project developed by the Joint Research Centre of the European Commission has elaborated a composite index as a tool for understanding the risk of humanitarian crisis and disasters (Marin-Ferrer et al., 2017). The INFORM Concept and Methodology framework define hazard-related risk as:

$$Risk = Hazard\&Exposure \times Vulnerability \times Lack\ of\ Coping\ Capacity$$

Where *Hazard&Exposure* measures the intensity and type of a natural and human disaster (UNDRR, 2019). The number of people or types of assets in a specific area can be combined with the specific vulnerability and capacity of the exposed elements to any particular hazard to estimate the quantitative risks associated with the

TABLE 4.1: Dimension, categories, components and data source of INFORM risk index

	Dimensions	Categories	Components	Data sources
INFORM Risk index	Hazard&Exposure (HA)	Natural (HA.NAT)	Earthquake	GSHAP (CIESIN)
			Tsunami	GAR 2015 (UNISDR)
			Flood	GAR 2015 (UNISDR); GloFAS (JRC)
			Tropical Cyclone	GAR 2015 (UNISDR)
			Drought	FAO; EM-DAT (CRED)
		Human (HA.HUM)	Current conflict intensity	Conflict Barometer (HIIK)
			Projected conflict intensity	GCRI (JRC)
	Vulnerability (VU)	Socio-economic (VU.SEV)	Development and deprivation	HDI, MPI (UNDP)
			Inequality	Gini, Gender Inequality Index (UNDP)
			Aid dependency	World Bank; UNOCHA
		Vulnerable groups (VU.VGR)	Uprooted people	UNHCR, IDMC
			Health conditions	WHO; UNICEF
			Children under 5	WHO; UNICEF
			Past shock	EM-DAT (CRED)
			Food Security	FAO
	Lack of coping strategy (CC)	Institutional (CC.INS)	Disaster Risk Reduction	UNISDR
			Governance	World Bank; Transparency International
		Infrastructure (CC.INF)	Communication	World Bank; Unesco
			Physical infrastructure	OpenStreetMap; WHO/UNICEF
			Access to health system	WHO

Note: Dimensions, categories and components of JRC's INFORM Index. *Source*: INFORM Index for Risk Management, Concept and Methodology, fourth version (Marin-Ferrer et al., 2017)

hazard in the area of interest (UNDRR, 2019). *Vulnerability* is the human dimension of risk connected to hazards and it is deeply interconnected with exposure. Vulnerability concerns the wider environmental and social conditions that limit people and communities to come with the impact of hazard (Birkmann, 2006). Every society is vulnerable to risk, but some suffer significantly more and recover more slowly than others. *Lack of coping capacity* pertains to the institutional dimension of risk, including conditions and ability of institutions to cope with the disastrous consequences of an event or the readiness to prevent damages to happen by the existence of efficient infrastructures.

Hazard&Exposure. This dimension includes two main categories: natural hazards and human hazards, aggregated by geometric mean, where both indices carry equal weight within the dimension (Marin-Ferrer et al., 2017). Natural hazards are categorised in earthquake, tsunami, flood, tropical cyclone and drought. All categories except droughts are measured in terms of annual average population exposed. Droughts are measured by frequency and the annual probability to have more than 30% of agriculture area affected by droughts added to exposed population measures. It is important to note also that some of the included hazards

Earthquakes are considered according to Modified Mercalli Intensity (MMI) scale VI and VIII
Cyclones included are according to wind speed measured by Saffir-Simpson category 1 and 3

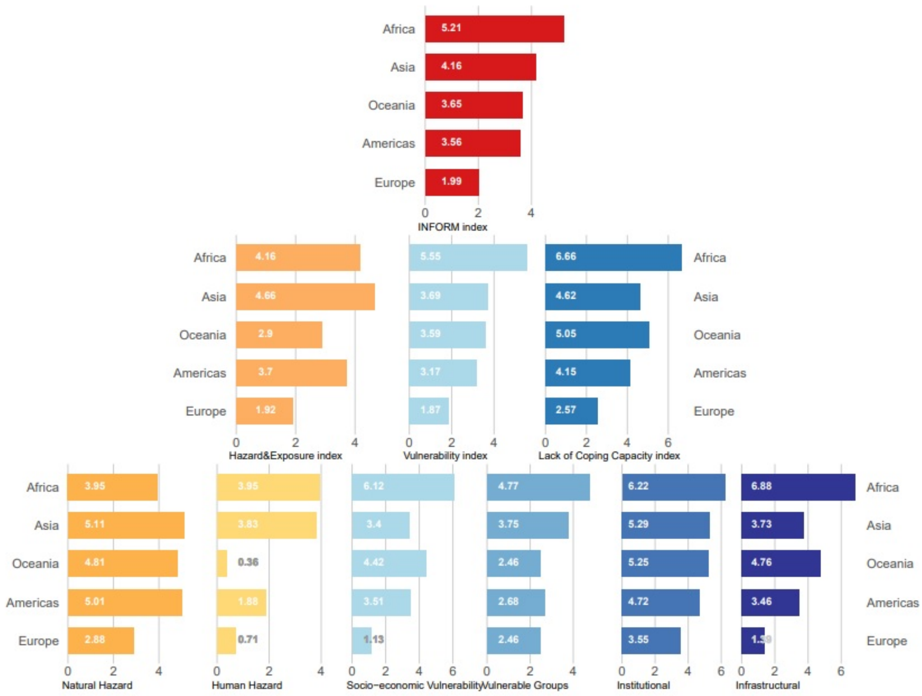
can be considered related to climate change, namely flooding, droughts and cyclones are crucially impacted by the variations of climatic conditions in our planet. *Hazard&Exposure* dimension also includes measures of man-made disasters, notably conflicts, civil wars or civil unrest, as potential causes of catastrophic consequences for populations and economies (Marin-Ferrer et al., 2017). Human hazards category includes conflicts (sub-national and national) measured by intensity according to the HIIK scale. Additionally, it includes also projected risk of conflict from the Global Conflict Risk Index (GRCI), included to capture a given country's risk of conflict if a country is not experiencing a conflict during the year of observation.

Vulnerability. Vulnerability addresses the "intrinsic predispositions of an exposed population to be affected or to be susceptible to the damaging effects of a hazard" (Marin-Ferrer et al., 2017). The assessment is made through hazard-independent indicators of economic, political and social dimensions of the community and most vulnerable groups. Socio-economic vulnerability is measured by indicators of development and deprivation (UNDP's Human Development Index and Multidimensional Poverty Index); inequality (GINI index calculated by the World Bank and gender inequality distribution from UNDP); aid dependency (total ODA in last 2 years per capita, global humanitarian funding per capita and net ODA received in percentage of GDP). Vulnerable group category refers to the portion of the at-higher-risk population that in case of crisis would potentially need supplementary humanitarian assistance. Groups are identified in diverse situations such as uprooted people (number of refugees, returned refugees and internally displaced persons); indicators of health conditions (number of people living with HIV above 15 years, tuberculosis prevalence, malaria mortality rate); children under 5 mortality and underweight, number of people affected by past natural shocks; and food insecurity (prevalence of undernourishment, average dietary energy supply adequacy, domestic food price level index, domestic food price volatility index).

Lack of coping capacity addresses the institutional dimension connected to risk, capturing which "issues the government has addressed to increase the resilience of the society and how successful their implementation is". It includes two main dimensions: institutions and infrastructures. The institutional dimension addresses specific disaster risk reduction strategies as measured by Hyogo Framework for Action self-assessment reports and general governments' performance, measured by

The HIIK approach distinguishes five intensity levels, determined by the number of casualties, refugees caused by conflict, personnel involved, weapons used and destruction caused (Marin-Ferrer et al., 2017)

FIGURE 4.1: Mean index by continent and income level



Note: Elaboration of data from 2015 extracted from INFORM Trend 2012-2021 dataset (JRC, 2021). First row reports mean values of overall INFORM index, *Hazard&Exposure*, *Vulnerability* and *Lack of coping capacity* aggregated by continent. Second row reports categories for each dimension by continent

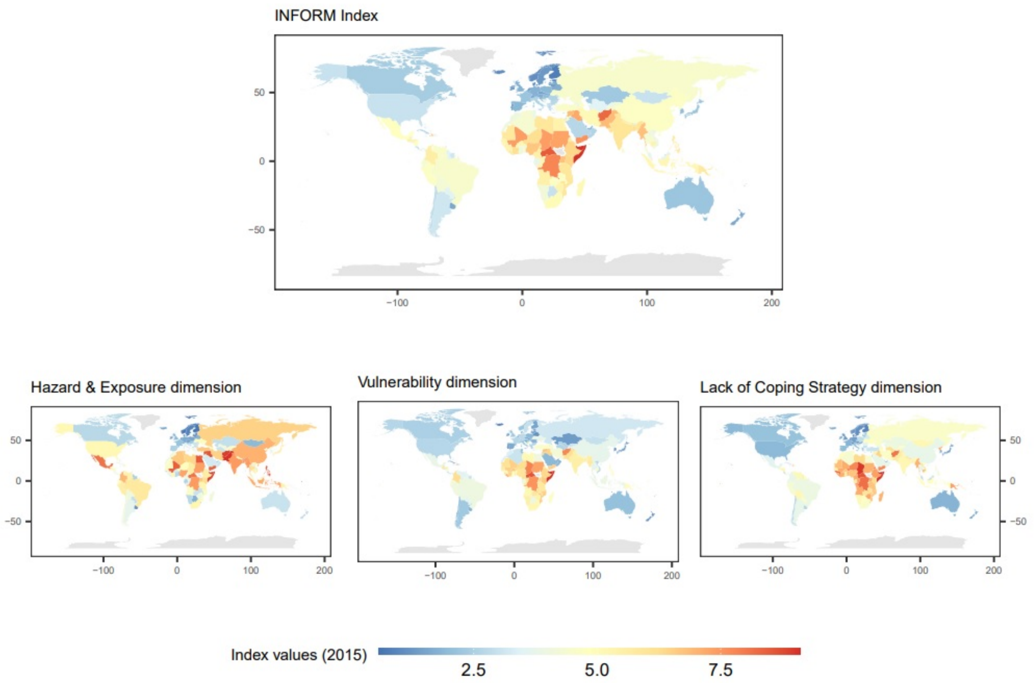
government effectiveness and corruption perception index. Infrastructure is categorised into three groups: communication (access to electricity, internet users and mobile cellular subscriptions and adult literacy rate), physical infrastructure (road density, water source, sanitation facilities) and access to the health system (physicians, health expenditure per capita, measles immunisation). Table 4.1 details every component and relative data source of each dimension.

The INFORM risk index builds upon 54 indicators combined together (Marin-Ferrer et al., 2017). According to different and adapted methodologies, data used to derive each component are scaled from 1 to 10 and aggregated by geometric or arithmetic averages or maximum values. Each dimension weights one third of the overall INFORM index, to obtain a synthetic index ranging from 1 to 10.

Figures 4.2 and figure 4.1 give a picture of the distribution of the index. Overall, the highest values of INFORM index are scored by African countries: the mean

For further details on the methodology, by category and dimension, see Marin-Ferrer et al. (2017)

FIGURE 4.2: Map of INFORM Index (2015) and its three dimensions



Note: Elaboration of data from 2015 extracted from INFORM Trend 2012-2021 dataset (JRC, 2021). Overall INFORM index, *Hazard&Exposure*, *Vulnerability* and *Lack of coping capacity* dimensions are mapped according to original scale 1 to 10.

by continent is the highest compared to any other continent and it is mainly driven by *Vulnerability* and the institutional component. It is important to note that even if Africa is not the continent most hit by natural hazards, it represents the riskier continent because of the interaction of the ensemble of the other categories and components, which potentially amplifies the impact of disasters. The role played by human hazards (HA.HUM) is also not negligible for the continent (especially for Somalia, Central African Republic, Sudan, Congo and Mali) along with the lack of preparedness and effectiveness of governments to disastrous events of both types and the incidence of unfavourable socio-economic conditions.

A similar picture emerges for certain Asian countries, especially those located in the Middle East (Yemen, Iraq and Syria) and southern countries such as Afghanistan and Pakistan, with long-lasting or predictable projected risk of conflicts. Most Asian countries also rank the highest values in the natural-hazard (HA.NAT) category, with 9 countries included in the top ten of the specific category. Furthermore, the Middle

Philippines, Bangladesh, Japan, India, Myanmar, Indonesia, China, Pakistan and Vietnam, constantly hit by flooding, earthquakes, and tropical cyclones.

East and Southern Asia are also the two most hazard-independent vulnerable areas of the continent, scoring as well high values in the institutional and infrastructural dimension. At the same time, by limiting the observation to Gulf countries it is also possible to find the lowest levels in the overall index and most of the other dimensions (exclusively comparable with European countries).

The American continent has its peculiarities: *Hazard&Exposure* indices among countries are quite high, but mainly driven by the natural-hazard category, rather than human (opposite to Africa), despite some exceptions.. Overall, the continent shows the second highest mean value of HA.NAT, with half of the countries with a value between 6 and 7 (tropical cyclones, earthquakes, droughts). Coping strategies, mainly in terms of preparedness and institutional quality (CC.INS), is mainly lacking in the Central and Southern part of the continent, which, combined with the exposure to hazards, is sometimes the reason of a higher INFORM score.

With few exceptions, the European continent seems a quite homogeneous area, with very low values of INFORM index. The high scores in Ukraine and Russia are likely led by the crisis in 2014 (HA.HUM is the highest in the entire continent, which has very low scores in general), accompanied by a high score of lack of institutional response. Few countries are exposed to severe natural disasters, and they are mainly located in the Mediterranean area (Albania, Greece, Italy, Croatia, Spain).

Oceania and especially Pacific Islands are among the most exposed area to climate-related hazards. In the islands, the high risk in HA.NAT is also accompanied by a generalised lack of coping capacity and infrastructures, as well as socio-economic vulnerability. A detailed representation of risk measures by country and continent is shown in figure 4.3.

4.3 A gravity model of migration

4.3.1 Data description

This analysis aims to identify the impact exacerbated by risk and its many dimensions to migratory flows. A major problem of migration data is that stocks of migrants in respective countries are usually available, unlike data on bilateral flows.

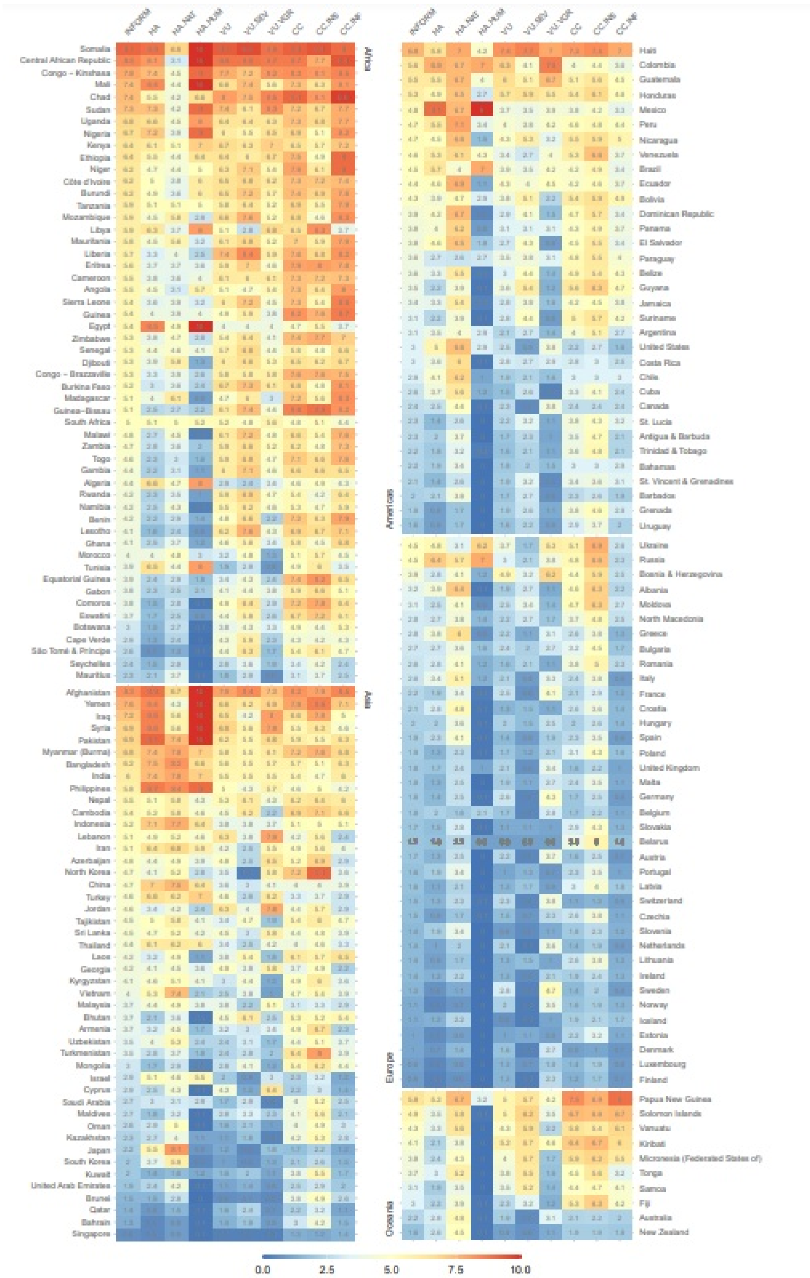
Bahrain, Qatar, UAE, Kuwait and Oman

Mexico scores one of the highest values of HA.HUM Social unrest and episodes of violence are also captured in the scores related to Colombia, Brazil and Venezuela

The impact of Haiti's earthquake in 2010, the lack of a strategy for reconstruction and the social unrest that followed are still visible in data and makes Haiti the riskier country of the continent

Mostly for Central American countries, such as Mexico

FIGURE 4.3: Heatmap of INFORM index, dimension and categories by country



Note: Elaboration of data from 2015 extracted from INFORM Trend 2012-2021 dataset (JRC, 2021). Overall INFORM index, *Hazard&Exposure*, *Vulnerability* and *Lack of coping capacity* and categories of each dimension reported by country, separated by continent and ordered by descending INFORM index.

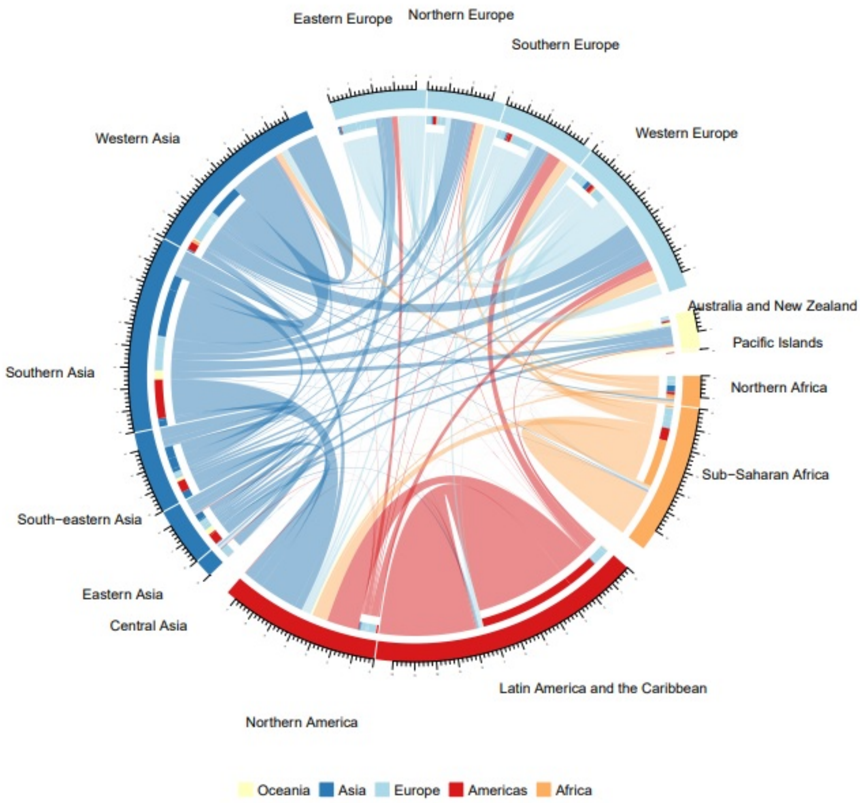
TABLE 4.2: Top countries by bilateral corridor, outflows and inflows

Origin		Destination	Flow	Country	Outflow	Country	Inflow
Venezuela	→	Colombia	1.539.003	Venezuela	3.750.771	USA	5.154.496
Syria	→	Turkey	1.206.139	India	3.116.808	Germany	3.680.675
India	→	USA	1.041.702	Bangladesh	2.376.921	UK	1.763.564
Venezuela	→	Peru	788.926	Syria	2.158.057	Turkey	1.755.091
Myanmar	→	Bangladesh	535.516	China	1.333.277	Colombia	1.591.038
Syria	→	Germany	478.103	Pakistan	1.165.951	Canada	1.292.256
Bangladesh	→	India	439.285	Germany	1.005.828	Italy	1.287.428
Mexico	→	USA	366.387	USA	889.914	Russia	1.087.875
Zimbabwe	→	South Africa	359.566	Myanmar	825.415	Saudi Arabia	1.059.679
Bangladesh	→	Saudi Arabia	343.696	Romania	722.087	Australia	1.040.033

Note: Elaboration of last round of data (2015-2020) on migration flows from Abel and Cohen (2019b). Estimates of flows according to *closed demographic accounting* methodology according to Abel (2018).

Flows are usually estimated or derived from available stock data in different ways (Abel and Cohen, 2019a). Moreover, few sources of bilateral stocks or flows are rarely available. The main examples of data sources frequently employed for the estimations in the literature (Beine and Parsons, 2015; Cattaneo and Peri, 2016) are the World Bank's Global Bilateral Migration dataset (Özden et al., 2011), a matrix of decadal bilateral stocks of migrants from 1960 to 2000. The matrix of stocks include all countries in the world and provided the most comprehensive dataset available, yet it refers to a 10-year lag and contains stocks of migrants defined as the number of foreign-born in each country. More frequent observations are provided by the OECD International Migration Database and its extensions, recording flows and stocks of migrants by year. The main limitation of this database (although widely used, such as in Ortega and Peri (2009), Coniglio and Pesce (2015), and Cai et al. (2016)) is that it only reports OECD destinations. For the purpose of this framework, neglecting a large part of destinations, especially the South-South corridor, might considerably bias the results. In fact, as already highlighted by the literature (Beine and Parsons, 2017), hazard- or climate-related migration likely occurs at a regional level and most likely between neighbouring countries, especially in light of the sudden unpredictable feature of some of the events. In line with previous findings, the present analysis will also find evidence of this reaction. To compensate for some of the limitations described, the main source of migration data will be Abel and Cohen (2019b, version 5), which provide a new dataset that contains a 200×200 matrix of dyadic flow estimates from origin to destination countries. The period covered is from 1990 to 2015 with a 5-year lag. The sample over which the econometric analysis is conducted comprises only the last round available, the 5-year period that starts in July 1^{st} 2015 and ends in June 30^{th} 2020. The estimates are made on most recently published International Migrant Stock data inputs by the United Nations (UNDESA, 2019). Abel and Cohen (2019b)'s dataset provides different methods of estimation of flows, reporting strategies that have been used in

FIGURE 4.4: Chord Diagram by continent and sub-region of aggregated migration flows 2015 - 2020



Note: Elaboration of last round of data (2015-2020) on migration flows from Abel and Cohen (2019a). Estimates of flows according to closed demographic accounting methodology according to Abel (2018). Each colour distinguishes one of the five continents, separated by sub-regions. Flows are aggregated by sub-regions and both as origin and destination. The direction of flows is represented by the colour and the gap between the sectors. The size of flows is proportional to the width of the segments.

literature and suggesting new estimation methods. The main analysis will make use of flows estimated according to the closed demographic accounting by minimisation methodology Abel (2018), which estimates migration flows to match increases or decreases in the bilateral stocks of migrants, births and deaths (Abel and Cohen, 2019a). Further details on the methodology are provided in Appendix **??**; alternative methodologies will be used to provide robustness checks to the main models.

Migration flows as represented in figure 4.4. The visualisation of colours by areas shows a prevalence of intra-regional flows for most macro-areas, with some intercontinental flows. This is particularly evident noticing that the densest area is not

Alternative methods of estimation of flows are summarised in the Appendix D the more inner area of the circle, which would highlight a high propensity to inter-regional mobility. Asian and African countries show mostly intra-regional directed flows (more than 80 percent of flows are directed toward a country of the same region, see table D.1 in Appendix D). It is also true for South American countries, while North America traditionally serves as receiving area, with the U.S. receiving flows of more than 5 million and Canada more than a million. The same applies to European countries, which shows as well consistent intra-regional mobility.

Additional data sources The model presented below takes into account a set of additional variables that enter the model to explain determinants of flows. Gravitational modelling traditionally includes geographical and cultural linkages. The empirical literature has extensively tested the negative effect of distance and the positive effect of being a neighbouring country to determine the direction of flows. At first look, these assumptions on geographical proximity fit the data as represented in figure 4.4. The model introduces also two measures of dyadic cultural linkages between origins and destinations: colonial history and sharing the same language exert additional effect to determine bilateral flows (Beine et al., 2016). The four additional gravitational variables (*distance*, *border*, *colony*, *language*) are taken from CEPII's Gravity Dataset.

4.3.2 Literature review

A detailed overview of the literature linking migration and environmental factors has already been introduced in Chapters 1 and 2. Here, I will provide an overview of the contributions that have exploited gravity approaches in general and in the specific matter of environmental migration to motivate the choice of this specific strategy.

Gravity has been applied to the modelling of migration flows in the flourishing literature that takes from trade gravity models. However, the first gravitational application credits Ravenstein (1885) and Ravenstein (1889), who pioneers the use of gravity to model migration patterns before the seminal contribution of Tinbergen (1962) on trade. Trade economists have the merit of having explored and provided tools for the theoretical foundations and the empirical application (Beine et al., 2016). Gravity equations to estimate migration flows have gained success and have been increasingly applied in recent times (Beine et al., 2016; Beine et al., 2011; Bertoli and Moraga, 2013; Bertoli and Moraga, 2015; Grogger and Hanson, 2011) thanks to the

Centre d'Etudes Prospectives et d'Informations Internationales, http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=8 increasing availability of dyadic data on bilateral stocks of migrants, often used to proxy flows of migration. Some kinds of estimations or approximations of flows have been introduced (see section 4.3).

One of the main advantages of gravity models has been the elaboration of theoretical foundations, based on micro models of choice. Most gravity models on migration rely on Random Utility Maximisation (RUM) models, based on Roy-Borjas model (Roy, 1951; Borjas, 1987), a useful tool to describe migration as a location decision choice of individuals in an origin i facing a set of destinations j with specific utilities and costs. Assuming i.i.d. extreme value type I distribution McFadden (1974), the model produces the probability that an individual moves to a specific destination j over any other potential destination maximising its utility (Beine et al., 2016). Many influencing contributions have used this kind of approach to analyse the composition of migration patterns directed to OECD countries (Grogger and Hanson, 2011; Beine et al., 2011) focusing on the role of wage differentials and migrants networks (Beine et al., 2011). Ortega and Peri (2009) applies the model and introduces a measure of migration policy at destination to investigate the role of restrictive measures to limit migration. Others have focused on different potential drivers or constraints to migration (credit constraints - Vogler and Rotte, 2000, linguistic proximity - Adsera and Pytlikova, 2015, cultural proximity - Belot and Ederveen, 2012).

RUM-founded gravity models have represented a useful tool to describe migration drivers (determinants) at a macro level, to provide a picture of human mobility across the world and policy indications to manage the phenomenon. As already pointed out in previous chapters, the role of environmental factors cannot be neglected nowadays when it comes to the analysis of motivations driving populations out of their origin country. The relevance of increasingly volatile climatic conditions and the occurrence of natural disasters is undeniable in shaping migration flows, as they have a direct impact on several factors affecting human life and livelihoods. Including environmental factors in a migration determinants framework is increasingly becoming crucial to understand how mobility is shaped by the environment, which are the channels that transmit the impact and which is the direction. A gravity setting might be helpful to map and describe the direction and the weight of the impact. The first attempt to use gravity models for environmental migration we found in our sample (cf. Chapter 1) is Afifi and Warner (2008), in which "naive" gravity equation is used to estimate a battery of 13 theory-established determinants

The definition of "naive" gravity is introduced in Head and Mayer (2014) to describe non-structural gravity equations, with the intent to point out potential bias for the negligence of structural parameters such as multilateral resistance terms and 13 environmental variables. Although useful to provide a picture of the role of different drivers in bilateral flows, the specification does not take into account what has been called in literature *multilateral resistance terms*, capturing the role of third destinations in determining the choice. Gravity literature has been stressing the fact that flows between a dyad of origin and destination countries "do not depend solely on the attractiveness of those two, but also on how this relates to the opportunities to move to other destinations" (Bertoli and Moraga, 2013). In trade literature, failing to take into account alternative receivers (destinations in the case of migration) has been considered a "gold medal mistake" in gravity specifications, producing biased estimates Baldwin and Taglioni (2006). This issue affects also Alexeev et al. (2011)'s model; nonetheless, it has the advantage to introduce interaction terms between weather-related disasters and some of the canonical determinants, assuming that the impact may depend on a country political and economic capacity to absorb the impact.

The first attempt to apply a structural approach to migration gravity models is introduced in a seminal contribution by Anderson (2011). Groschl (2012) adapts the structural model in general equilibrium proposed by Anderson, introducing aggregated disasters at origin and destination. Frequency of disasters at origin and destination are introduced in the utility maximisation function of an individual, to obtain a tractable gravity equation that takes into account MR terms (derived from a Taylor expansion Baier and Bergstrand, 2009). The equation includes a vector of canonical determinants, time-invariant country-pair dummies and year dummies. Conditional models and a set of robustness check account for various sources of heterogeneity and obtain evidence of migration being considered as an adaptation strategy to climate change, particularly evident in the case of middle income countries affected by weather-related events rather than geophysical disasters. The most comprehensive study of international migration and climatic factors is provided in Beine and Parsons (2015) and its extension Beine and Parsons (2017), estimating the largest origin-destination dyads, the longest time span and the most diverse set of potential environmental factors. The theoretical background is based on a utility maximisation approach to derive a partial equilibrium gravity equation on migration rates (ratio between migrants and stayers). MR terms are not modelled in the theoretical framework, but the authors argue that including destination time-varying fixed effects completely control for inward MR terms and the structure of large panel has been proven to provide similar results to the estimation with the full set of theoretically-consistent origin-time fixed effects. The latter is not controlled

They do so by including interactions with GDP per capita and foreign aid because the model estimates directly origin-specific variables such as political stability, dependency ratio and environmental factors. A full set of country-pair variables is included (distance, contiguity, linguistic proximity and migrants network), as well as the canonical wage ratio. Alternatively to previous contributions, Beine and Parsons (2015) estimates the empirical model with a Pseudo-Poisson Maximum Likelihood according to Silva and Tenreyro (2006), an estimation strategy that allows to account for the large number of zeros in the dependent variable (which is due to the fact that not every dyad is linked) and not to distort data. An important feature of this contribution is to include also South-South migration, which has been often neglected by studying only OECD-destinations. Results show a non-significant impact of shortage in rainfall, while natural hazards seem to spur some impact on rural-urban mobility. In their revision in 2017, the authors revise their empirical strategy introducing a richer set of fixed effects and excluding the explicit origin-specific variables, they obtain evidence of diverse responses conditioned to income levels and the emergence of financial constraints in poorer countries.

Building on the same model as Beine and Parsons (2015), Coniglio and Pesce (2015) use a dataset restricted to only OECD-destinations (ruling out the important South-South corridor) and introduce future expected utility in the utility function. The contributions of the paper are the use of a rich variety of measurements of temperature and rainfall (level, variation and anomaly) that serves to provide more insightful information on the behaviour of such phenomena and the interaction of each of them with the specific origin and destination macro-areas, to isolate potential heterogeneous responses across the world. Backhaus et al. (2015) and Cai et al. (2016) use as well dataset with only OECD destination and estimate a non-structural gravity model (no micro-foundations), focusing their analyses on the agricultural linkage between climate and migration, obtaining evidence that for highly agriculture-dependent countries, worsened climatic conditions correspond to higher international mobility.

4.3.3 Theoretical model

The model draws on Anderson (2011) structural model, and closely follows Groschl and Steinwachs (2017) in the introduction of environmental variables in the gravity setting. However, instead of exclusively considering the occurrence or intensity of

A common way to overcome the problem of zeros before the introduction of PPML in the canonical estimation of gravity estimation was to add a unit to every flow, which allowed to consider the dependent variable in logarithm without the need to exclude important observations

Cai et al. (2016) find that the increase of 1°C in temperature for the first quartile of countries ordered by agricultural dependency corresponds to a 5% increase in out-migration natural disasters, it introduces the measure of risk captured by the INFORM index and then decomposes it to evaluate and weigh the role of each of its components as drivers of migration flows.

Let us consider an individual h born in country i who decides whether to migrate to another country j in the set of possible destinations $k = 1, ..., D$ or stay in the origin country i. The decision derives from utility maximisation that takes into account expected income at destination (as in standard canonical migration literature), the costs of moving to another country and the evaluation of the level of *risk* in the country of origin and potentially in the destination. Additionally, individuals have their preferences toward migration, unobservable for the econometrician. Individuals also have a certain degree of risk aversion that affects their decision. In simple terms, individual h decides to migrate if $(w_j / C_{ij} R_j)\varepsilon_{ij,h} > w_i / R_i$, where w_j is the expected income at destination, w_i is the income at origin, C_{ij} are the costs of migrating from i to j, R_j and R_i are the index of hazard risk respectively at destination and at origin. Assuming the expected utility as a logarithmic constant relative risk aversion function,, in which the parameter σ captures a measure of elasticity of substitution that can be also interpreted as a risk aversion parameter, utility can be expressed as:

$$u_{ij,h} = (1-\sigma)lnw_j - (1-\sigma)lnC_{ij} - (1-\sigma)lnR_j \\ - [(1-\sigma)lnw_i - (1-\sigma)lnR_i] + \varepsilon_{ij,h} \quad (4.1)$$

Following the assumptions in McFadden (1974) on the unobservable term $\varepsilon_{ij,h}$ (i.i.d. extreme value, type I), individuals can be aggregated up to a representative individual and in order derive the probability that individual h living in country i will move to country j over all other alternatives $k \in D$ that maximises his utility as:

$$P(u_{ij}) = Pr[u_{ij} = \max_k u_{ik}] = \frac{e^{u_{ij}}}{\sum_k^D e^{u_{ik}}} \quad (4.2)$$

Assuming that the aggregated level of discrete choice represents the probability of migration flows from i to j for the entire population, flows can be represented as the share of natives in origin i multiplied by the probability to migrate of the representative individual:

$$M_{ij} = P(u_{ij})N_i \quad (4.3)$$

The specification of the utility function has been used also in Groschl and Steinwachs (2017) from which the choice is drawn. However, this particular utility function produces similar tractable gravity equations as canonical RUM model (Groschl and Steinwachs, 2017) where N_i is the total population originating from i. Following Groschl and Steinwachs (2017), I build a cost-risk measure combining the components of shock and costs in the utility function, $\theta_{ij} = C_{ij}R_j/R_i$, which can be decomposed at any moment. Thus, equation 4.3 can be rewritten as:

$$M_{ij} = \frac{(w_j/\theta_{ij})^{1-\sigma}}{\sum_k (w_k/\theta_{ik})^{1-\sigma}} N_i \tag{4.4}$$

Taking $\Omega_i = \sum_k^D (w_k/\theta_{ik})^{1-\sigma}$ and defining the market clearing condition $N_j = \sum_i M_{ij}$, meaning that labour demand at destination equals the labour force supplied to j from all origins i (including j itself), equation 4.4 can be rewritten as:

$$N_j = w_j^{1-\sigma} \sum_i \frac{\theta_{ij}^{1-\sigma}}{\Omega_i} N_i \tag{4.5}$$

from which the equilibrium wage at destination is derived:

$$w_j^{1-\sigma} = \frac{N_j}{\sum_i \theta_{ij}^{1-\sigma}/\Omega_i} N_i \tag{4.6}$$

with $\Omega_j = \sum_i \frac{\theta_{ij}^{1-\sigma}}{\Omega_i} \frac{N_i}{N}$ the equilibrium wage is $w_j^{1-\sigma} = \frac{N_j}{\Omega_j N}$.

These passages yield the formulation of a tractable gravity equation:

$$M_{ij} = \frac{N_i N_j}{N} \left(\frac{\theta_{ij}}{\bar{\Omega}_i \bar{\Omega}_j} \right)^{\sigma-1} \tag{4.7}$$

where the inward migration friction (multilateral resistance term) is

$$\bar{\Omega}_j = \left[\sum_i \frac{\theta_{ij}^{1-\sigma}}{\Omega_i} \frac{N_i}{N} \right]^{1/(1-\sigma)} \tag{4.8}$$

and the outward migration friction is

$$\bar{\Omega}_i = \left[\sum_j \frac{\theta_{ij}^{1-\sigma}}{\Omega_j} \frac{N_j}{N} \right]^{1/(1-\sigma)} \tag{4.9}$$

In Equation 4.7 the first part represents a frictionless migration, representing the probability to find migrants originating in i in country j proportional to their share

Assuming a totally rigid labour demand at destination (Bertoli and Moraga, 2017) of world population. The second term of equation 4.7 contains important theoretical parameters: $\bar{\Omega}_j$ is the inward multilateral resistance term (IMRT) as specified in equation 4.8. It is analogous to IMRTs defined in trade literature, which can be interpreted in the case of migration as the barriers for all migrants to destination j irrespective of their origin. The IMRT aggregates all the barriers to *im*migration from a hypothetical origin world to destination j. $\bar{\Omega}_i$ is outward multilateral resistance term (OMRT) as specified in equation 4.9. Similarly to the other, it can be interpreted as the barriers for all migrants from origin i to migrate irrespective of their destination. The OMRT aggregates all outward barriers to *e*migration to a hypothetical destination world. IMRT and OMRT are general equilibrium concepts because their solution in the simultaneous system involves every bilateral migration cost in the world.

Decomposition of risk-cost measure. In order to obtain the tractable gravity equation and following Anderson (2009) and Groschl and Steinwachs (2017), the model includes a risk-cost parameter θ_{ij} composed by bilateral migration costs and hazard risks in country i and j. Decomposing the index yields:

$$M_{ij} = \frac{N_i N_j}{N} \left(\frac{1/C_{ij}}{\bar{\Omega}_i \bar{\Omega}_j} \right)^{1-\sigma} \left(\frac{R_i}{R_j} \right)^{1-\sigma} \tag{4.10}$$

Model 4.10 predicts that flows are expected to decrease for higher migration costs $(1/C_{ij})$ and lower hazard risk at destination (R_j) while a higher risk at origin (R_i) would generate an increase in flows. As described in section 4.2, the measure of risk introduced can be further decomposed into three dimensions:

$$R_i = f(HA_i, VU_i, CC_i) \tag{4.11}$$

where HA represents the *Hazard&Exposure* index of the country, VU is the *Vulnerability* index and CC measures the lack of coping capacity, as detailed in section 4.2. Each of these components contributes to the score of risk.

The vector of bilateral costs is composed of well-recognised covariates canonically introduced in the literature:

$$C_{ij} = g(d_{ij}, b_{ij}, l_{ij}, c_{ij}) \tag{4.12}$$

where d_{ij} is the weighted distance between country i and j, b_{ij} is a dummy for shared border between i and j, l_{ij} is a dummy for common official language, c_{ij} is a dummy for colonial past.

4.4 Empirical strategy

Taking equation 4.10 in logs yields an estimable equation:

$$ln(M_{ij}) = lnN_i + lnN_j - lnN - (1-\sigma)lnC_{ij} - (1-\sigma)ln\bar{\Omega}_i - (1-\sigma)ln\bar{\Omega}_j + (1-\sigma)ln(R_i/R_j) \quad (4.13)$$

where N represents world population, which can be excluded for being constant in a cross-section analysis. The function of costs is defined in equation 4.12. MRTs $\bar{\Omega}_i$ and $\bar{\Omega}_j$ are accounted for in the estimation by including origin and destination fixed effects, as a standard strategy adopted by the literature since Anderson and Wincoop (2003). N_i and N_j are respectively populations in i and population in j, which will be absorbed by and controlled for by fixed effects. A well-known problem prompted by bilateral data is the presence of a consistent number of zeros. In the sample, the percentage of non-linked dyads ij of countries is 66%. To deal with the presence of zeros, all models will be estimated through Pseudo-Poisson Maximum Likelihood, following Silva and Tenreyro (2006), which allows to include all observations in the dataset without distorting data by adding a constant or excluding zeros.

$$M_{ij} = exp\left[\Omega_i + \Omega_j + \mathbf{C_{ij}}\alpha + \beta ln(R_i/R_j)\right] \times \epsilon_i \quad (4.14)$$

$$M_{ij} = exp\left[\gamma_i + \gamma_j + \alpha_1 ln(d_{ij}) + \alpha_2 b_{ij} + \alpha_3 l_{ij} + \alpha_4 c_{ij} + \beta ln(R_i/R_j)\right] \times \epsilon_i \quad (4.15)$$

The model does not take into account the time dimension and only consider cross-sectional observations referred to the five-year period 2015-2020, for which data are available. Another potential issue is represented by the interdependence of countries. Dyadic observations typically violate the assumptions of independence of observations, so that it is impossible to rely on the assumption of i.i.d. stochastic term. One solution is to use the robust standard errors, but they may not be sufficient

Traditional literature has also used other strategies. When the dependent variable is taken in logs, the presence of zero flows will entail the drop of many meaningful observations. One solution widely used in gravity models before the introduction of PPML as the standard empirical strategy has been to add a unit to the value of flows, then take it in logs $log(M_{ij}+1)$ and estimated through OLS. However, this strategy is strongly advised against.

to correct. At the country-pair level, it may exist some clustering. Therefore, errors are clustered by symmetric country-pairs (De Benedictis and Taglioni, 2011).

Country-specific and bilateral covariates In equation 4.15 the monadic terms of risk are kept together. The bilateral term of risk might be interpreted as a bilateral measure of distance (or similarity) of risks between the two countries. This strategy is motivated by two reasons: firstly, the aim is to investigate whether flows happen between countries with different levels of risks. The assumption behind this is that people from a highly risky country may decide to migrate to countries with a lower level of risk to minimise the hazards and not-hazard related risks. Contrarily, it may also predict that people move between equally or similarly risky countries: this might happen in a variety of cases, for example following sudden outbreaks of natural hazards or conflicts, or because of restrictive entry policies in wealthier (and less risky) countries. In order to investigate these mechanisms, an index of distance is introduced (drawn from gravity models for intra-industry trade) that measures whether migration occurs between countries with similar levels of risks (intra-flows) or between different levels of risks (inter-flows). The second reason leading to this choice is also the fact that considering risk at origin and at destination separately would make them enter the equation as country-specific covariates. This would create a problem with a theory-consistent estimation: in fact, a structural gravity equation must be estimated including fixed effects which allow for controlling multilateral resistance terms, which are essential theoretical tools to take into account alternative destinations. Introducing a bilateral index, resulting from the combination of values of risks at both sides of the flow, allows obtaining correct estimates of gravity. However, it implies the impossibility to investigate the directions and role of country-specific levels of risk to the determination of flows. To do recover this information, I will additionally apply an estimation strategy that allows for the inclusion of country-specific covariates in a theory-consistent estimation of the gravity model.

The issue of the inclusion of monadic variables in dyadic gravity estimations is not new to the literature. With country fixed effects, a variety of potentially interesting determinants can no longer be identified and estimated in a structural gravity equation, as those will be absorbed by them (Head and Mayer, 2014). Trade gravity literature has confronted this issue and attempted to suggest solutions to the impact of variables that exclusively affect either exporter or importer countries (Yotov et al., 2016). The first attempt introduced, and later strongly advised against (Anderson and Wincoop, 2003), is the inclusion of “remoteness indices” to control for MRTs instead of directional fixed effects. This strategy has been discarded and criticised for not properly accounting for the MRTs and producing biased gravity estimate (Yotov et al., 2016). A second alternative approach that has been used to estimate the effect of non-discriminatory trade policies through structural gravity consists in the inclusion in the model also intra-national trade flows along with international. The assumption relies on the fact that the variable of interest does not affect internal trade flows (Yotov et al., 2016). This strategy is not viable in the case of migration as data on internal migration flows are rare to find and not available for most of the countries included in the sample. Finally, another strategy can be implemented through a two-stage approach in which: (i) a canonical structural gravity model of migration is estimated; (ii) the outward and inward multilateral resistance terms Ω_i and Ω_j are recovered from the estimated country-specific fixed effects; (iii) a new estimation is done on country-specific variables with the vector of specific fixed effects as the dependent variable. The logic behind this approach relies on the definition of OMRTs, which in the theoretical model represent the barriers that all individuals from origin i experience when they decide to migrate, irrespectively to their destination, by aggregating all barriers to emigration to a hypothetical destination world; accordingly IMRTs represents the aggregated incentives from an origin world to migrate to destination j. The two-stage approach is particularly useful in the case of models to be estimated with theory-consistent fixed effects (avoiding the *gold medal error* Baldwin and Taglioni, 2006) which prevents the identification of country-specific effects (Head and Mayer, 2014). It is consistent to regress hazard-related variables on outward and inward multilateral resistance terms given that the analysis focuses on drivers (and barriers) of potential migrants, specifically on the role of hazard-connected risk, which is specific to the country of origin or destination (monadic variables). A similar methodology has been implemented by Head and Ries (2008) for the case of FDI: in this paper, FDI is regressed on a vector of geographical and cultural distance measures and outward and inward fixed effects, which are then extracted and regressed on variables predicted by the model, scale of the country and development. This approach is derived from labour economics, specifically discussed and implemented in Baker and Fortin (2001) for the case of occupational gender composition in Canada. In non-gravity literature, especially in the case of microeconomic modelling, the two-stage fixed-effect approach has also been used in the analysis of demand parameters in differentiated products demand model (Berry et al., 2004). Examples of two-stage fixed-effect model applied to trade gravity models are Eaton and Kortum (2002), Anderson and Yotov (2016), and Melitz (2008) and, for the case of FDI, Head and Ries (2008). In the specific field of environmental migration, some examples are microeconomic structural models such as Bayer et al. (2009) which proposes a residential sorting model on migration choices according to the evaluation of air quality in cities; Fan et al. (2016) uses a structural location choice model to assess the impact of extreme weather on U.S. mobility across educational levels, starting from a canonical RUM model, estimating a multinomial logit model for the discrete choice problem and extracting parameters of indirect utility regressed on environmental variables. More recently Oliveira and Pereda (2020b) provided a spatial equilibrium framework with discrete-choice techniques to model workers' locational choices for the case of internal migration in Brazil: they firstly identify indirect utilities for each year by parametrizing migration costs and extracting a location-sector-year vector of fixed effects which is successively decomposed and regressed on wages, rents and amenities, including climate.

4.5 Results and discussion

4.5.1 Baseline results

The first attempt to include risk measures to estimate their impact on migration flows is made through a "naive" gravity equation without including fixed effects, as a preliminary estimation to investigate the direction of the impact. The signs of covariates of traditional gravity variables in Table 4.3 column (1) are as expected, distance is always negative and significant, predicting decreasing flows at increasing distance; contiguity of countries increases the probability of flows, through the *borde*r dummy positive and highly significant; cultural factors such as language proximity and colonial past are as well positive and determinant for flows. Column (2) is the correct specification with theory-consistent fixed effect accounting for inward and outward multilateral resistance terms as derived from the theoretical model (Ω_i and Ω_j) without the introduction of risk measures. Distance takes higher values, coherent with previous gravity models in the literature. Starting from column (3), measures of risk are introduced at different time lags and both at origin and destination: t_0 is 2015, the first year of the 5-year period of flows. Risk at origin is positive and significant as expected, meaning that higher risks correspond to higher incentives to migrate; risk at destination is negative as expected, with higher risk at destination retaining people to choose a specific country as destination. The decision to migrate might be taken long before actually being able to migrate, thus lags are introduced at 1, 2 and 3 years before the period of the observed flow. Estimates show similar magnitudes, manifesting a constant impact in time or, alternatively, a constant trend of risk in the short term (3-year lag). Following these results, only 2015 indices will be used in the following regressions. The introduction of fixed effects completely absorbs risk indices: to partially capture the impact, in column (7-8) I include risk measures in the model reported in column (2) introducing one at a time risk measures and excluding the corresponding vector of fixed effect. As already

TABLE 4.3: Naive gravity for different lags of risk measures

Dependent Variable:				M_{ij}				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Distance	-0.388^{***}	-1.36^{***}	-0.432^{***}	-0.429^{***}	-0.434^{***}	-0.436^{***}	-1.04^{***}	-0.631^{***}
	(0.085)	(0.070)	(0.087)	(0.088)	(0.088)	(0.089)	(0.089)	(0.086)
Border	1.96^{***}	0.663^{***}	1.97^{***}	1.99^{***}	2.00^{***}	1.99^{***}	1.25^{***}	1.60^{***}
	(0.332)	(0.155)	(0.317)	(0.317)	(0.319)	(0.317)	(0.258)	(0.278)
Colony	1.62^{***}	0.847^{***}	1.62^{***}	1.62^{***}	1.62^{***}	1.63^{***}	0.839^{***}	1.65^{***}
	(0.360)	(0.167)	(0.366)	(0.367)	(0.369)	(0.367)	(0.221)	(0.342)
Language	0.551^{**}	0.883^{***}	0.540^{**}	0.544^{**}	0.541^{**}	0.539^{**}	0.441^{**}	0.848^{***}
	(0.224)	(0.143)	(0.225)	(0.226)	(0.227)	(0.226)	(0.205)	(0.230)
$R_{i,t-3}$			1.01^{***}					
			(0.124)					
$R_{j,t-3}$			-0.779^{***}					
			(0.108)					
$R_{i,t-2}$				1.04^{***}				
				(0.144)				
$R_{j,t-2}$				-0.805^{***}				
				(0.106)				
$R_{i,t-1}$					0.972^{***}			
					(0.132)			
$R_{j,t-1}$					-0.766^{***}			
					(0.086)			
R_{i,t_0}						0.993^{***}	1.49^{***}	
						(0.134)	(0.139)	
R_{j,t_0}						-0.753^{***}		-0.686^{***}
						(0.082)		(0.075)
Fixed-effects								
Origin	No	Yes	No	No	No	No	No	Yes
Destination	No	Yes	No	No	No	No	Yes	No
Fit statistics								
Observations	31.862	30.453	31.862	31.862	31.862	31.862	30.972	31.328
Pseudo R^2	0.176	0.801	0.211	0.213	0.218	0.218	0.558	0.461

Note: Dependent variable: 2015-2020 migration flows from Abel and Cohen (2019a). Independent variables: distance, border, colony and language from CEPII Gravity database (Conte et al., 2021); Risk indes from INFORM trend 2012-2021 (JRC, 2021); distance and risk variables are taken in logs. Estimation through PPML. Country-pair clustered standard errors in parentheses. Significance codes: *** 0.01, ** 0.05, * 0.1.

mentioned, this strategy might produce biased estimates. Column (7) include risk at origin and exclude destination fixed effects, and the opposite applies to column (8). Estimates show positive and significant estimates of the impact of risk at origin, confirming that higher risk at origin leads to higher migration, even controlling for destination-specific factors (traditionally capturing characteristics of the destination country and potential barriers to entry, such as restrictive migratory policies). Table 4.3 yields significant results but cannot be considered theory-consistent as they do not take into account the multilateral resistance terms through fixed effects. Two solutions are presented in the next sections, to recover theory-consistent estimates. The first solution attempts to explore the differences in risk indices between origin and destination. The second will apply a two-stage approach to decompose risk dimensions of hazard, vulnerability and lack of coping capacity.

TABLE 4.4: Correlations, means and standard deviations of dimensions and categories of the risk index

	Mean	SD	HA	HA.NAT	HA.HUM	VU	VU.SEV	VU.VGR	CC	CC.INS	CC.INF
HA	3.67	2.18	1.00								
HA.NAT	4.27	1.73	0.76***	1.00							
HA.HUM	2.67	3.05	0.92***	0.46***	1.00						
VU	3.77	2.00	0.61***	0.35***	0.63***	1.00					
VU.SEV	3.81	2.35	0.43***	0.29***	0.43***	0.87***	1.00				
VU.VGR	3.52	2.21	0.64***	0.33***	0.70***	0.86***	0.51***	1.00			
CC	4.73	2.01	0.50***	0.30***	0.52***	0.83***	0.89***	0.54***	1.00		
CC.INS	5.09	1.77	0.46***	0.27***	0.48***	0.67***	0.72***	0.43***	0.90***	1.00	
CC.INF	4.19	2.51	0.47***	0.28***	0.49***	0.85***	0.93***	0.55***	0.94***	0.71***	1.00

Note: Descriptive statistics and correlation matrix of data from 2015 extracted from INFORM Trend 2012-2021 dataset (JRC, 2021). Overall INFORM index, *Hazard&Exposure*, *Vulnerability* and *Lack of coping capacity* dimensions and categories according to original scale 1 to 10.

Decomposition of risk Before proceeding with bilateral and two-stage estimation, results of decomposed index dimensions are shown. This is particularly interesting with respect to the broader aim of the investigation, which is determining the weight of the various dimension of hazard-related risk on migration, including those which are hazard-independent. Table 4.1 showed how the overall risk index can be decomposed into three main dimensions: hazard and exposure (HA), vulnerability (VU) and lack of coping strategy (CC). Each dimension can be further decomposed into two categories each (see Table 4.1). Table 4.4 reports descriptive statistics of each index and their correlation. Despite the high collinearity among each other, it might be interesting to investigate the direction and the weight of each component on migration flows. Thus, separate regressions for each dimension and category at origin and destination are shown below. Models in table 4.5 report the estimates of each of the three dimensions and their respective categories relative to the origin country. The aim is to explore the role of each component singularly in generating flows of migrants from a country. Each of the three main dimensions is positive and highly significant; in terms of magnitude *Hazard&Exposure* seem to play a prominent role compared to the other two. Therefore, the positive coefficient in table 4.3 column (8) is mainly explained by it. Nonetheless, hazard-independent dimension *Vulnerability* and the institutional dimension *Lack of coping capacity*, even if to a lesser extent, show highly significant and positive estimates, raising the evidence that occurrence and intensity of hazard are not responsible alone to the determination of flows. When indices are further decomposed, the role of single indicators can be disentangled from one another. Natural and human-induced catastrophes both have a significant role, but the impact of environmental hazards aggregated in the category HA.NAT (measured in terms of average population exposed to earthquake, tsunami, flood, tropical cyclones and damages caused by floods) is higher than human hazards. Socio-economic vulnerability (VU.SEV) and the proportion of vulnerable groups (VU.VGR)

TABLE 4.5: Decomposition of risk - Origin-specific indices

Dependent Variable:				M_{ij}				
	Hazard&Exposure			*Vulnerability*			*Lack of Coping Capacity*	
Model:	(1)	(2)		(3)	(4)		(5)	(6)
Variables								
ln(Distance)	-1.05^{***}	-1.11^{***}		-0.909^{***}	-0.916^{***}		-0.864^{***}	-0.920^{***}
	(0.085)	(0.078)		(0.085)	(0.088)		(0.088)	(0.083)
Border	1.15^{***}	1.12^{***}		1.27^{***}	1.21^{***}		1.36^{***}	1.32^{***}
	(0.243)	(0.236)		(0.279)	(0.277)		(0.285)	(0.290)
Colony	0.841^{***}	0.815^{***}		0.917^{***}	0.891^{***}		0.858^{***}	0.907^{***}
	(0.221)	(0.253)		(0.239)	(0.233)		(0.262)	(0.271)
Language	0.574^{***}	0.645^{***}		0.413^{**}	0.446^{**}		0.453^{**}	0.371
	(0.213)	(0.210)		(0.210)	(0.211)		(0.210)	(0.226)
HA_i	1.61^{***}		VU_i	0.851^{***}		CC_i	0.739^{***}	
	(0.107)			(0.115)			(0.135)	
$\mathsf{HA.NAT}_i$		2.15^{***}	$\mathsf{VU.SEV}_i$		0.220^{***}	$\mathsf{CC.INS}_i$		-0.093
		(0.179)			(0.066)			(0.319)
$\mathsf{HA.HUM}_i$		0.293^{***}	$\mathsf{VU.VGR}_i$		0.669^{***}	$\mathsf{CC.INF}_i$		0.646^{***}
		(0.045)			(0.092)			(0.170)
Fixed-effects								
Origin	No	No		No	No		No	No
Destination	Yes	Yes		Yes	Yes		Yes	Yes
Fit statistics								
Observations	30.972	30.972		30.972	30.972		30.972	30.972
Pseudo R^2	0.605	0.627		0.528	0.537		0.516	0.519

Note: Dependent variable: 2015-2020 migration flows from Abel and Cohen (2019a). Independent variables: distance, border, colony and language from CEPII Gravity database (Conte et al., 2021); Risk index, dimensions and categories from INFORM trend 2012-2021 (JRC, 2021); distance and risk variables are taken in logs. Estimation through PPML. Country-pair clustered standard errors in parentheses. Significance codes: *** 0.01, ** 0.05, * 0.1.

play an important role in driving migratory flows out of vulnerable origin countries. Interestingly, the decomposition of the CC components shows a non-significant role of the institutional dimension, which includes disaster risk management strategy and quality of governance, while a lower index associated with diverse infrastructures shows a positive impact on generating flows.

The picture changes when characteristics at origin are controlled for by fixed effects and destination-specific indices are introduced. *Vulnerability* and *Lack of Coping Capacity* play a discouraging role in flows towards a specific destination (negative signs indicates that more vulnerable and institutionally lacking countries are less likely to be chosen as destination area). Each category related to coping capacity, both in terms of institutions and infrastructure, shows negative and significant coefficients, indicating that the institutional dimension and the well functioning of the governance and the infrastructures of a country seem to attract considerably potential migrants. Socio-economic conditions in the host country also affect negatively the probability of choosing a destination with lower scores in VU.SEV index along with countries with high human hazard (HA.HUM) index, which can be clearly explained

TABLE 4.6: Decomposition of risk - Destination-specific indices

Dependent Variable:			M_{ij}					
	Hazard&Exposure			*Vulnerability*			*Lack of Coping Capacity*	
Model:	(1)	(2)		(3)	(4)		(5)	(6)
Variables								
Distance	−0.684***	−0.687***		−0.636***	−0.699***		−0.640***	−0.630***
	(0.082)	(0.079)		(0.084)	(0.102)		(0.093)	(0.098)
Border	1.33***	1.34***		1.56***	1.42***		1.72***	1.77***
	(0.249)	(0.247)		(0.273)	(0.281)		(0.289)	(0.295)
Colony	1.72***	1.71***		1.67***	1.44***		1.42***	1.36***
	(0.335)	(0.335)		(0.347)	(0.345)		(0.312)	(0.367)
Language	0.791***	0.781***		0.848***	1.03***		0.899***	0.938***
	(0.222)	(0.219)		(0.227)	(0.247)		(0.227)	(0.244)
HA_j	0.056		VU_j	−0.540***		CC_j	−1.50***	
	(0.076)			(0.066)			(0.078)	
$\mathsf{HA.NAT}_j$		0.491***	$\mathsf{VU.SEV}_j$		−0.825***	$\mathsf{CC.INS}_j$		−0.664***
		(0.130)			(0.045)			(0.181)
$\mathsf{HA.HUM}_j$		−0.089**	$\mathsf{VU.VGR}_j$		0.499***	$\mathsf{CC.INF}_j$		−0.786***
		(0.037)			(0.103)			(0.145)
Fixed-effects								
Origin	Yes	Yes		Yes	Yes		Yes	Yes
Destination	No	No		No	No		No	No
Fit statistics								
Observations	31.328	31.328		31.328	31.328		31.328	31.328
Pseudo R^2	0.444	0.448		0.458	0.534		0.521	0.522

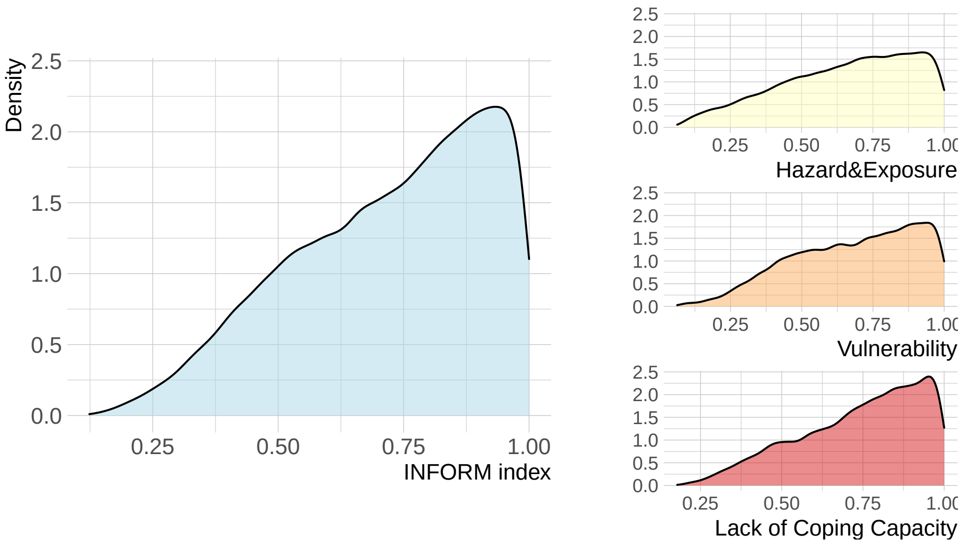
Note: Dependent variable: 2015-2020 migration flows from Abel and Cohen (2019a). Independent variables: distance, border, colony and language from CEPII Gravity database (Conte et al., 2021); Risk index, dimensions and categories from INFORM trend 2012-2021 (JRC, 2021); distance and risk variables are taken in logs. Estimation through PPML.Country-pair clustered standard errors in parentheses. Significance codes: *** 0.01, ** 0.05, * 0.1.

by the fact that a potential migrant would not choose a country with an ongoing or projected conflict. Interestingly, while the overall *Hazard&Exposure* is not significant, the natural hazard index shows a positive and significant coefficient. This might be associated with immediate displacement after the outburst of a disaster to neighbouring countries that show similar levels of risk. Furthermore, the incidence of vulnerable groups also shows a positive sign. Further investigations on the direction of flows according to the risk and its components will be shown in section 4.5.3

4.5.2 Risk index origin-destination

This section introduces a measure of bilateral risk to capture the impact of differences between two countries' risks in driving migration flows. Many different indices have been tested to choose the best representation of the distance between two countries' risks and to check for robustness (an overview is reported in section **??**

FIGURE 4.5: Descriptive statistics of Grubel-Lloyd index of bilateral risk distance



Index	Mean	SD	Min	25%	Median	75%	Max
R_{ij}^{GL}	0.72	0.19	0.12	0.58	0.75	0.89	1.00
HA_{ij}^{GL}	0.65	0.23	0.06	0.49	0.69	0.85	1.00
VU_{ij}^{GL}	0.68	0.21	0.06	0.52	0.71	0.87	1.00
CC_{ij}^{GL}	0.74	0.19	0.18	0.61	0.77	0.90	1.00

of the Appendix D). Bilateral risk index will take hereby the structure of a Grubel-Lloyd index which is expressed as:

$$R_{ij}^{GL} = 1 - \frac{|R_i - R_j|}{R_i + R_j} \tag{4.16}$$

In the extreme case of $R_{ij}^{GL} = 1$, only intra-flows occur, and no inter-flows: this is the case in which the value of risk at origin i is the same as the one at destination j, thus flows occur between two similarly risky countries. Conversely, in the opposite extreme case of $R_{ij}^{GL} = 0$, no intra-flows occur, but only inter-flows. This would mean that country i and country j have considerably different levels of risk (in the extreme case, one country is very risky and the other is not at risk at all), thus the flows occur between countries with different levels of risk. However R_{ij}^{GL} is a useful tool to explain the role of risks in promoting or hindering mobility, the bilateral index does not capture the direction of the risk: in fact, it could be near to 0 both if the origin is riskier than the destination and in the opposite case. The direction of difference in risks has been partially introduced in the previous section and it will be further explored in the two-step model (4.5.3). **Note**: Density plots and descriptive statistics

The Grubel-Lloyd index has been introduced in Grubel and Lloyd (1975) as $GL_i = 1 - \frac{|X_i - M_i|}{X_i + M_i}$ where X_i represents exports in industry i and M_i represents imports in industry i. The aim was to recover a measure of the portion of intra- and inter-industry trade between countries of Grubel-Lloyd index calculated on data from 2015 extracted from INFORM Trend 2012-2021 dataset (JRC, 2021). Overall INFORM index, *Hazard&Exposure*, *Vulnerability* and *Lack of coping capacity* dimensions.

In figure and table 4.5.2, it can be noticed that the bilateral index tends to be more likely near to 1 and takes high values, rather than lower values. Means and medians for the index and for each respective dimension (for which the bilateral version is calculated) are around a value of 0.7. The dyads included in the sample are more likely to be similar to one another than completely different. To explore how this reflects into the migratory flows, table 4.7 column (1) reports the estimates of the Grubel-Lloyd index of bilateral risk distance. The coefficient is not significant, yet negative. A negative coefficient indicates that higher values of the index correspond to lower flows of migrants. However, taken for the overall sample of dyads, the index does not show statistical significance, even when only positive flows are taken into account, in column (2). At a first glance, it seems that migrants do not take into account the distance in risk measures between their origin country and the destination, while every other variable remains with the same magnitude and sign.

To further investigate, the decomposition of the index is introduced. It emerges that distance in *Hazard&Exposure* is indeed taken into account and plays a role in determining flows. Columns (5) shows that distances in *Vulnerability* and *Lack of Coping Capacity* indices do not intervene in driving migration flows. Between the two categories of *Hazard&Exposure*, natural-induced disaster and the distance between the risk at origin and destination determine the impact on flows, with a strong negative relation. Potential migrants tend to take into account the different levels of risk of natural hazard at destination, choosing countries in which the risk is different. Interestingly, the two categories of *Vulnerability* when taken disaggregated become highly significant in driving flows. Differences in development, inequality and every dimension of vulnerability included in VU.SEV and VU.VGR between two countries strongly influence the choice of a destination. This figure might capture the direction of migration flows from less developed countries toward more developed ones, already pointed out in the classic literature. *Lack of Coping Capacity*, the institutional and infrastructural dimension, does not seem to enter as determinants of flows.

Conditional regression by continent As highlighted in figure 4.4 and 4.3, each macro-area has its own specific characteristics in terms of the direction of flows, the intensity of risk and choice of destination. In this section, the overall sample will be split according to continents and macro-areas, to investigate potential heterogeneous behaviour across different parts of the world. African and Asian migratory

Section **??** in the appendix shows that this result is consistent with robustness checks when different calculations of measures of distance/similarity are included in the model

TABLE 4.7: Bilateral risk index (Grubel-Lloyd)

	M_{ij}	$M_{ij} > 0$				M_{ij}			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Distance	−1.37 ***	−1.08 ***	−1.39 ***	−1.36 ***	−1.37 ***	−1.39 ***	−1.44 ***	−1.42 ***	−1.35 ***
	(0.073)	(0.067)	(0.072)	(0.071)	(0.076)	(0.076)	(0.078)	(0.077)	(0.079)
Border	0.668***	0.613***	0.679***	0.662***	0.662***	0.669***	0.770***	0.740***	0.660***
	(0.155)	(0.139)	(0.154)	(0.155)	(0.156)	(0.154)	(0.162)	(0.156)	(0.156)
Colony	0.838***	0.745***	0.830***	0.847***	0.839***	0.829***	0.838***	0.828***	0.853***
	(0.170)	(0.164)	(0.173)	(0.167)	(0.171)	(0.176)	(0.188)	(0.175)	(0.175)
Language	0.880***	0.883***	0.872***	0.884***	0.885***	0.876***	0.886***	0.895***	0.894***
	(0.144)	(0.164)	(0.145)	(0.144)	(0.144)	(0.146)	(0.156)	(0.142)	(0.143)
R_{ij}^{GL}	−0.191	−0.144							
	(0.234)	(0.219)							
HA_{ij}^{GL}			−0.366**			−0.413**			
			(0.155)			(0.169)			
VU_{ij}^{GL}				0.012		0.189			
				(0.178)		(0.217)			
CC_{ij}^{GL}					−0.129	0.009			
					(0.251)	(0.306)			
HA.NAT_{ij}^{GL}							−0.716**		
							(0.306)		
HA.HUM_{ij}^{GL}							0.027		
							(0.051)		
VU.SEV_{ij}^{GL}								−0.264**	
								(0.113)	
VU.VGR_{ij}^{GL}								−0.404***	
								(0.135)	
CC.INS_{ij}^{GL}									−0.253
									(0.368)
CC.INF_{ij}^{GL}									0.146
									(0.194)
Fixed-effects									
Origin	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	30.453	10.549	30.453	30.453	30.453	30.453	21.028	30.453	30.453
Pseudo R^2	0.802	0.789	0.802	0.801	0.801	0.802	0.799	0.804	0.802

Note: Dependent variable: 2015-2020 migration flows from Abel and Cohen (2019a). Independent variables: distance, border, colony and language from CEPII Gravity database (Conte et al., 2021); Risk index, dimensions and categories calculated on data retrieved from INFORM trend 2012-2021 (JRC, 2021); distance and risk variables are taken in logs. Estimation through PPML. Country-pair clustered standard errors in parentheses. Significance codes: *** 0.01, ** 0.05, * 0.1.

flows are predominantly directed towards countries within the same continent (see table D.1 and figure 4.4). Migrants from African countries seem to privilege similarly risky countries, showing a positive and highly significant estimate of R_{ij}^{GL} (table 4.8, panel A). As already highlighted in the literature, African migration occurs mainly internally or between neighbouring countries. Not surprisingly, the *border* dummy that captures whether origin and destination are contiguous countries sharing a border, is the highest among any other area. Furthermore, migration occurs between countries showing a similar level of *Vulnerability* index, which mainly drives the estimates of the overall index, while hazard-related and institutional characteristics do not play any significant role. These findings are not new to the literature and confirm the tendency of potential migrants from African countries (with no substantial differences between sub-regions - panel D) to engage in short-distance migration patterns toward neighbouring similar countries, including by level of income (panel C). As shown in figure 4.2 most African countries report some of the highest levels of the overall risk index and each of its categories, making it the overall most risky continent when considering every dimension of risk. It scores comparatively the highest mean scores for every indicator (except for the pure *Hazard&Exposure*, for which Asian countries are on top), mainly driven by human hazards, while comparatively less concerned by natural hazards. Mobility in Africa seems less driven by the natural disasters included in the risk index, but by high levels of vulnerability in many areas (including environmental stressors). Higher scores of risk at origin countries are connected with migration toward countries with similar levels of risk (panel E).

Estimates from the Asian continent show the opposite picture. The sign of the overall risk index is negative and still very significant, showing a predominant tendency to move to countries with a different level of risk (panel A). Mobility coming from Asia seems more oriented to diversify risk by moving from one place to another, especially for Middle East (Western Asia), Eastern Asia (including China and Japan) and Southern countries, which includes countries with the highest number of migrants in the world per country (India, Bangladesh and Pakistan, see table 4.2). Those areas are also the origin countries of most consistent corridors, such as Syria to Turkey and Germany, India to the USA, Bangladesh to India and Saudi Arabia. Both for natural and human hazards those areas are the riskiest in the world, and the dimension *Hazard&Exposure* estimates a direction towards less risky countries, which can be explained by looking at corridors originating from countries with long-lasting ongoing conflicts (Afghanistan, Iraq, Pakistan, Syria, Yemen) and areas constantly hit by natural disasters (Philippines, Bangladesh, Japan, India, Myanmar, Indonesia). The same applies to the index capturing *Vulnerability*, which shows as

TABLE 4.8: Conditional regression by continent of origin

	Africa	Americas	Asia	Europe	Oceania
Panel A: Overall risk index					
Distance	−1.48 ***	−1.42 ***	−1.38 ***	−0.208	−3.16 ***
	(0.149)	(0.289)	(0.156)	(0.255)	(0.627)
Border	1.69 ***	−0.088	1.20 ***	0.608**	−9.72 ***
	(0.238)	(0.365)	(0.234)	(0.256)	(1.81)
Colony	0.281	0.652	0.911***	0.606***	−0.528
	(0.244)	(0.505)	(0.238)	(0.211)	(0.536)
Language	1.26 ***	1.14 ***	0.146	1.17 ***	−10.2 ***
	(0.146)	(0.298)	(0.251)	(0.199)	(1.12)
R_{ij}^{GL}	2.87 ***	2.32 ***	−1.33 ***	0.487	1.12 *
	(0.594)	(0.751)	(0.387)	(0.734)	(0.628)
Panel B: Decomposition					
HA_{ij}^{GL}	0.421	2.52 ***	−1.18 ***	−0.056	−2.43 **
	(0.265)	(0.443)	(0.309)	(0.295)	(0.969)
VU_{ij}^{GL}	2.84 ***	−1.81 ***	−1.02 ***	0.496	0.395
	(0.804)	(0.701)	(0.332)	(0.521)	(0.439)
CC_{ij}^{GL}	0.418	1.27	2.22 ***	−0.284	−0.262
	(1.06)	(0.815)	(0.641)	(0.549)	(0.532)
Panel C: Interactions: $R_{ij}^{GL} \times$ Income level					
Low income	3.18 ***	1.24	−1.69 **		
	(0.599)	(1.40)	(0.776)		
Lower-middle income	2.26 ***	0.029	−1.29 **	4.56 ***	0.773
	(0.637)	(1.38)	(0.550)	(1.66)	(1.53)
Upper-middle income	3.17 ***	3.08 ***	−2.85 ***	2.85 **	4.12
	(0.906)	(0.880)	(0.596)	(1.39)	(2.90)
High income	−3.02	−0.934	−0.831	−1.57 ***	0.177
	(2.04)	(1.04)	(0.717)	(0.563)	(0.915)
Panel D: Interactions: $R_{ij}^{GL} \times$ Sub-region					
North Africa	3.16*** (0.678)	LAC 2.45*** (0.759)	Central 0.025 (2.02)	Eastern 3.17*** (0.947)	Australia New Zealand 0.081 (0.905)
Sub-Saharan Africa	2.84*** (0.601)	North America -2.49 (1.59)	Eastern -2.36*** (0.503)	Northern -1.12** (0.561)	Pacific Islands 2.43* (1.43)
			South East 0.354 (0.721)	Southern -0.050 (0.546)	
			Southern -1.37*** (0.425)	Western -2.51*** (0.642)	
			Western -1.74*** (0.560)		
Panel E: Interactions: $R_{ij}^{GL} \times$ Risk at origin					
Very low		1.02	−0.772	−1.93 ***	1.07
		(2.92)	(1.14)	(0.590)	(0.971)
Low	−1.43	−0.957	−1.85 **	0.391	1.27
	(1.09)	(1.23)	(0.784)	(1.09)	(0.893)
Medium	4.06 ***	3.75 ***	−2.43 ***	4.55 ***	1.41
	(0.988)	(1.01)	(0.731)	(1.32)	(1.63)
High	2.40 ***	1.14	−1.46 **		0.002
	(0.645)	(1.20)	(0.618)		(0.705)
Very high	3.05 ***	1.56	−1.08		
	(0.568)	(1.45)	(0.738)		
Fixed-effects					
Origin	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes
Observations	7.854	4.389	7.129	5.846	1.322

Note: Dependent variable: 2015-2020 migration flows from Abel and Cohen (2019a). Independent variables: distance, border, colony and language from CEPII Gravity database (Conte et al., 2021) (included but not reported in panel B to E); Risk index and dimensions are calculated on data retrieved from INFORM trend 2012-2021 (JRC, 2021); distance and risk variables are taken in logs. Estimation through PPML. Heteroskedasticity-robust standard-errors in parentheses. Significance codes: *** 0.01, ** 0.05, * 0.1.

well a negative sign. By contrast, the institutional dimension shows a positive sign, with flows going towards countries with similar institutional quality and infrastructure (panel B).

Overall estimates concerning the American continent are mostly driven by Latin-American and Caribbean countries, while North America do not show significant estimates (panel D). The coefficient is positive and significant, manifesting a trend of moving toward similarly risky countries, most of all in terms of natural and human hazards (panel B). Americas equally receive inter- (43.9%) and intra-continental (56.1%) flows. Intra-continental flows are potentially led by internal crisis during the 5-year period (Venezuela) and from well-established historical consistent flows from Mexico to the U.S. Most origin areas score the highest HA.NAT and HA.HUM indices. The U.S. manifest constantly over the years the highest absolute number of inflows globally, accompanied by Colombia and Canada for the specific time window 2015-2020. Flows originating in European countries do not seem to be impacted by overall risk and its three dimensions.

4.5.3 Two-stage estimation

An attempt to recover the effect of origin-specific variables can be implemented through a two-stage approach in which: a canonical structural gravity model of migration is estimated, from which the inward and outward effects, $\hat{\Omega}_i$ and $\hat{\Omega}_j$, are recovered from the estimated country-specific fixed effects. After the extraction, a new estimation is done on country-specific variables with FEs as the dependent variable. The two-stage approach is particularly useful in the case of models to be estimated with theory-consistent fixed effects which prevent the identification of country-specific effects Head and Mayer (2014). It is consistent to regress hazard-related variables on outward multilateral resistance terms given that the analysis focuses on drivers (or barriers) of potential migrants, specifically on the role of risk connected to natural hazard, which is specific to the country of origin (monadic variable).

The first step consists in the estimation of the structural gravity model for migration, including fixed effects and dyadic covariates (without measures of risk):

$$M_{ij} = exp[\Omega_i + \Omega_j - \gamma_1 ln(d_{ij}) + \gamma_2 b_{ij} + \gamma_3 c_{ij} + \gamma_4 l_{ij}] \times \varepsilon_{ij} \tag{4.17}$$

Results are already shown and discussed in table 4.3 column (2). From the estimation of 4.17, the values of the outward effects $\hat{\Omega}_i$ and inward effects $\hat{\Omega}_j$ are recovered and

TABLE 4.9: Second-stage estimation

Dependent Variable:			Outward FEs $\hat{\Omega}_i$					
Panel A: Origin-specific variables								
R_i	1.44*** (0.220)							
Hazard&Exposure			*Vulnerability*			*Lack of Coping Capacity*		
HA_i	1.59*** (0.159)		VU_i	0.747*** (0.200)		CC_i	0.833*** (0.247)	
HA.NAT_i		1.63*** (0.268)	VU.SEV_i		0.306** (0.146)	CC.INS_i		−0.316 (0.530)
HA.HUM_i		0.307*** (0.071)	VU.VGR_i		0.459*** (0.171)	CC.INF_i		0.809*** (0.308)
Observations	179	179		179	179		179	179

Dependent Variable:			Inward FEs $\hat{\Omega}_j$					
Panel B: Destination-specific variables								
R_j	-0.557** (0.214)							
Hazard&Exposure			*Vulnerability*			*Lack of Coping Capacity*		
HA_j	0.203 (0.175)		VU_j	-0.610*** (0.201)		CC_j	-1.37*** (0.284)	
HA.NAT_j		0.639* (0.343)	VU.SEV_j		-0.826*** (0.175)	CC.INS_j		-0.962 (0.610)
HA.HUM_j		-0.097 (0.104)	VU.VGR_j		0.410 (0.256)	CC.INF_j		-0.465 (0.302)
Observations	179	179		179	179		179	179

Note: Second-stage estimation. Dependent variable: origin and destination fixed effects extracted from model (2) in table 4.3. Independent variables: Risk index, dimensions and categories from INFORM trend 2012-2021 taken in logs. Heteroskedasticity-robust standard errors in parentheses. Weights: inverse of standard errors ($1/se$). Significance codes: *** 0.01, ** 0.05, * 0.1.

regressed on country-specific covariates.

$$\begin{aligned}\hat{\Omega}_i &= \alpha_1 + \beta_1 R_i + \psi \\ \hat{\Omega}_j &= \alpha_2 + \beta_2 R_j + \psi\end{aligned} \tag{4.18}$$

where βs are the coefficients related to risk connected to hazards at origin and destination. Models 4.18 is estimated with Weighted Least Squares. Observations drop to 179, which are one less than the total number of countries in the sample since one country serves as the reference category.

Results of the estimation of the second stage shown in table 4.9 panel A confirm a strong and positive role of risk connected to hazards in driving migration out of origin. The effect of the overall INFORM index on the outward term can be interpreted as the ensemble of drivers (or barriers) to *e*migration from the specific origin country

Following Head and Ries (2008), to correct for heteroskedasticity, the observations are weighted by the inverse of the standard errors from the first stage to a hypothetical destination world, which in this case configures as a strong determinant to out-migration. Similarly, the inward term regressed on INFORM index at destination theoretically represents all barriers to specific destination j from a hypothetical origin world: panel B shows that riskier countries are less attractive to migration flows. The positive impact of risk in driving out-migration is mainly driven by the *Hazard&Exposure* dimension, both in terms of natural and human hazards. Flows increases also with the increase of both categories of *Vulnerability*, while the impact of *Lack of Coping Capacity* is mainly driven by the infrastructural dimension, while institutional preparedness to cope with disasters and governance do not show any significant effect. The inward term is negative and significant and it is mainly driven by *Vulnerability* and *Lack of Coping Capacity* dimensions. Unfavourable socio-economic conditions are considerably less attractive than those with the lowest level of VU.SEV component.

4.6 Concluding remarks

The aim of the analysis is to investigate the role of dimensions connected to the risk of hazards in determining migration flows. The basic assumption builds on the idea that the impact of natural hazards is not exerted exclusively by their occurrence, frequency or intensity, motivated by the concern that measuring the impact of natural disasters on migration considering exclusively their intensity might produce biased results if other dimensions are not taken into account. The measure of risk hereby used includes hazards in an extensive framework of various sources of dimensions that might influence the resulting impact of natural hazards on a specific country. This conceptual framework has then been included in a structural gravity model to assess its impact among migration determinants. From a macroeconomic perspective, this contribution provides a pathway for a more comprehensive vision of environmental impact on migration. The estimates produced show indeed that other dimensions play a role in the migratory response to natural hazards. Preexisting vulnerabilities, in terms of ongoing conflicts, development, inequality, food security, health conditions and the presence of vulnerable groups, as well as a lack of infrastructures increase the probability of mobility for those countries who show high levels of those indicators. Regional differences are also considerable, as shown by conditional models. The decomposition of risk shows heterogeneous responses according to the distance in the level of each indicator. However, this framework only focuses on international migration and it is based on observations over a 5-year period, which can explain only a part of mobility response to risk. Further investigation should be made on internal mobility, which is likely to be the consequent response to sudden shocks.

Conclusions

This thesis provides additional elements to the ongoing debate on the complex linkages between environmental factors and human mobility. By offering an empirical overview and detailed analysis of the most extensive sample of contributions on the subject produced until now, it explores the many sources of heterogeneity that drive the absence of a cohesive literature.

Merging together results from community detection on the citation-based network with a conditional meta-analysis, it introduces a new hybrid methodology able to isolate and detect contributions aggregating and converging toward a certain outcome, which highly influence the final estimated average effect of different kind of environmental events on mobility.

The complexity of migration, originating from the many forms it can take (international, domestic, temporary, etc.) and its multi-causal nature calls for a greater research effort to disentangle the various factors that links it to linking environmental change. The empirical applications in last chapters provide and suggest a broader point of view on the link between environmental events and human mobility, exploiting alternative methodologies and a richer conceptual framework. Although the important channel of internal migration and displacement is neglected in this analysis and for which further investigations are needed, the results point to the importance of intrinsic characteristics of vulnerability and coping capacity of affected area and extreme regional differences.

Overall, the nexus between environmental factors and migration still needs to be fully unfolded. Migratory responses are likely to be affected in different ways and through different channelling factors by both sudden and gradual environmental events, which will shape the decades to come.

Appendix A

Appendix A

List of Articles

Table B.1 lists the 151 papers included in the reviewed sample.

Author(s)	Title	Year	Pub	Cluster
Abel et al.	*Climate, conflict and forced migration*	2018		C3
Afifi and Warner	*The impact of environmental degradation on migration flows across countries*	2008		C4
Ager et al.	*How the 1906 San Francisco earthquake shaped economic activity in the American West*	2020	x	C2
Ahsan	*Climate-induced migration impacts on social structures and justice in Bangladesh*	2019	x	C1
Alem et al.	*Migration as an adaptation strategy to weather variability: an instrumental variables probit analysis*	2016		C1
Alexeev et al.	*Weather-related disasters and international migration*	2011		C4
Auffhammer and Kahn	*The farmers climate change adaptation challenge in least developed countries*	2018	x	C3
Backhaus et al.	*Do climate variations explain bilateral migration? A gravity model analysis*	2015	x	C4
Barassi et al.	*Climate anomalies and migration between Chinese provinces 1987-2015*	2018	x	C4
Bardsley	*Limits to adaptation or a second modernity responses to climate change risk in the context of failing socio-ecosystems*	2014	x	C1
Baronchelli and Ricciuti	*Climate change, rice production, and migration in Vietnamese households*	2018		C3
Barrios et al.	*Climatic change and rural-urban migration the case of Sub-Saharan Africa*	2006	x	C4
Beine and Parsons	*Climatic factors as determinants of international migration*	2015	x	C4
Beine and Parsons	*Climatic factors as determinants of international migration (redux)*	2017	x	C4
Benonnier et al.	*Climate change, migration, and irrigation*	2019		C3
Berlemann and Steinhardt	*Climate change natural disasters and migration: a survey of the empirical evidence*	2017	x	C3
Berlemann and Tran	*Climate-related hazards and internal migration empirical evidence for rural Vietnam*	2020	x	C3
Bertoli et al.	*Weather shocks and migration intentions in Western Africa: insights from a multilevel analysis*	2020		C3
Bettin and Nicolli	*Does climate change foster emigration from less developed countries? Evidence from bilateral data*	2012		C4

Author(s)	Title	Year	Pub	Cluster
Bhargava	*Climate change demographic pressures and global sustainability*	2019	x	C3
Bohra-Mishra et al.	*Non-linear permanent migration response to climatic variations but minimal response to disasters*	2014	x	C3
Boustan et al.	*Moving to higher ground: migration response to natural disasters in the early twentieth century*	2012	x	C2
Boustan et al.	*The effect of natural disasters on economic activity in U.S. counties a century of data*	2020	x	C2
Bruckner	*Economic growth, size of the agricultural sector, and urbanization in Africa*	2012	x	C4
Burzynski et al.	*Climate change, inequality, and human migration*	2019		C3
Cai et al.	*Climate variability and international migration the importance of the agricultural linkage*	2016	x	C4
Carattini and Veronesi	*Trust, temperature fluctuations, and asylum applications*	2020		C3
Castells-Quintana et al.	*Adaptation to climate change a review through a development economics lens*	2018	x	C2
Cattaneo and Massetti	*Migration and climate change in rural Africa*	2015		C3
Cattaneo and Peri	*The migration response to increasing temperatures*	2016	x	C3
Cattaneo and Bosetti	*Climate-induced international migration and conflicts*	2017	x	C4
Cattaneo and Massetti	*Does harmful climate increase or decrease migration evidence from rural households in Nigeria*	2019	x	C3
Cattaneo et al.	*Human migration in the era of climate change*	2019	x	C3
Chen and Flatnes	*Credit access, migration, and climate change adaptation in rural Bangladesh*	2019		C1
Chernina	*Natural shocks and migration decisions: the case of Kyrgyzstan*	2019		C2
Chort	*New insights into the selection process of Mexican migrants. What can we learn from discrepancies between intentions to migrate and actual moves to the U.S.?*	2012		C3
Chort and Rupelle	*Managing the impact of climate change on migration: evidence from Mexico*	2017		C3
Chort and De La Rupelle	*Managing the impact of climate on migration: evidence from Mexico*	2019		C3
Coniglio and Pesce	*Climate variability and international migration: an empirical analysis*	2015	x	C4
Dallmann and Millock	*Climate variability and interstate migration in India*	2017	x	C4
Damette and Gittard	*Climate change and migrations: remittances as a buffer?*	2017	x	C4
Defrance et al.	*Is migration drought-induced in Mali? An empirical analysis using panel data on Malian localities over the 1987-2009 period*	2020		C3
Desmet and Rossi-Hansberg	*On the spatial economic impact of global warming*	2015	x	C3
Deuster	*Climate change, education and mobility in Africa*	2019		C3
Diallo and Renou	*Climate change and migration the emerging structure of a scientific field and the process of public policy formulation*	2015	x	C1
Dillon et al.	*Migratory responses to agricultural risk in Northern Nigeria*	2011	x	C2
Docquier et al.	*Emigration and democracy*	2016	x	C4
Drabo and Mbaye	*Climate change, natural disasters and migration: an empirical analysis in developing countries*	2011		C4
Drabo and Mbaye	*Natural disasters, migration and education: an empirical analysis in developing countries*	2015	x	C4
Erwin et al.	*Inter-sectionality shapes adaptation to social-ecological change*	2020	x	C1

Author(s)	Title	Year	Pub	Cluster
Falco et al.	*Climate change, agriculture and migration: a survey*	2018		C3
Fan et al.	*Does extreme weather drive inter-regional brain drain in the U.S. evidence from a sorting model*	2016	x	C2
Fan et al.	*Climate change migration and regional economic impacts in the United States*	2018	x	C2
Farbotko et al.	*Transformative mobilities in the pacific promoting adaptation and development in a changing climate*	2018	x	C1
Felli	*Managing climate insecurity by ensuring continuous capital accumulation climate refugees and climate migrants*	2013	x	C1
Feng et al.	*The perils of modelling how migration responds to climate change*	2016		C2
Feng et al.	*Linkages among climate change, crop yields and Mexico-U.S. cross-border migration*	2010	x	C1
Feng et al.	*Climate change, crop yields, and internal migration in the United States*	2012		C3
Fernández et al.	*Climate change-induced migration in Morocco*	2018	x	C1
Galizzi	*Demographic explosion in Sub-Saharan Africa subsistence agriculture and the problem of migrants*	2017	x	C4
Ghimire et al.	*Flood-induced displacement and civil conflict*	2015	x	C1
Gignoux and Menéndez	*Benefit in the wake of disaster long-run effects of earthquakes on welfare in rural Indonesia*	2016	x	C2
Goldbach	*Out-migration from coastal areas in Ghana and Indonesia: the role of environmental factors*	2017	x	C1
Grace et al.	*Examining rural Sahelian out-migration in the context of climate change: an analysis of the linkages between rainfall and out-migration in two Malian villages from 1981 to 2009*	2018	x	C1
Gray	*Environment, land, and rural out-migration in the Southern Ecuadorian Andes*	2009	x	C1
Gray and Mueller	*Natural disasters and population mobility in Bangladesh*	2012	x	C1
Gray and Mueller	*Drought and population mobility in rural Ethiopia*	2012	x	C1
Gray and Bilsborrow	*Environmental influences on human migration in rural Ecuador*	2013	x	C1
Gray and Wise	*Country-specific effects of climate variability on human migration*	2016	x	C1
Gröger and Zylberberg	*Internal labor migration as a shock coping strategy evidence from a typhoon*	2016	x	C2
Groen et al.	*Storms and jobs the effect of hurricanes on individuals employment and earnings over the long term*	2020	x	C2
Groschl	*Climate change and the relocation of population*	2012		C4
Groschl and Steinwachs	*Do natural hazards cause international migration?*	2017	x	C4
Halliday	*Migration, risk, and liquidity constraints in El Salvador*	2006	x	C2
Halliday	*Intra-household labour supply, migration, and subsistence constraints in a risky environment: evidence from rural El Salvador*	2012	x	C2
Hanson and McIntosh	*Birth rates and border crossings: Latin American migration to the U.S., Canada, Spain and the U.K.*	2012	x	C4
Harper	*Population-environment interactions European migration population composition and climate change*	2013	x	C1
Henderson et al.	*Has climate change driven urbanization in Africa*	2017	x	C3
Henry et al.	*Modelling inter-provincial migration in Burkina Faso, West Africa: the role of socio-demographic and environmental factors*	2003	x	C1

Author(s)	Title	Year	Pub	Cluster
Herny2004	*The impact of rainfall on the first out-migration: a multi-level event-history analysis in Burkina Faso*	2004	x	C1
Hirvonen	*Temperature changes, household consumption, and internal migration: evidence from Tanzania*	2016	x	C3
Hornbeck	*The enduring impact of the American dust bowl: short- and long-run adjustments to environmental catastrophe*	2012	x	C2
Hunter et al.	*Rainfall patterns and U.S. Migration from rural Mexico*	2013	x	C1
Iqbal and Roy	*Climate change agriculture and migration evidence from Bangladesh*	2015	x	C1
Jamero et al.	*In-situ adaptation against climate change can enable relocation of impoverished small islands*	2019	x	C1
Jennings and Gray	*Climate variability and human migration in the Netherlands, 1865-1937*	2015	x	C1
Jessoe et al.	*Climate change and labour allocation in rural Mexico evidence from annual fluctuations in weather*	2018	x	C3
Joseph and Wodon	*Is internal migration in Yemen driven by climate or socio-economic factors?*	2013	x	C1
Joseph et al.	*Is climate change likely to lead to higher net internal migration? The republic of Yemen's case*	2014		C1
Kabir et al.	*Seasonal drought thresholds and internal migration for adaptation lessons from northern Bangladesh*	2017	x	C1
Kawawaki	*Economic analysis of population migration factors caused by the Great East Japan earthquake and tsunami*	2018	x	C2
Khamis and Li	*Environment matters: new evidence from Mexican migration*	2020	x	C4
Klaiber	*Migration and household adaptation to climate a review of empirical research*	2014	x	C2
Koubi et al.	*The role of environmental perceptions in migration decision-making: evidence from both migrants and non-migrants in five developing countries*	2016	x	C1
Koubi et al.	*Environmental stressors and migration evidence from Vietnam*	2016	x	C1
Kubik and Maurel	*Weather shocks agricultural production and migration evidence from Tanzania*	2016	x	C1
Lewin et al.	*Do rainfall conditions push or pull rural migrants evidence from Malawi*	2012	x	C1
Mahajan and Yang	*Taken by storm: hurricanes, migrant networks, and U.S. immigration*	2020	x	C2
Marchiori and Schumacher	*When nature rebels international migration, climate change and inequality*	2011	x	C1
Marchiori et al.	*The impact of weather anomalies on migration in Sub-Saharan Africa*	2012	x	C4
Marchiori et al.	*Is environmentally induced income variability a driver of human migration?*	2017	x	C1
Mason	*Climate change and migration a dynamic model*	2017	x	C3
Mastrorillo et al.	*The influence of climate variability on internal migration flows in South Africa*	2016	x	C3
Maurel and Zaneta	*Climate variability and migration: evidence from Tanzania*	2014		C1
Maurel and Tuccio	*Climate instability, urbanisation and international migration*	2016	x	C4
Mbaye and Zimmermann	*Natural disasters and human mobility*	2016	x	C2
Millock	*Migration and environment*	2015	x	C1
Missirian and Schlenker	*Asylum applications respond to temperature fluctuations*	2017	x	C3

Author(s)	Title	Year	Pub	Cluster
Mueller et al.	*Heat stress increases long-term human migration in rural Pakistan*	2014	x	C1
Mueller et al.	*Temporary migration and climate variation in Eastern Africa*	2020	x	C3
Naqvi	*Deep impact geo-simulations as a policy toolkit for natural disasters*	2017	x	C2
Naqvi and Rehm	*A multi-agent model of a low income economy simulating the distributional effects of natural disasters*	2014	x	C2
Naudé	*Conflict, disasters, and no jobs: reasons for international migration from Sub-Saharan Africa*	2008		C4
Naudé	*Natural disasters and international migration from Sub-Saharan Africa*	2009	x	C4
Naudé	*The determinants of migration from Sub-Saharan African countries*	2010	x	C4
Nawrotzki et al.	*Do rainfall deficits predict U.S.-bound migration from rural Mexico? Evidence from the Mexican census*	2013	x	C1
Nawrotzki and Bakhtsiyarava	*International climate migration: evidence for the climate inhibitor mechanism and the agricultural pathway*	2017	x	C1
Ng'ang'a et al.	*Migration and self-protection against climate change a case study of Samburu county Kenya*	2016	x	C1
Noy	*To leave or not to leave climate change exit and voice on a pacific island*	2017	x	C3
Oliveira and Pereda	*The impact of climate change on internal migration in Brazil*	2020	x	C2
Olper et al.	*Climate change, agriculture and migration: is there a causal relationship?*	2018		C3
Ouattara and Strobl	*Hurricane strikes and local migration in U.S. coastal counties*	2014	x	C2
Owen and Wesselbaum	*On thresholds in the climate-migration relationship*	2020	x	C3
Pajaron and Vasquez	*Weathering the storm weather shocks and international labour migration from the Philippines*	2020	x	C2
Pan	*Protections from natural disasters as local public goods migration and local adaptations*	2020	x	C3
Peri and Sasahara	*The impact of global warming on rural-urban migrations: evidence from global big data*	2019		C3
Perkiss and Moerman	*A dispute in the making: a critical examination of displacement, climate change and the Pacific islands*	2018	x	C1
Pismennaya et al.	*Impact of climate change on migration from Vietnam to Russia as a factor of transformation of geopolitical relations*	2015	x	C1
Radel et al.	*Toward a political ecology of migration land labour migration and climate change in northwestern Nicaragua*	2018	x	C1
Ragazzi	*Climate change and migration: a gravity model approach*	2012		C4
Rao et al.	*Managing risk changing aspirations and household dynamics implications for well-being and adaptation in semiarid Africa and India*	2020	x	C1
Reuveny and Moore	*Does environmental degradation influence migration? Emigration to developed countries in the late 1980s and 1990s*	2009	x	C4
Robalino et al.	*The effect of hydro-meteorological emergencies on internal migration*	2015	x	C1
Ruiz	*Do climatic events influence internal migration? Evidence from Mexico*	2017		C4
Ruyssen and Rayp	*Determinants of intra-regional migration in Sub-Saharan Africa 1980-2000*	2014	x	C4
Saldaña-Zorrilla and Sandberg	*Impact of climate-related disasters on human migration in Mexico: a spatial model*	2009	x	C2

Author(s)	Title	Year	Pub	Cluster
Sedova and Kalkuhl	*Who are the climate migrants and where do they go evidence from rural India*	2020	x	C3
Simonelli	*Migration and climate change*	2018	x	C1
Spencer and Urquhart	*Hurricane strikes and migration: evidence from storms in Central America and the Caribbean*	2018	x	C4
Spitzer et al.	*International migration responses to natural disasters: evidence from modern Europe's deadliest earthquake*	2020		C2
Suliman	*Rethinking about civilizations the politics of migration in a new climate*	2016	x	C4
Thiede et al.	*Climate variability and inter-provincial migration in South America, 1970-2011*	2016	x	C1
Thiede and Gray	*Heterogeneous climate effects on human migration in Indonesia*	2017	x	C1
Valsson and Ulfarsson	*Mega-patterns of global settlement typology and drivers in a warming world*	2012	x	C1
Viswanathan and Kumar	*Weather, agriculture and rural migration: evidence from state and district level migration in India*	2015	x	C1
Waldinger	*The effects of climate change on internal and international migration: implications for developing countries*	2015		C2
Weinthal et al.	*Securitizing water climate and migration in Israel, Jordan and Syria*	2015	x	C4
Wesselbaum and Aburn	*Gone with the wind: international migration*	2019	x	C4
Wyett	*Escaping a rising tide sea level rise and migration in Kiribati*	2014	x	C1
Yuan and Zhu	*Shock and roam migratory responses to natural disasters*	2016	x	C2
Zhou	*Climate change health and migration in urban China*	2011	x	C3

Appendix B

Appendix B

List of articles

Author(s)	Title	Year	Pub
Cluster 1			
Afifi and Warner	The impact of environmental degradation on migration flows across countries	2008	0
Alexeev et al.	Weather-related disasters and international migration	2011	0
Backhaus et al.	Do climate variations explain bilateral migration? A gravity model analysis	2015	1
Barassi et al.	Climate anomalies and migration between Chinese provinces 19872015	2018	1
Barrios et al.	Climatic change and rural-urban migration the case of Sub-Saharan Africa	2006	1
Beine and Parsons	Climatic factors as determinants of international migration	2015	1
Beine and Parsons	Climatic factors as determinants of international migration: redux	2017	1
Bettin and Nicolli	Does climate change foster emigration from less developed countries? Evidence from bilateral data	2012	0
Bruckner	Economic growth, size of the agricultural sector, and urbanization in Africa	2012	1
Cai et al.	Climate variability and international migration the importance of the agricultural linkage	2016	1
Cattaneo and Bosetti	Climate-induced international migration and conflicts	2017	1
Coniglio and Pesce	Climate variability and international migration: an empirical analysis	2015	1
Dallmann and Millock	Climate variability and interstate migration in India	2017	1
Damette and Gittard	Climate change and migrations: remittances as a buffer?	2017	1
Docquier et al.	Emigration and democracy	2016	1
Drabo and Mbaye	Climate change, natural disasters and migration: an empirical analysis in developing countries	2011	0
Drabo and Mbaye	Natural disasters, migration and education: an empirical analysis in developing countries	2015	1
Groschl	Climate change and the relocation of population	2012	0
Groschl and Steinwachs	Do natural hazards cause international migration?	2017	1

Author(s)	Title	Year	Pub
Hanson and McIntosh	Birth rates and border crossings: Latin American migration to the US, Canada, Spain and the UK	2012	1
Khamis and Li	Environment matters: new evidence from Mexican migration	2020	1
Marchiori et al.	The impact of weather anomalies on migration in Sub-Saharan Africa	2012	1
Maurel and Tuccio	Climate instability, urbanisation and international migration	2016	1
Naudé	Conflict, disasters, and no jobs: reasons for international migration from Sub-Saharan Africa	2008	0
Naudé	Natural disasters and international migration from Sub-Saharan Africa	2009	1
Naudé	The determinants of migration from Sub-Saharan African countries	2010	1
Ragazzi	Climate change and migration: a gravity model approach	2012	0
Reuveny and Moore	Does environmental degradation influence migration? Emigration to developed countries in the late 1980s and 1990s	2009	1
Ruiz	Do climatic events influence internal migration? Evidence from mexico	2017	0
Ruyssen and Rayp	Determinants of intra-regional migration in Sub-Saharan Africa 1980-2000	2014	1
Spencer and Urquhart	Hurricane strikes and migration: evidence from storms in central America and the Caribbean	2018	1
Wesselbaum and Aburn	Gone with the wind: international migration	2019	1
Cluster 2			
Abel et al.	Climate, conflict and forced migration	2018	0
Baronchelli and Ricciuti	Climate change, rice production, and migration in Vietnamese households	2018	0
Benonnier et al.	Climate change, migration, and irrigation	2019	0
Berlemann and Tran	Climate-related hazards and internal migration empirical evidence for rural Vietnam	2020	1
Bohra-Mishra et al.	Nonlinear permanent migration response to climatic variations but minimal response to disasters	2014	1
Carattini and Veronesi	Trust, temperature fluctuations, and asylum applications	2020	0
Cattaneo and Peri	The migration response to increasing temperatures	2016	1
Cattaneo and Massetti	Does harmful climate increase or decrease migration evidence from rural households in Nigeria	2019	1
Chort and Rupelle	Managing the impact of climate change on migration: evidence from Mexico	2017	0
Chort and De La Rupelle	Managing the impact of climate on migration: evidence from Mexico	2019	0
Defrance et al.	Is migration drought-induced in Mali? An empirical analysis using panel data on Malian localities over the 1987-2009 period	2020	0
Deuster	Climate change, education and mobility in Africa	2019	0
Henderson et al.	Has climate change driven urbanization in Africa	2017	1
Hirvonen	Temperature changes, household consumption, and internal migration: evidence from Tanzania	2016	1
Jessoe et al.	Climate change and labour allocation in rural Mexico evidence from annual fluctuations in weather	2018	1

Author(s)	Title	Year	Pub
Mastrorillo et al.	The influence of climate variability on internal migration flows in south Africa	2016	1
Missirian and Schlenker	Asylum applications respond to temperature fluctuations	2017	1
Mueller et al.	Temporary migration and climate variation in eastern Africa	2020	1
Olper et al.	Climate change, agriculture and migration: is there a causal relationship?	2018	0
Peri and Sasahara	The impact of global warming on rural-urban migrations: evidence from global big data	2019	0
Sedova and Kalkuhl	Who are the climate migrants and where do they go evidence from rural India	2020	1
Cluster 3			
Ager et al.	How the 1906 San Francisco earthquake shaped economic activity in the American west	2020	1
Boustan et al.	Moving to higher ground: migration response to natural disasters in the early twentieth century	2012	1
Boustan et al.	The effect of natural disasters on economic activity in US counties a century of data	2020	1
Chernina	Natural shocks and migration decisions: the case of Kyrgyzstan	2019	0
Dillon et al.	Migratory responses to agricultural risk in northern Nigeria	2011	1
Fan et al.	Does extreme weather drive inter-regional brain drain in the US: evidence from a sorting model	2016	1
Gignoux and Menéndez	Benefit in the wake of disaster long-run effects of earthquakes on welfare in rural Indonesia	2016	1
Gröger and Zylberberg	Internal labor migration as a shock coping strategy evidence from a typhoon	2016	1
Halliday	Migration, risk, and liquidity constraints in El Salvador	2006	1
Halliday	Intra-household labor supply, migration, and subsistence constraints in a risky environment: evidence from rural El Salvador	2012	1
Hornbeck	The enduring impact of the American dust bowl: short- and long-run adjustments to environmental catastrophe	2012	1
Kawawaki	Economic analysis of population migration factors caused by the great east japan earthquake and tsunami	2018	1
Mahajan and Yang	Taken by storm: hurricanes, migrant networks, and US immigration	2020	1
Ouattara and Strobl	Hurricane strikes and local migration in US coastal counties	2014	1
Pajaron and Vasquez	Weathering the storm weather shocks and international labor migration from the Philippines	2020	1
Saldaña-Zorrilla and Sandberg	Impact of climate-related disasters on human migration in mexico: a spatial model	2009	1
Spitzer et al.	International migration responses to natural disasters: evidence from modern Europe's deadliest earthquake	2020	0
Cluster 4			
Chen and Flatnes	Credit access, migration, and climate change adaptation in rural Bangladesh	2019	0
Feng et al.	Linkages among climate change, crop yields and Mexico-US cross-border migration	2010	1

Author(s)	Title	Year	Pub
Goldbach	Out-migration from coastal areas in Ghana and Indonesia-the role of environmental factors	2017	1
Grace et al.	Examining rural Sahelian out-migration in the context of climate change an analysis of the linkages between rainfall and out-migration in two Malian villages from 1981 to 2009	2018	1
Gray	Environment, land, and rural out-migration in the southern Ecuadorian Andes	2009	1
Gray and Mueller	Natural disasters and population mobility in Bangladesh	2012	1
Gray and Mueller	Drought and population mobility in rural Ethiopia	2012	1
Gray and Bilsborrow	Environmental influences on human migration in rural Ecuador	2013	1
Gray and Wise	Country-specific effects of climate variability on human migration	2016	1
Henry et al.	Modelling inter-provincial migration in Burkina Faso, west Africa: the role of socio-demographic and environmental factors	2003	1
Henry et al.	The impact of rainfall on the first out-migration: a multi-level event-history analysis in Burkina Faso	2004	1
Hunter et al.	Rainfall patterns and u.s. Migration from rural Mexico	2013	1
Jennings and Gray	Climate variability and human migration in the Netherlands, 18651937	2015	1
Joseph and Wodon	Is internal migration in Yemen driven by climate or socio-economic factors?	2013	1
Joseph et al.	Is climate change likely to lead to higher net internal migration? The republic of Yemen's case	2014	0
Koubi et al.	The role of environmental perceptions in migration decision-making: evidence from both migrants and non-migrants in five developing countries	2016	1
Koubi et al.	Environmental stressors and migration evidence from Vietnam	2016	1
Lewin et al.	Do rainfall conditions push or pull rural migrants evidence from Malawi	2012	1
Marchiori et al.	Is environmentally induced income variability a driver of human migration?	2017	1
Mueller et al.	Heat stress increases long-term human migration in rural Pakistan	2014	1
Nawrotzki et al.	Do rainfall deficits predict u.s.-bound migration from rural Mexico? Evidence from the Mexican census	2013	1
Nawrotzki and Bakhtsiyarava	International climate migration: evidence for the climate inhibitor mechanism and the agricultural pathway	2017	1
Robalino et al.	The effect of hydro-meteorological emergencies on internal migration	2015	1
Thiede et al.	Climate variability and inter-provincial migration in south America, 19702011	2016	1
Thiede and Gray	Heterogeneous climate effects on human migration in Indonesia	2017	1
Viswanathan and Kumar	Weather, agriculture and rural migration: evidence from state and district level migration in India	2015	1

Slow-onset events

Table B.2 shows the results of the MRA on evidence of the impact of slow-onset events for the entire sample (1) and separately cluster by cluster (columns 2-5). All covariates are included in this specification.

TABLE B.2: MRA Results for slow-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
Standard Error (FAT): $\hat{\beta}_1$	-0.086	-5.654**	-29.959***	-0.006	-0.591*
	(0.208)	(2.182)	(0.264)	(0.679)	(0.341)
Constant (PET): $\hat{\beta}_0$	-0.012	-2.043**	0.321***	-0.028	0.120***
	(0.013)	(0.822)	(0.002)	(0.031)	(0.027)
Precipitation measures					
- levels	-0.000	0.000***		-0.006***	-0.022**
	(0.000)	(0.000)		(0.002)	(0.008)
- deviation	-0.000	0.000***		-0.007**	-0.001
	(0.000)	(0.000)		(0.003)	(0.006)
- anomaly	-0.003	0.003***		-0.000	-0.012
	(0.003)	(0.001)		(0.004)	(0.008)
Time lag	-0.000*	-0.000***		-0.001	0.001
	(0.000)	(0.000)		(0.001)	(0.001)
Temperature measures					
- levels	0.000	0.000***	0.000***	-0.000	-0.020**
	(0.000)	(0.000)	(0.000)	(0.003)	(0.008)
- deviation	0.000	0.000***		0.001	-0.005
	(0.000)	(0.000)		(0.004)	(0.006)
- anomaly	-0.003	-0.004**		-0.013***	-0.006
	(0.004)	(0.002)		(0.004)	(0.006)
Time lag	-0.000***	-0.000***	0.021***	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Soil Degradation	-0.003	0.010***		-0.067***	-0.001
	(0.011)	(0.003)		(0.006)	(0.015)
Corridor					
- Internal	0.008	0.003**		-0.004	0.012*
	(0.005)	(0.001)		(0.010)	(0.006)
- International	0.005	0.001		-0.004	-0.016
	(0.005)	(0.001)		(0.010)	(0.010)
- Urbanization	0.008	0.003**		0.006	
	(0.005)	(0.001)		(0.010)	
Measurement					
- Flows	-0.024***	1.946**		-0.024	-0.004
	(0.008)	(0.715)		(0.021)	(0.026)
- Stock	-0.000				
	(0.011)				
Region of origin					
- Africa	-0.004	0.294*		-0.028***	-0.007
	(0.004)	(0.147)		(0.009)	(0.006)
- Asia	0.005	0.290*		-0.003	-0.003*

TABLE B.2: MRA Results for slow-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
	(0.004)	(0.147)		(0.027)	(0.002)
- Europe	0.025**				0.035*
	(0.011)				(0.018)
- LAC	-0.008	0.349*		0.133**	-0.017**
	(0.007)	(0.180)		(0.059)	(0.008)
- MENA	-0.018	0.327*			0.016
	(0.024)	(0.168)			(0.010)
- North America	-0.026*		-0.299***		
	(0.013)		(0.002)		
Destination					
- High income	-0.000	-0.000**		-0.059***	-0.004
	(0.000)	(0.000)		(0.018)	(0.003)
- Upper-middle income	-0.000	-0.000***		-0.059***	0.002*
	(0.000)	(0.000)		(0.018)	(0.001)
- Lower-middle income	0.000	0.000***		0.003***	-0.006
	(0.000)	(0.000)		(0.000)	(0.025)
- Low income	-0.002	0.001		0.054	-0.003*
	(0.003)	(0.010)		(0.049)	(0.002)
Paper features					
- Preferred specification	-0.001	-0.006		-0.003	0.000
	(0.001)	(0.006)		(0.003)	(0.001)
- Published articles	0.001	-0.110*		0.013	-0.005
	(0.005)	(0.055)		(0.021)	(0.009)
- Publication Impact-factor	-0.000	0.025*		-0.000	-0.002
	(0.000)	(0.013)		(0.000)	(0.006)
Sample features					
Time span	-0.000	-0.002	0.011***	-0.001	-0.000
	(0.000)	(0.003)	(0.000)	(0.001)	(0.001)
Source of data					
- Census	0.019***	-0.801**			-0.085***
	(0.007)	(0.303)			(0.023)
- Official statistics				-0.079*	-0.012
				(0.042)	(0.008)
- Research data	-0.006	-0.140***		-0.014	
	(0.005)	(0.015)		(0.030)	
- Survey	0.004	-0.359***			
	(0.007)	(0.088)			
Unit of analysis					
- Household	-0.002	1.766***		0.046	
	(0.012)	(0.608)		(0.029)	
- Individual	-0.014	1.457***		-0.009	
	(0.013)	(0.482)		(0.021)	
- Country level	0.012*	-0.556		0.126	-0.072**
	(0.007)	(0.327)		(0.076)	(0.030)
Estimation:					
- Panel	0.021**	0.083		0.055*	

TABLE B.2: MRA Results for slow-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
	(0.009)	(0.064)		(0.031)	
- Poisson	0.002			0.134***	-0.002
	(0.006)			(0.034)	(0.014)
- OLS and ML	0.007	0.920**		0.007	0.015
	(0.007)	(0.406)		(0.011)	(0.012)
- IV	0.040***	0.700**			0.035***
	(0.011)	(0.295)			(0.010)
- Logit	-0.005	0.883**	0.017***		
	(0.008)	(0.409)	(0.000)		
Controls:					
- Slow and fast included	0.000	0.005		-0.046***	0.009
	(0.002)	(0.006)		(0.008)	(0.007)
- Income	0.006**	0.159*		0.018	0.000
	(0.003)	(0.091)		(0.014)	(0.002)
- Conflict	-0.001	0.181**		-0.003	0.003
	(0.005)	(0.079)		(0.003)	(0.008)
- Political stability	0.005	-0.075*		-0.008	0.007
	(0.006)	(0.039)		(0.008)	(0.007)
- Population	0.006	0.162*		0.024	0.010
	(0.004)	(0.081)		(0.019)	(0.007)
- Diaspora	-0.003	-0.222*			-0.000
	(0.004)	(0.110)			(0.002)
- Past migration	-0.002	-0.203**	0.007***		0.000
	(0.003)	(0.095)	(0.000)		(0.000)
- Poverty	0.007	0.034		0.001	-0.018*
	(0.005)	(0.037)		(0.009)	(0.010)
- Culture	-0.002	0.467*		0.003	-0.003
	(0.003)	(0.237)		(0.008)	(0.003)
- Geography	0.002	-0.160**		-0.002	-0.003
	(0.003)	(0.066)		(0.007)	(0.003)
- Agriculture	0.004**	-0.546**	0.004***	-0.013	0.001
	(0.002)	(0.262)	(0.000)	(0.013)	(0.001)
- Labour	0.002	-0.009		-0.030	0.005
	(0.004)	(0.018)		(0.022)	(0.019)
- Urban	-0.016***	0.377*		-0.021***	0.001
	(0.005)	(0.184)		(0.006)	(0.017)
- International aids	-0.029***			-0.044***	
	(0.010)			(0.009)	
Interacted terms (channels):					
- Agriculture	0.000	-0.009	-0.055***	-0.001	0.003*
	(0.001)	(0.016)	(0.000)	(0.002)	(0.001)
- International aid	0.022	-0.001***		0.034***	
	(0.014)	(0.000)		(0.001)	
- Culture	-0.005*				-0.007***
	(0.003)				(0.002)
- Destination	0.004	0.163**			-0.008
	(0.004)	(0.075)			(0.007)

TABLE B.2: MRA Results for slow-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
- Poverty	-0.025 (0.021)			-0.077*** (0.008)	0.094 (0.087)
- Income and agriculture	0.019*** (0.007)			0.027*** (0.003)	
- Education	-0.000*** (0.000)	-0.000*** (0.000)		-0.001 (0.002)	
- Environment	-0.000*** (0.000)	-0.000*** (0.000)		0.004** (0.001)	0.000 (0.001)
- Geography	-0.004 (0.003)			-0.001 (0.005)	-0.002 (0.002)
- Income	-0.041 (0.028)	-0.004** (0.001)		-0.028** (0.013)	-0.063 (0.042)
- Origin	-0.000 (0.000)	-0.000*** (0.000)		-0.059*** (0.009)	-0.018* (0.009)
- Past migration	-0.010*** (0.003)	-0.008*** (0.002)			
- Political stability	-0.045*** (0.008)			-0.002 (0.001)	-0.046*** (0.005)
- Population	-0.013 (0.010)			-0.025 (0.019)	
- Urban	0.012* (0.006)			0.021*** (0.001)	
PEESE Correction: β_0	-0.013 (0.012)	-1.992** (0.710)	0.060*** (0.000)	-0.027 (0.027)	0.115*** (0.030)
N	3897	932	100	1814	1051

Note: Controls are grouped by paper features, dependent variable, independent variable, sample and regression characteristics. PCC precision square weights ($1/se_i^2$); robust standard errors clustered by study in parentheses; 95% confidence intervals in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Fast-onset events

Table B.3 shows the results of the MRA on evidence of the impact of fast-onset events for the entire sample (1) and separately cluster by cluster (columns 2-5). All covariates are included in this specification.

TABLE B.3: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
Constant (PET): $\hat{\beta}_0$	0.056 (0.053)	-0.058 (0.053)	-0.092*** (0.020)	0.066** (0.022)	0.355* (0.197)

TABLE B.3: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
Standard Error (FAT): $\hat{\beta_1}$	0.467	-4.517	-0.116	6.412***	-0.098
	(0.420)	(3.508)	(0.094)	(0.972)	(1.965)
Paper features					
- Preferred specification	-0.005	-0.006	0.001	0.001***	-0.005
	(0.004)	(0.009)	(0.001)	(0.000)	(0.004)
- Published articles	0.008		2.164***	0.075***	0.076
	(0.010)		(0.210)	(0.007)	(0.082)
- Publication Impact-factor	0.004	0.057**	-0.484***	-0.064***	0.025
	(0.003)	(0.020)	(0.024)	(0.003)	(0.036)
Type of event					
- Geophysical	0.006		-0.055***	-0.030***	-0.001
	(0.006)		(0.003)	(0.000)	(0.006)
- Meteorological	0.006	0.003**	-0.063***	-0.069***	0.005
	(0.006)	(0.001)	(0.006)	(0.000)	(0.007)
- Hydrogeological	0.012*	0.008***	-0.054***	-0.032***	0.008
	(0.007)	(0.003)	(0.002)	(0.000)	(0.007)
- Climatological	0.004	0.003	-0.065***		0.001
	(0.006)	(0.002)	(0.007)		(0.007)
- Multiple disasters	-0.007	0.020***			-0.001
	(0.006)	(0.005)			(0.008)
Time lag	0.000	-0.004	0.002***	-0.000	0.003**
	(0.001)	(0.004)	(0.000)	(0.003)	(0.001)
Measurement					
- Frequency	0.005	0.042***	-0.023***		0.000
	(0.006)	(0.005)	(0.000)		(0.006)
- Intensity	0.008	-0.002*	-0.984***	-0.063***	-0.032
	(0.010)	(0.001)	(0.073)	(0.000)	(0.051)
- Occurrence	0.000	0.001	0.024***		-0.013
	(0.007)	(0.002)	(0.001)		(0.039)
- Duration	0.005	1.033***			-0.007
	(0.018)	(0.256)			(0.054)
Corridor					
- Internal	0.013*	-0.000	0.001	0.041*	-0.020
	(0.007)	(0.001)	(0.001)	(0.017)	(0.019)
- International	0.004		0.004***	0.039*	0.013
	(0.005)		(0.000)	(0.018)	(0.054)
- Urbanization	0.010		0.003***		
	(0.012)		(0.001)		
Measurement					
- Flows	-0.031	0.531***	0.101	-0.122***	-0.324***
	(0.031)	(0.111)	(0.090)	(0.029)	(0.096)
- Stock	-0.034		-0.087***		-0.336***
	(0.028)		(0.012)		(0.091)
Region of Origin					
- Africa	-0.019	-0.047			-0.006
	(0.013)	(0.038)			(0.004)

TABLE B.3: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
- Asia	0.000	-0.044	0.077		-0.002
	(0.007)	(0.039)	(0.114)		(0.003)
- Europe	0.001				-0.010
	(0.016)				(0.011)
- LAC	0.015		-0.278	0.063***	0.000
	(0.020)		(0.223)	(0.010)	(0.013)
- MENA	-0.003				-0.007*
	(0.007)				(0.004)
- North America	-0.050		-1.502***		
	(0.032)		(0.158)		
Destination					
- High income	0.001	-0.001		-0.000	-0.003
	(0.003)	(0.001)		(0.001)	(0.002)
- Upper-middle income	0.003	-0.082		-0.003**	-0.000
	(0.005)	(0.060)		(0.001)	(0.004)
- Lower-middle income	0.001	-0.003***	-0.002***	0.021***	-0.022***
	(0.007)	(0.001)	(0.000)	(0.000)	(0.003)
- Low income	-0.002	-0.000			0.001
	(0.003)	(0.029)			(0.001)
Sample					
Time span	0.000**	0.017***	0.030***	-0.001*	-0.000
	(0.000)	(0.003)	(0.005)	(0.000)	(0.000)
Source of data					
- Census	0.014		-0.004***		-0.003
	(0.013)		(0.000)		(0.201)
- Official statistics	0.002		0.002***		0.174
	(0.001)		(0.000)		(0.169)
- Research data	-0.004	0.317	-2.108***		
	(0.011)	(0.185)	(0.230)		
- Survey	0.022	0.009	-2.208***	-0.142***	
	(0.015)	(0.021)	(0.112)	(0.032)	
Unit of analysis					
- Household	-0.024	-0.523***	0.294***	0.757***	
	(0.021)	(0.138)	(0.054)	(0.068)	
- Individual	-0.046		0.126***		
	(0.038)		(0.036)		
- Country level	0.002			-0.092**	-0.278
	(0.013)			(0.025)	(0.163)
Estimation					
- Panel	-0.042***	-1.331***	0.816***		-0.088***
	(0.010)	(0.347)	(0.051)		(0.031)
- Poisson	-0.008				0.045
	(0.014)				(0.026)
- OLS and ML	-0.033	-0.006***	0.000	0.003***	0.054*
	(0.021)	(0.000)	(0.000)	(0.000)	(0.030)
- IV	-0.091**		0.856***		0.044

TABLE B.3: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
	(0.043)		(0.063)		(0.040)
- Logit	-0.048	0.024***	0.007		
	(0.032)	(0.007)	(0.093)		
Controls					
- Slow and fast included	-0.026*	-0.024		-0.105***	-0.007
	(0.015)	(0.017)		(0.001)	(0.008)
- Income	0.002	-0.016	0.008***	-0.009***	0.158
	(0.006)	(0.022)	(0.000)	(0.001)	(0.107)
- Conflict	0.025**				-0.081
	(0.010)				(0.052)
- Political stability	0.017**	0.067	0.002***		0.111***
	(0.008)	(0.053)	(0.000)		(0.038)
- Population	0.014	0.708***	0.001	0.008***	-0.057
	(0.009)	(0.200)	(0.001)	(0.001)	(0.051)
- Diaspora	-0.047**	-0.666***	-0.043***		-0.020
	(0.019)	(0.199)	(0.001)		(0.034)
- Past migration	0.014	0.019**	0.000		-0.112
	(0.011)	(0.007)	(0.001)		(0.073)
- Poverty	-0.022	-0.053	-0.001**		0.071
	(0.015)	(0.043)	(0.000)		(0.083)
- Culture	-0.006	0.372**	1.208***		-0.010
	(0.006)	(0.144)	(0.131)		(0.008)
- Geography	0.011	-0.082***	-0.006***		0.006
	(0.008)	(0.010)	(0.000)		(0.007)
- Agriculture	0.004*	-0.022	0.002*	0.008***	-0.001
	(0.002)	(0.060)	(0.001)	(0.002)	(0.002)
- Labour	0.005	0.013	-0.002		-0.091***
	(0.004)	(0.017)	(0.002)		(0.031)
- Urban	0.024	0.078		-0.017**	0.000
	(0.028)	(0.083)		(0.005)	(0.038)
- International aids	-0.001		-0.001***	-0.029***	0.092*
	(0.008)		(0.000)	(0.004)	(0.046)
- Education	-0.011	-0.006	-0.000	-0.000	-0.013
	(0.009)	(0.029)	(0.004)	(0.003)	(0.021)
Interacted terms (channels)					
- Agriculture	0.004**	-0.001	0.007**	-0.005***	-0.014
	(0.002)	(0.003)	(0.003)	(0.001)	(0.018)
- International aid	-0.036***	-0.034***			-0.040***
	(0.007)	(0.000)			(0.007)
- Culture	0.034***	0.009			0.037***
	(0.006)	(0.006)			(0.002)
- Destination	-0.016	-0.033***			0.048
	(0.017)	(0.004)			(0.049)
- Diaspora	0.001		0.004**		
	(0.003)		(0.001)		
- Poverty	0.002		0.003***	0.008***	-0.043
	(0.004)		(0.001)	(0.000)	(0.044)

TABLE B.3: MRA Results for fast-onset events

	(1) All	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cluster 4
- Education	0.018	0.027***			
	(0.015)	(0.006)			
- Environment	-0.010			0.016***	
	(0.019)			(0.004)	
- Geography	-0.002		0.024***		-0.002
	(0.009)		(0.001)		(0.009)
- Income	0.002	-0.005***	0.010***		-0.016**
	(0.007)	(0.000)	(0.001)		(0.007)
- Origin	-0.023**				-0.018***
	(0.009)				(0.006)
- Past migration	0.011	0.008	0.020***		
	(0.008)	(0.006)	(0.000)		
- Political stability	-0.017**		-0.000***		
	(0.008)		(0.000)		
- Population	0.000		-0.001		
	(0.002)		(0.002)		
- Urban	0.012			0.038***	-0.284***
	(0.022)			(0.000)	(0.089)
PEESE Correction: β_0	0.062	-0.101***	0.850***	0.133***	0.495***
N	2062	176	789	409	688

Note: Controls are grouped by paper features, dependent variable, independent variable, sample and regression characteristics. PCC precision square weights ($1/se_i^2$); robust standard errors clustered by study in parentheses; 95% confidence intervals in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C

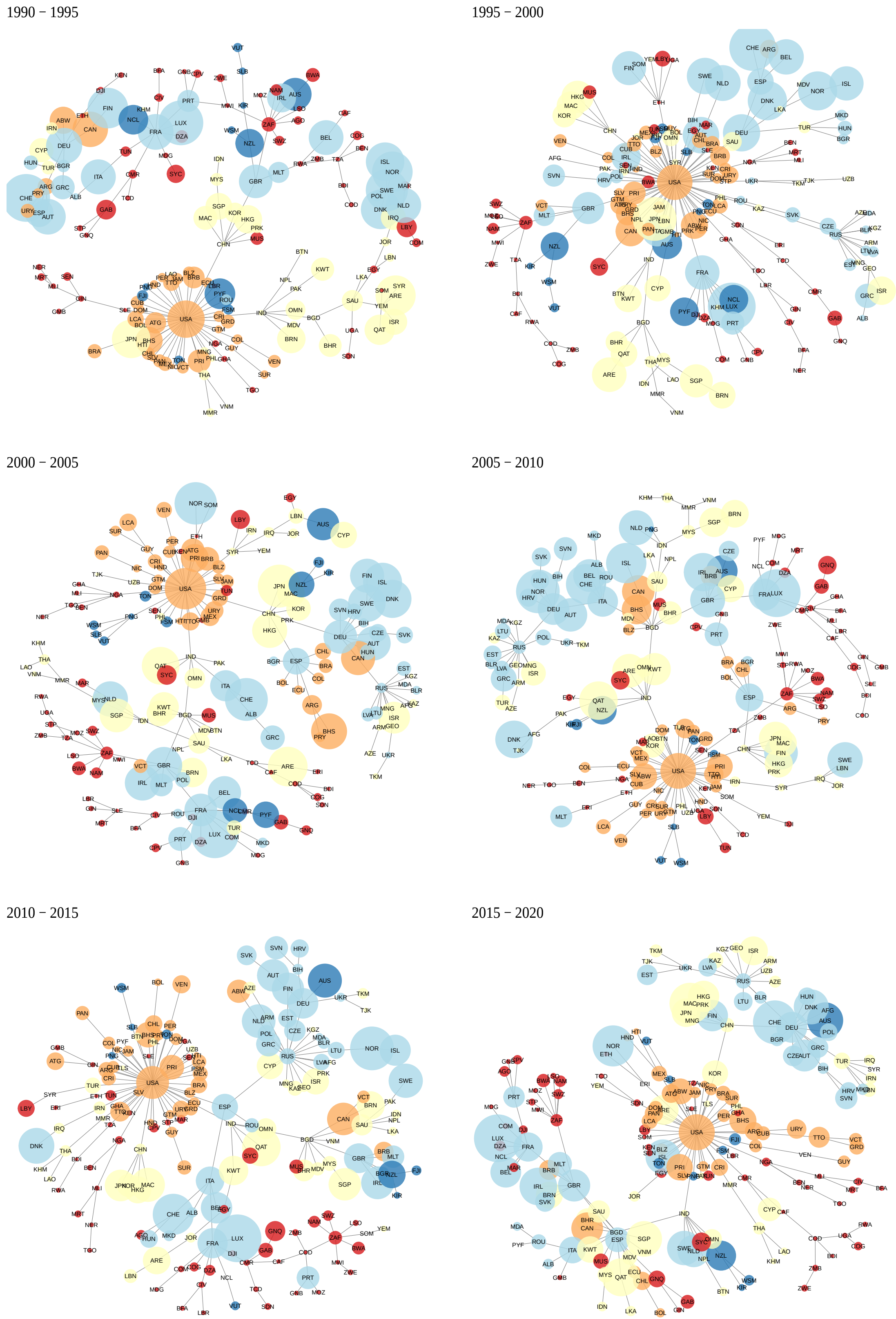
Appendix C

Additional centralisation measures

	1990-95	*1995-00*	*2000-05*	*2005-10*	*2010-15*	*2015-20*
N. of nodes	163	185	185	186	186	186
N. of edges	9012	11 394	11 553	11 667	11 394	11 109
Out-degree centralisation	0.436	0.426	0.416	0.429	0.453	0.493
In-degree centralisation	0.578	0.611	0.628	0.601	0.609	0.607
Closeness centralisation	0.548	0.589	0.575	0.555	0.576	0.591
Betweenness centralisation	0.051	0.054	0.041	0.034	0.053	0.043

Minimal spanning tree

FIGURE C.1: Minimum spanning tree of WMN



Note: Minimal spanning tree of the undirected weighted migration network. Size of nodes represents per capita GDP (World Bank's World Development Indicators), each continent is assigned to a colour: red (Africa), orange (Americas), yellow (Asia), light blue (Europe) and darker blue (Oceania). Each node has only one edge. Edge size is proportional to the bilateral flow between the two nodes. Fruchterman-Reingold algorithm used for forced layout.

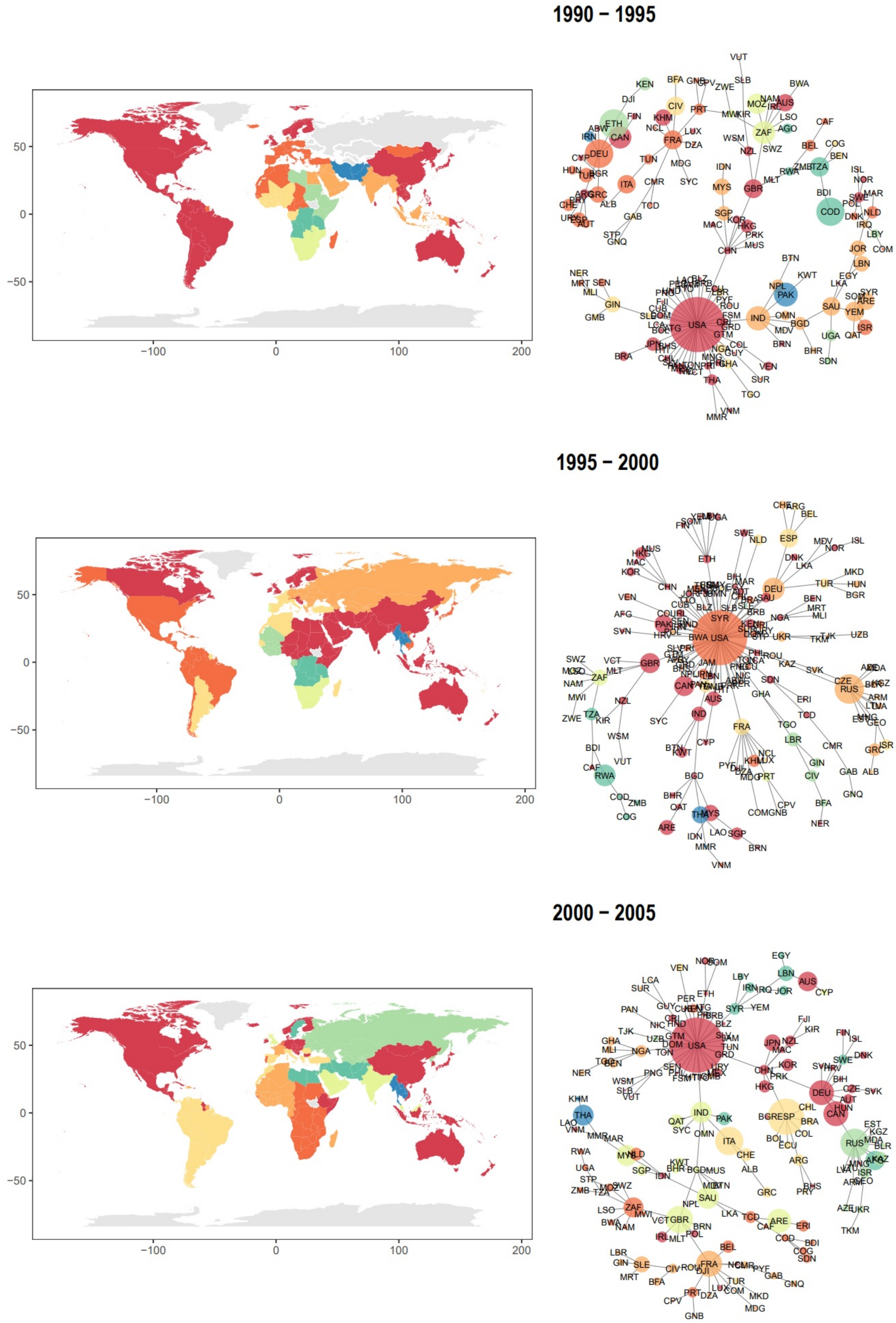
EMDAT dataset

TABLE C.1: Classification of natural hazards

Category	Definition	Type of hazard
Geophysical	Hazard originating from solid earth	Earthquake Mass movement (rock fall, landslide) Volcanic activity.
Meteorological	Hazard caused by short-lived extreme weather and atmospheric conditions that last form minutes to days	Storm (tropical and extra-tropical storm, convective storm) Extreme temperature (cold wave, heat wave, severe winter) Fog
Hydrological	Hazard caused by the occurrence, movement, and distribution of water	Flood Landslide (wet) Wave action
Climatological	Hazard caused by atmospheric processed ranging from intra-seasonal to multi-decadal climate variability	Drought Glacial lake Wildfire
Others	Hazard caused by other causes, such as exposure to toxic substances, vector-borne diseases carried by living organisms, impact of extraterrestrial objects	Epidemics Insect infection Miscellaneous*

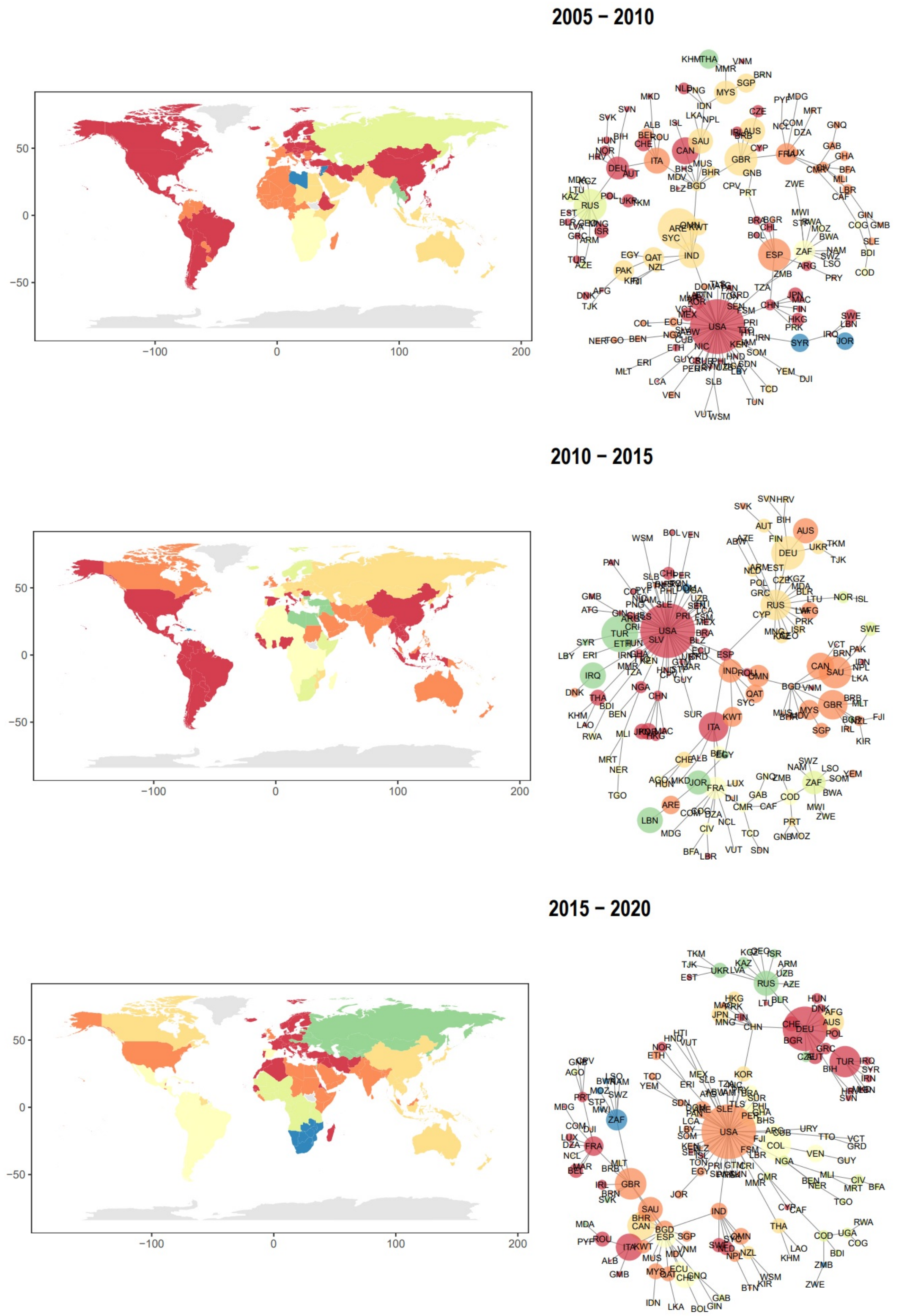
Note: Classification made within the framework of the EM-DAT (*Emergency Events Database*) developed by the Centre for Research on the Epidemiology of Disasters (CRED). https://www.emdat.be/classification
*This category includes biological and extraterrestrial events which, however, are marginally covered by the literature in a small number of contributions.

FIGURE C.2: Community detection and minimal spanning tree



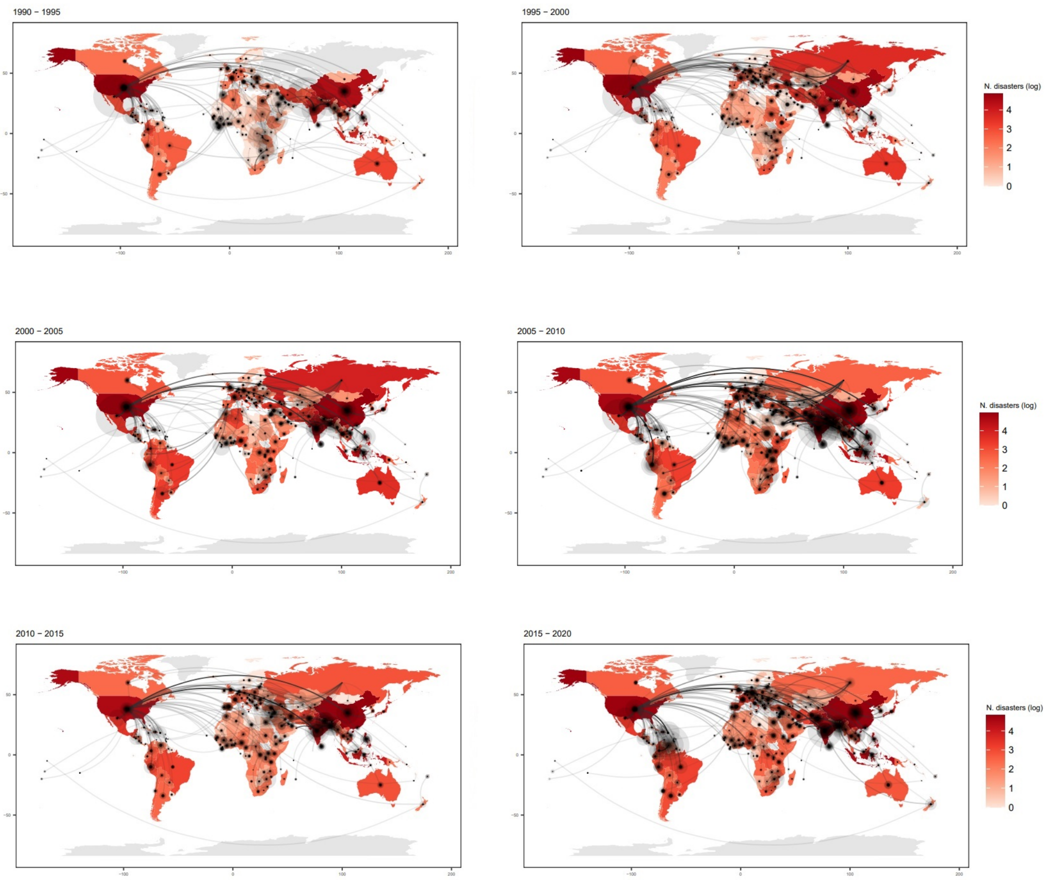
Note: Map of migration flows from Abel and Cohen (2019b), estimates according to closed demographic accounting methodology by to Abel (2018). Thickness and transparency of edges (lines) show the size of flows (all flows are included). Size of nodes (points) captures the size of population in the country. The colour of each point scales the frequency of natural disasters in each country (data from EM-DAT, n.d.).

FIGURE C.3: Community detection and minimal spanning tree



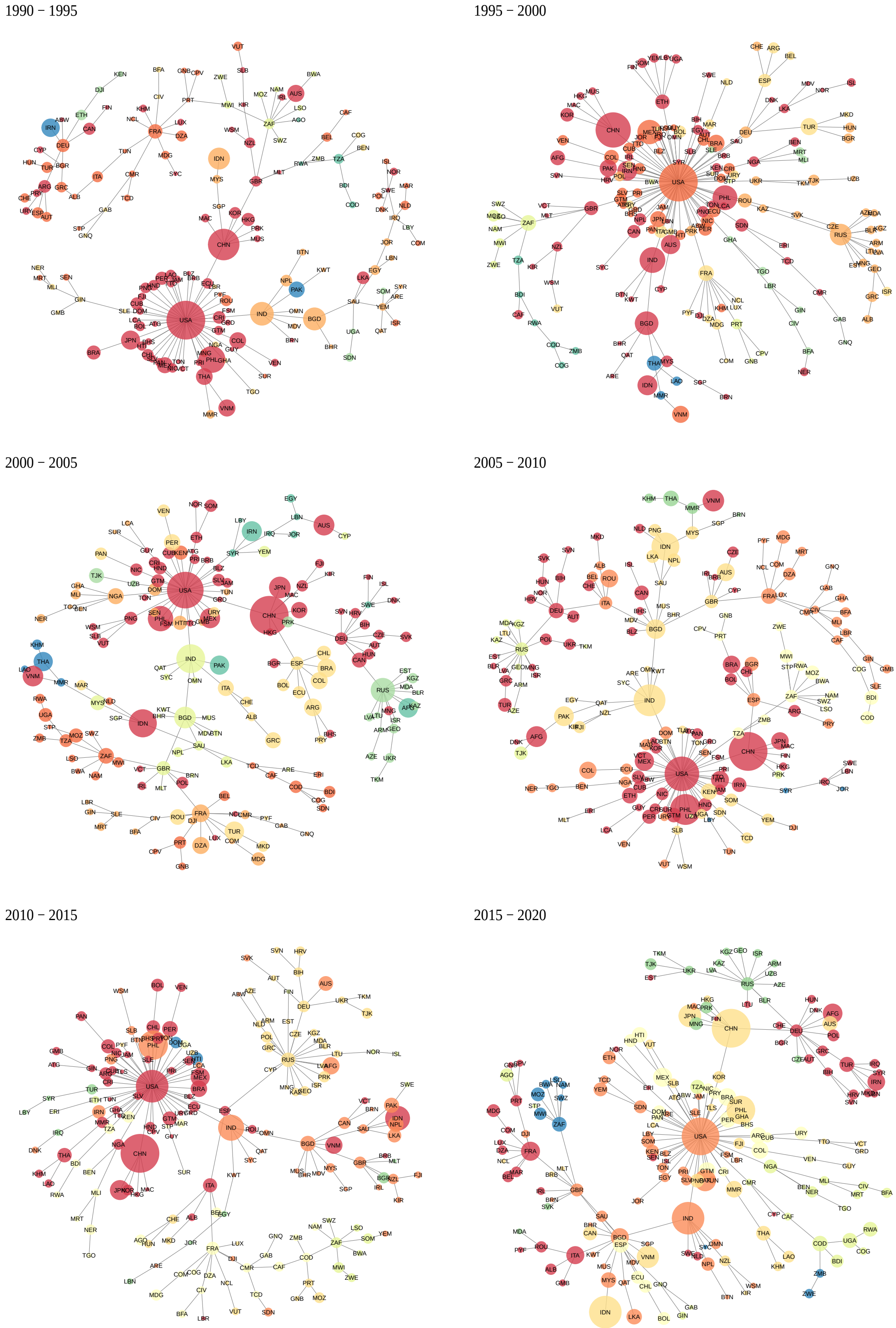
Note: Map of migration flows from Abel and Cohen (2019b), estimates according to closed demographic accounting methodology by to Abel (2018). Thickness and transparency of edges (lines) show the size of flows (all flows are included). Size of nodes (points) captures the size of population in the country. The colour of each point scales the frequency of natural disasters in each country (data from EM-DAT, n.d.).

FIGURE C.4: Map of occurrence of natural disasters and MSTs



Note: WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018) and represented in links between countries. Displayed links correspond to the edges included in the MST. The size of nodes is proportional to migration flows. Each country is coloured according to frequency of natural disasters (in logs). Data are retrieved from EM-DAT.

FIGURE C.5: Minimal spanning tree of WMNs



Note: Minimal spanning tree of the undirected weighted migration network. Each continent is assigned to a colour a community detected in WMNs for periods 1990-95, 1995-00, 2000-05, 2005-10, 2010-15, 2015-20. Data of migration flows issued from Abel and Cohen (2019b), estimates of flows according to closed demographic accounting methodology (Abel, 2018).Node size is proportional to to the number of natural disasters occurred in the country-node in the corresponding period. Data are retrieved from EM-DAT. Fruchterman-Reingold algorithm used for forced layout.

Appendix D

Appendix D

Alternative measures of flow

Abel and Cohen (2019a) provide different methods of estimation of flows, reporting strategies that have been used in literature and suggesting new estimation methods.

1. Stock differencing: mainly takes the difference between two round of observations of migrant stocks ($Stock_{ij,t_o} - Stock_{ij,t-1}$). Two different strategies have been adopted to deal with the case in which the difference results in negative values, which would not have any meaning.

    (a) Drop negative: whenever the difference between two successive stocks is negative, the value of resulting flows is set to zero.

    (b) Reverse negative: negative flows resulting from the difference between two successive stocks are considered as return migration and reported to the inverse flow ($M_{ij} \rightarrow M_{ji}$) (this strategy has been used in Beine and Parsons, 2015)

2. Demographic accounting: includes three methods of estimation. At the basis, this methodology rearranges the tables of bilateral stock into an array of birthplace-specific migration flow data and control for changes in births and deaths of countries' population (including natives and migrants) in migrant stocks over the unit interval. Each migrant stock at the beginning of the period is adjusted by the number of deaths; migrant stocks at the end are adjusted by the number of births.

    (a) Open demographic accounting by minimisation: people can move to or from countries beyond the set of those in the input bilateral migrant stock tables Abel (2013)

(b) Closed demographic accounting by minimisation: people either move, do not move, are born or die in the same set of countries Abel (2018)

(c) Closed pseudo-Bayesian demographic accounting: migration flows are a weighted average of the estimates of minimum migration flows and an independent log-linear model estimates (estimated without the terms for diagonal cells) Azose and Raftery (2019)

Abel and Cohen (2019a) show that the best performer estimations of migratory flows are the two closed demographic accounting approaches. The main analysis will make use of Abel (2018)'s estimated flows. Robustness checks with other methods of derivation of flows are presented in table D.2.

Table D.1 shows summary statistics by continent.

TABLE D.2: Comparison of flow estimation strategies

Model:	Abel, 2018 (1)	Azose and Raftery, 2019 (2)	Abel, 2013 (3)	Beine and Parsons, 2015 (4)
Variables				
ln(Distance)	-1.37***	-1.36***	-1.54***	-1.56***
	(0.073)	(0.073)	(0.082)	(0.079)
Border	0.668***	0.707***	0.624***	0.642***
	(0.155)	(0.159)	(0.168)	(0.175)
Colony	0.838***	1.05***	0.879***	0.723***
	(0.170)	(0.162)	(0.168)	(0.207)
Language	0.880***	0.733***	0.856***	0.742***
	(0.144)	(0.148)	(0.137)	(0.146)
R_{ij}^{GL}	-0.191	-1.17	-0.355	-0.259
	(0.234)	(0.212)	(0.316)	(0.312)
Fixed-effects				
Origin	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes
Fit statistics				
Observations	30,453	31,862	29,758	31,862
Pseudo R^2	0.80153	0.76772	0.81299	0.79587

Clustered (Country pairs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

TABLE D.1: Descriptives of migration flows 2015-2020 by continent

	Africa	Americas	Asia	Europe	Oceania
N. of countries	53	33	46	37	10
Sender countries	52	33	44	37	10
Receiver countries	51	33	45	37	8
Total number of migrants					
N. of emigrants (sender) in millions	5.4	8.5	16.9	6.7	0.5
N. of immigrants (receiver) in millions	3.1	11.8	8.5	13.4	1.3
% of world migration accounted by continent					
as sender	14.17	22.31	44.42	17.71	1.39
as receiver	8.02	30.97	22.28	35.31	3.42
% of flows intra-continental over total flows by continent	88.81	56.11	88.28	39.60	12.06
% of flows inter-continental over total flows by continent	11.19	43.89	11.72	60.40	87.94
% of outflows by sub-region over world total (and continent)					
Northern Africa	3.07 (21.68)				
Sub-Saharan Africa	11.1 (78.32)				
Latin America and the Caribbean		19.6 (87.91)			
Northern America		2.7 (12.09)			
Central Asia			1.43 (3.23)		
Eastern Asia			4.77 (10.75)		
South-eastern Asia			7.29 (16.42)		
Southern Asia			20.5 (46.24)		
Western Asia			10.4 (23.36)		
Eastern Europe				5.09 (28.77)	
Northern Europe				2.58 (14.58)	
Southern Europe				4.96 (28.00)	
Western Europe				5.07 (28.65)	
Australia and New Zealand					1.2 (86.47)
Pacific Islands					0.19 (13.53)
% of inflows by sub-region over world total (and continent)					
Northern Africa	0.76 (9.52)				
Sub-Saharan Africa	7.25 (90.48)				
Latin America and the Caribbean		14.0 (45.34)			
Northern America		16.9 (54.66)			
Central Asia			0.7 (3.14)		
Eastern Asia			2.33 (10.47)		
South-eastern Asia			2.61 (11.74)		
Southern Asia			3.55 (15.92)		
Western Asia			13.1 (58.73)		
Eastern Europe				6.65 (18.82)	
Northern Europe				6.93 (19.62)	
Southern Europe				6.66 (18.87)	
Western Europe				15.1 (42.69)	
Australia and New Zealand					3.41 (99.67)
Pacific Islands					0.01 (0.33)

Note: Elaboration of last round of data (2015-2020) on migration flows from Abel and Cohen (2019a). Estimates of flows according to *closed demographic accounting* methodology according to Abel (2018).

Alternative measures of distance

As robustness checks, few measures of distance (or similarity) have been tested.

- *Euclidean distance* is the absolute value of the difference between two indices of risk, namely risk level in country i and the one in country j, in absolute value.

$$R_{ij}^{ed} = |R_i - R_j|$$

- *Squared differences* are expressed as

$$R_{ij}^{sd} = (R_i - R_j)^2$$

.

- *Weighted squared differences* is an index similar to the previous but weighted by the mean of the distance between all possible alternatives

$$R_{ij}^{wsd} = \frac{(R_i - R_j)^2}{\sum_k \frac{1}{n}(R_i - R_k)^2}$$

- *Grubel-Lloyd index* is expressed as

$$R_{ij}^{GL} = 1 - \frac{|R_i - R_j|}{R_i + R_j}$$

- *Helpman similarity index* expressed as

$$R_{ij}^{H} = 1 - \left(\frac{R_i}{R_i + R_j}\right)^2 - \left(\frac{R_j}{R_i + R_j}\right)^2$$

The higher the index, the more similar the risk in the two countries is.

TABLE D.3: Alternative measures of distance between risk indices

Dependent Variable:			M_{ij}		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
ln(Distance)	-1.34***	-1.35***	-1.35***	-1.37***	-1.37***
	(0.071)	(0.071)	(0.071)	(0.074)	(0.073)
Border	0.656***	0.657***	0.657***	0.666***	0.668***
	(0.155)	(0.154)	(0.154)	(0.155)	(0.155)
Colony	0.840***	0.847***	0.846***	0.841***	0.838***
	(0.169)	(0.166)	(0.166)	(0.170)	(0.170)
Language	0.905***	0.890***	0.890***	0.881***	0.880***
	(0.148)	(0.144)	(0.144)	(0.144)	(0.144)
R_{ij}^{ed}	-0.029				
	(0.054)				
R_{ij}^{sd}		-0.007			
		(0.013)			
R_{ij}^{wsd}			-0.007		
			(0.013)		
R_{ij}^{H}				-0.373	
				(0.444)	
R_{ij}^{GL}					-0.191
					(0.234)
Fixed-effects					
Origin	Yes	Yes	Yes	Yes	Yes
Destination	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	29,976	30,453	30,453	30,453	30,453
Pseudo R^2	0.80208	0.80146	0.80147	0.80153	0.80153

Clustered (Country pairs) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Comparison between unidirectional FEs and second-stage estimation

TABLE D.4: Comparison between table 4.5-4.6 and 4.9

	Origin		*Destination*	
Dependent Variables:	FE_i	M_{ij}	FE_j	M_{ij}
Model:	OLS	Poisson	OLS	Poisson
R	1.441***	1.490***	-0.5571**	-0.6861***
	(0.2196)	(0.1350)	(0.2143)	(0.0773)
HA	1.588***	1.612***	0.2034	0.0565
	(0.1591)	(0.0922)	(0.1748)	(0.1170)
HA.NAT	1.627***	2.147***	0.6388*	0.4909***
	(0.2685)	(0.2162)	(0.3432)	(0.1458)
HA.HUM	0.3069***	0.2929***	-0.0969	-0.0891**
	(0.0712)	(0.0429)	(0.1038)	(0.0445)
VU	0.7466***	0.8508***	-0.6104***	-0.5395***
	(0.1996)	(0.1098)	(0.2005)	(0.1025)
VU.SEV	0.3060**	0.2204***	-0.8257***	-0.8248***
	(0.1458)	(0.0616)	(0.1749)	(0.0566)
VU.VGR	0.4588***	0.6692***	0.4101	0.4985***
	(0.1714)	(0.0855)	(0.2562)	(0.1429)
CC	0.8326***	0.7394***	-1.369***	-1.502***
	(0.2466)	(0.1359)	(0.2840)	(0.1129)
CC.INS	-0.3155	-0.0935	-0.9616	-0.6636***
	(0.5305)	(0.3775)	(0.6104)	(0.2142)
CC.INF	0.8089***	0.6464***	-0.4652	-0.7864***
	(0.3076)	(0.2073)	(0.3022)	(0.1689)
Fixed-effects				
Destination		Yes		
Origin				Yes
Fit statistics				
Observations	179	30,972	179	31,328

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Bibliography

Abel, G et al. (2018). *Climate, Conflict and Forced Migration*. Tech. rep. 272. WU Vienna University of Economics and Business.

Abel, Guy J (2013). "Estimating global migration flow tables using place of birth data". In: *Demographic Research* 28, pp. 505–546.

— (2018). "Estimates of global bilateral migration flows by gender between 1960 and 20151". In: *International Migration Review* 52.3, pp. 809–852.

Abel, Guy J and Joel E Cohen (2019a). "Bilateral international migration flow estimates for 200 countries". In: *Scientific data* 6.1, pp. 1–13.

— (2019b). *Bilateral international migration flow estimates for 200 countries (1990-1995 to 2015-2020)*. data retrieved from https://doi.org/10.6084/m9.figshare.7731233.v5, version 5 [Dataset posted on 1/02/2021.

Abel, Guy J et al. (2021). "The form and evolution of international migration networks, 1990–2015". In: *Population, Space and Place* 27.3, e2432.

Adsera, Alicia and Mariola Pytlikova (2015). "The Role of Language in Shaping International Migration". In: *ECONOMIC JOURNAL* 125.586, F, F49–F81. ISSN: 0013-0133. DOI: {10.1111/ecoj.12231}.

Afifi, T. and K. Warner (2008). "The Impact of Environmental Degradation on Migration Flows across Countries". In: *UNU-EHS Working Paper* 5/2008.

Ager, Philipp et al. (2020). "How the 1906 San Francisco earthquake shaped economic activity in the American West". In: *EXPLORATIONS IN ECONOMIC HISTORY* 77. DOI: {10.1016/j.eeh.2020.101342}.

Ahsan, R. (2019). "Climate-Induced Migration: Impacts on Social Structures and Justice in Bangladesh". In: *South Asia Research* 39.2, pp. 184–201. DOI: 10.1177/0262728019842968.

Alem, Yonas, Mathilde Maurel, and Katrin Millock (2016). *Migration as an Adaptation Strategy to Weather Variability: An Instrumental Variables Probit Analysis*. Working Paper 665. Dept. of Economics, University of Gothenburg.

Aleskerov, Fuad et al. (2016). "Network analysis of international migration". In: *International Conference on Network Analysis*. Springer, pp. 177–185.

Alexeev, Alexander, David H Good, and Rafael Reuveny (2011). "Weather-related disasters and international migration". In.

Anderson, James E (2009). *Gravity, productivity and the pattern of production and trade*. NBER Working Papers. National Bureau of Economic Research, Inc.

— (2011). "The gravity model". In: *Annu. Rev. Econ.* 3.1, pp. 133–160.

Anderson, James E. and Eric van Wincoop (2003). "Gravity with Gravitas: A Solution to the Border Puzzle". In: *American Economic Review* 93.1, pp. 170–192. DOI: 10.1257/000282803321455214.

Anderson, James E. and Yoto V. Yotov (2016). "Terms of trade and global efficiency effects of free trade agreements, 1990–2002". In: *Journal of International Economics* 99, pp. 279–298. DOI: https://doi.org/10.1016/j.jinteco.2015.10.006.

Aria, M. and C. Cuccurullo (2017). "bibliometrix: An R-tool for comprehensive science mapping analysis". English. In: *Journal of Informetrics* 11.4, pp. 959–975. ISSN: 17511577. DOI: 10.1016/j.joi.2017.08.007.

Auffhammer, M and M.E. Kahn (2018). "The farmer's climate change adaptation challenge in least developed countries". In: *Handbook of Environmental Economics* 4. Ed. by Smith V.K. Dasgupta P. Pattanayak S.K., pp. 193–229. DOI: 10.1016/bs.hesenv.2018.04.001.

Azose, Jonathan J and Adrian E Raftery (2019). "Estimation of emigration, return migration, and transit migration between all pairs of countries". In: *Proceedings of the National Academy of Sciences* 116.1, pp. 116–122.

Backhaus, A., I. Martinez-Zarzoso, and C. Muris (2015). "Do climate variations explain bilateral migration? A gravity model analysis". In: *IZA Journal of Migration* 4.1. DOI: 10.1186/s40176-014-0026-3.

Baier, Scott L and Jeffrey H Bergstrand (2009). "Bonus vetus OLS: A simple method for approximating international trade-cost effects using the gravity equation". In: *Journal of International Economics* 77.1, pp. 77–85.

Baker, Michael and Nicole M Fortin (2001). "Occupational gender composition and wages in Canada, 1987–1988". In: *Canadian Journal of Economics/Revue canadienne d'économique* 34.2, pp. 345–376.

Baldwin, Richard and Daria Taglioni (2006). *Gravity for dummies and dummies for gravity equations*. Tech. rep. National bureau of economic research.

Bar-Ilan, J. (2008). "Which h-index? - A comparison of WoS, Scopus and Google Scholar". English. In: *Scientometrics* 74.2, pp. 257–271. ISSN: 01389130. DOI: 10.1007/s11192-008-0216-y.

Barassi, M. R. et al. (2018). "Climate Anomalies and Migration between Chinese Provinces: 1987-2015". In: *ENERGY JOURNAL* 39.1, 123–144.

Bardsley, D.K. (2014). "Limits to adaptation or a second modernity? Responses to climate change risk in the context of failing socio-ecosystems". In: *Environment, Development and Sustainability* 17.1, pp. 41–55. ISSN: 1387585X. DOI: 10.1007/s10668-014-9541-x.

Baronchelli, Adelaide and Roberto Ricciuti (2018). *Climate change, rice production, and migration in Vietnamese households*. Working Paper wp-2018-86. World Institute for Development Economic Research (UNU-WIDER).

Barrios, S., L. Bertinelli, and E. Strobl (2006). "Climatic change and rural-urban migration: The case of sub-Saharan Africa". English. In: *Journal of Urban Economics* 60.3, pp. 357–371. DOI: 10.1016/j.jue.2006.04.005.

Bayer, P., N. Keohane, and C. Timmins (2009). "Migration and hedonic valuation: The case of air quality". In: *Journal of Environmental Economics and Management* 58.1, pp. 1–14.

Beine, M. and C. Parsons (2015). "Climatic factors as determinants of international migration". English. In: *Scandinavian Journal of Economics* 117.2, pp. 723–767. ISSN: 03470520. DOI: 10.1111/sjoe.12098.

Beine, Michel, Simone Bertoli, and Jesús Fernández-Huertas Moraga (2016). "A practitioners' guide to gravity models of international migration". In: *The World Economy* 39.4, pp. 496–512. DOI: 10.1111/twec.12265.

Beine, Michel, Frédéric Docquier, and Çağlar Özden (2011). "Diasporas". In: *Journal of Development Economics* 95.1, pp. 30–41.

Beine, Michel and Lionel Jeusette (2019). *A Meta-Analysis of the Literature on Climate Change and Migration*. IZA Discussion Papers 12639. Institute of Labor Economics (IZA).

— (2021). "A meta-analysis of the literature on climate change and migration". In: *Journal of Demographic Economics* 87.3, 293–344. DOI: 10.1017/dem.2019.22.

Beine, Michel and Christopher R. Parsons (2017). "Climatic Factors as Determinants of International Migration: Redux". English. In: *CESIFO ECONOMIC STUDIES* 63.4, 386–402. ISSN: 1610-241X. DOI: {10.1093/cesifo/ifx017}.

Belot, Michèle and Sjef Ederveen (2012). "Cultural barriers in migration between OECD countries". In: *Journal of Population Economics* 25.3, pp. 1077–1105.

Benonnier, T, K Millock, and V Taraz (2019). *Climate change, migration, and irrigation*. Tech. rep. HAL.

Berlemann, M. and M.F. Steinhardt (2017). "Climate change, natural disasters, and migration-a survey of the empirical evidence". In: *CESifo Economic Studies* 63.4, pp. 353–385. ISSN: 1610241X. DOI: 10.1093/cesifo/ifx019.

Berlemann, M. and T.X. Tran (2020). "Climate-Related Hazards and Internal Migration Empirical Evidence for Rural Vietnam". In: *Economics of Disasters and Climate Change* 4.2, pp. 385–409. DOI: 10.1007/s41885-020-00062-3.

Berry, Steven, James Levinsohn, and Ariel Pakes (2004). "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market". In: *Journal of Political Economy* 112.1, pp. 68–105.

Bertoli, Simone and Jesús Fernández-Huertas Moraga (2013). "Multilateral resistance to migration". In: *Journal of development economics* 102, pp. 79–100. DOI: 10.1016/j.jdeveco.2012.12.001.

— (2015). "The size of the cliff at the border". In: *Regional Science and Urban Economics* 51, pp. 1–6.

— (2017). "Gravity models in the migration and development nexus". In: *Revue d'economie du developpement* 25.3, pp. 69–91.

Bertoli, Simone et al. (2020). *Weather Shocks and Migration Intentions in Western Africa: Insights from a Multilevel Analysis*. Working Papers 8064. CESifo.

Bettin, G. and F. Nicolli (2012). "Does climate change foster emigration from less developed countries? Evidence from bilateral data". In: *Università degli Studi di Ferrara, Working Papers*, p. 25.

Bhargava, A. (2019). "Climate change, demographic pressures and global sustainability". In: *Economics and Human Biology* 33, pp. 149–154. ISSN: 1570677X. DOI: 10.1016/j.ehb.2019.02.007.

Blondel, V.D. et al. (2008). "Fast unfolding of communities in large networks". In: *Journal of Statistical Mechanics: Theory and Experiment* 2008.10. DOI: 10.1088/1742-5468/2008/10/P10008.

Bohra-Mishra, P., M. Oppenheimer, and S.M. Hsiang (2014). "Nonlinear permanent migration response to climatic variations but minimal response to disasters". English. In: *Proceedings of the National Academy of Sciences of the United States of America* 111.27, pp. 9780–9785. ISSN: 00278424. DOI: 10.1073/pnas.1317166111.

Borjas, George J (1987). "Self-selection and the earnings of immigrants". In: *The American economic review*, pp. 531–553.

Boustan, L.P., M.E. Kahn, and P.W. Rhode (2012). "Moving to higher ground: Migration response to natural disasters in the early twentieth century". In: *American Economic Review* 102.3, pp. 238–244. ISSN: 00028282. DOI: 10.1257/aer.102.3.238.

Boustan, L.P. et al. (2020). "The effect of natural disasters on economic activity in US counties: A century of data". In: *Journal of Urban Economics* 118. ISSN: 00941190. DOI: 10.1016/j.jue.2020.103257.

Boyack, K.W. and R. Klavans (2010). "Co-citation analysis, bibliographic coupling, and direct citation: Which citation approach represents the research front most accurately?" In: *Journal of the American Society for Information Science and Technology* 61.12, pp. 2389–2404. DOI: 10.1002/asi.21419.

Brada, Josef C, Zdenek Drabek, and Ichiro Iwasaki (2021). "Does Investor Protection Increase Foreign Direct Investment? A Meta-Analysis". In: *Journal of Economic Surveys* 35.1, pp. 34–70. DOI: 10.1111/joes.12392.

Bruckner, M. (2012). "Economic growth, size of the agricultural sector, and urbanization in Africa". In: *Journal of Urban Economics* 71.1, pp. 26–36. ISSN: 00941190. DOI: 10.1016/j.jue.2011.08.004.

Burzynski, M et al. (2019). *Climate Change, Inequality, and Human Migration*. Tech. rep. Université catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES).

Cai, R.H. et al. (2016). "Climate variability and international migration: The importance of the agricultural linkage". In: *Journal of Environmental Economics and Management* 79, pp. 135–151. ISSN: 00950696. DOI: 10.1016/j.jeem.2016.06.005.

Cappart, Quentin and Adrien Thonet (2015). "The World Migration Network: rankings, groups and gravity models". In: *IEEE EUROCON 2015-International Conference on Computer as a Tool (EUROCON)*. IEEE, pp. 1–6.

Carattini, Stefano and Marcella Veronesi (2020). *Trust, Temperature Fluctuations, and Asylum Applications*. Working Papers 17/2020. University of Verona, Department of Economics.

Castells-Quintana, D., M.D.P. Lopez-Uribe, and T.K.J. McDermott (2018). "Adaptation to climate change: A review through a development economics lens". In: *World Development* 104, pp. 183–196. DOI: 10.1016/j.worlddev.2017.11.016.

Cattaneo, C. and V. Bosetti (2017). "Climate-induced international migration and conflicts". In: *CESifo Economic Studies* 63.4, pp. 500–528. ISSN: 1610241X. DOI: 10.1093/cesifo/ifx010.

Cattaneo, C and E Massetti (2015). *Migration and Climate Change in Rural Africa*. Tech. rep. 2015.29. Fondazione Eni Enrico Mattei.

Cattaneo, C. and E. Massetti (2019). "Does harmful climate increase or decrease migration? Evidence from rural households in Nigeria". In: *Climate Change Economics* 10.4. ISSN: 20100078. DOI: 10.1142/S2010007819500131.

Cattaneo, C. et al. (2019). "Human migration in the era of climate change". In: *Review of Environmental Economics and Policy* 13.2, pp. 189–206. ISSN: 17506816. DOI: 10.1093/reep/rez008.

Cattaneo, Cristina and Giovanni Peri (2016). "The migration response to increasing temperatures". In: *JOURNAL OF DEVELOPMENT ECONOMICS* 122, 127–146. ISSN: 0304-3878. DOI: {10.1016/j.jdeveco.2016.05.004}.

Cepeda-López, Freddy et al. (2019). "The evolution of world trade from 1995 to 2014: A network approach". In: *The Journal of International Trade & Economic Development* 28.4, pp. 452–485.

Chen, Joyce and Jon Flatnes (2019). *Credit Access, Migration, and Climate Change Adaptation in Rural Bangladesh*. Tech. rep. Agricultural and Applied Economics Association.

Chernina, Eugenia (2019). *NATURAL SHOCKS AND MIGRATION DECISIONS: THE CASE OF KYRGYZSTAN*. Working Papers WP BRP 214/EC/2019. National Research University Higher School of Economics.

Chort, Isabelle (2012). *New insights into the selection process of Mexican migrants.What can we learn from discrepancies between intentions to migrate and actual moves to the U.S.?* Tech. rep. HAL.

Chort, Isabelle and Maelys De La Rupelle (2019). *Managing the Impact of Climate on Migration: Evidence from Mexico*. Tech. rep. 2018-2019. CATT - UPPA - Université de Pau et des Pays de l'Adour.

Chort, Isabelle and Maelys de la Rupelle (2017). *Managing the Impact of Climate Change on Migration: Evidence from Mexico*. Tech. rep. DIAL (Développement, Institutions et Mondialisation).

Cipollina, Maria and Luca Salvatici (2010). "Reciprocal trade agreements in gravity models: A meta-analysis". In: *Review of International Economics* 18.1, pp. 63–80. DOI: 10.1111/j.1467-9396.2009.00877.x.

Coniglio, N.D. and G. Pesce (2015). "Climate variability and international migration: An empirical analysis". In: *Environment and Development Economics* 20.4, pp. 434–468. ISSN: 1355770X. DOI: 10.1017/S1355770X14000722.

Conte, Maddalena, Pierre Cotterlaz, and Thierry Mayer (2021). *The CEPII gravity database*. data retrieved from http://www.cepii.fr.

Dallmann, Ingrid and Katrin Millock (2017). "Climate Variability and Inter-State Migration in India". In: *CESIFO ECONOMIC STUDIES* 63.4, 560–594. ISSN: 1610-241X. DOI: {10.1093/cesifo/ifx014}.

Damette, O. and M. Gittard (2017). "Climate change and migrations: Remittances as a buffer? [Changement climatique et migrations: Les transferts de fonds des migrants comme amortisseurs ?]" In: *Mondes en Developpement* 179.3, pp. 85–102. ISSN: 03023052. DOI: 10.3917/med.179.0085.

Danchev, Valentin and Mason A Porter (2018). "Neither global nor local: Heterogeneous connectivity in spatial network structures of world migration". In: *Social Networks* 53, pp. 4–19.

Davis, Kyle F et al. (2013). "Global spatio-temporal patterns in human migration: a complex network perspective". In: *PloS one* 8.1, e53723.

De Benedictis, Luca and Daria Taglioni (2011). "The gravity model in international trade". In: *The trade impact of European Union preferential policies*. Springer, pp. 55–89.

Defrance, Dimitri, Esther Delesalle, and Flore Gubert (2020). *Is migration drought-induced in Mali? An empirical analysis using panel data on Malian localities over the 1987-2009 period*. Tech. rep. 2020003. Université catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES).

Desmet, K and E. Rossi-Hansberg (2015). "On the spatial economic impact of global warming". In: *Journal of Urban Economics* 88, pp. 16–37. ISSN: 00941190. DOI: 10.1016/j.jue.2015.04.004.

Deuster, Christoph (2019). *Climate change, education and mobility in Africa*. Tech. rep. wp1904. Universidade Nova de Lisboa, Faculdade de Economia, NOVAFRICA.

Diallo, A. and Y. Renou (2015). "Climate change and migration: The emerging structure of a scientific field and the process of public policy formulation [Changement climatique et migrations: Qualification d'un problème, structuration d'un champ scientifique et activation de politiques publiques]". In: *Mondes en Developpement* 172.4, pp. 87–107. ISSN: 03023052. DOI: 10.3917/med.172.0087.

Dillon, A., V. Mueller, and S. Salau (2011). "Migratory responses to agricultural risk in northern Nigeria". English. In: *American Journal of Agricultural Economics* 93.4, pp. 1048–1061. ISSN: 00029092. DOI: 10.1093/ajae/aar033.

Docquier, F. et al. (2016). "Emigration and democracy". In: *Journal of Development Economics* 120, pp. 209–223. DOI: 10.1016/j.jdeveco.2015.12.001.

Doucouliagos, Chris (2005). "Publication bias in the economic freedom and economic growth literature". In: *Journal of Economic Surveys* 19.3, pp. 367–387. DOI: 10.1111/j.0950-0804.2005.00252.x.

Doucouliagos, Chris and Mehmet Ali Ulubasoglu (2006). "Economic freedom and economic growth: Does specification make a difference?" In: *European journal of political economy* 22.1, pp. 60–81. DOI: 10.1016/j.ejpoleco.2005.06.003.

Drabo, A and LM Mbaye (2011). *Climate Change, Natural Disasters and Migration: An Empirical Analysis in Developing Countries*. Tech. rep. Institute of Labor Economics (IZA).

Drabo, A. and L.M. Mbaye (2015). "Natural disasters, migration and education: An empirical analysis in developing countries". In: *Environment and Development Economics* 20.6, pp. 767–796. DOI: 10.1017/S1355770X14000606.

Eaton, Jonathan and Samuel Kortum (2002). "Technology, geography, and trade". In: *Econometrica* 70.5, pp. 1741–1779.

Eck, Nees Jan van and Ludo Waltman (2009). "How to normalize cooccurrence data? An analysis of some well-known similarity measures". In: *Journal of the American Society for Information Science and Technology* 51.8, pp. 1635–1651. ISSN: 0002-8231.

EM-DAT, CRED (n.d.). URL: www.public.emdat.be(Accessdate:May23th,202014:25).

Erwin, A. et al. (2020). "Intersectionality shapes adaptation to social-ecological change". In: *World Development* 138. DOI: 10.1016/j.worlddev.2020.105282.

Fagiolo, Giorgio and Marina Mastrorillo (2013). "International migration network: Topology and modeling". In: *Physical Review E* 88.1, p. 012812.

Falco, C, F Donzelli, and A Olper (2018). "Climate Change, Agriculture and Migration: A Survey". In: *Sustainability* 10.5, pp. 1–21. DOI: 10.3390/su10051405.

Fan, Q., H. Allen Klaiber, and K. Fisher-Vanden (2016). "Does extreme weather drive interregional brain drain in the U.S.? Evidence from a sorting model". In: *Land Economics* 92.2, pp. 363–388. DOI: 10.3368/le.92.2.363.

Fan, Q., K. Fisher-Vanden, and H.A. Klaiber (2018). "Climate change, migration, and regional economic impacts in the United States". In: *Journal of the Association of Environmental and Resource Economists* 5.3, pp. 643–671. DOI: 10.1086/697168.

Farbotko, C. et al. (2018). "Transformative mobilities in the Pacific: Promoting adaptation and development in a changing climate". In: *Asia and the Pacific Policy Studies* 5.3, pp. 393–407. DOI: 10.1002/app5.254.

Felli, R. (2013). "Managing Climate Insecurity by Ensuring Continuous Capital Accumulation: 'Climate Refugees' and 'Climate Migrants'". In: *New Political Economy* 18.3, pp. 337–363. DOI: 10.1080/13563467.2012.687716.

Feng, B, M Partridge, and M Rembert (2016). *The Perils of Modelling How Migration Responds to Climate Change*. Tech. rep. 77059. University Library of Munich, Germany.

Feng, S., A.B. Krueger, and M. Oppenheimer (2010). "Linkages among climate change, crop yields and Mexico-US cross-border migration". In: *Proceedings of the National Academy of Sciences of the United States of America* 107.32, pp. 14257–14262. DOI: 10.1073/pnas.1002632107.

Feng, Shuaizhang, Michael Oppenheimer, and Wolfram Schlenker (2012). "Climate Change, Crop Yields, and Internal Migration in the United States". In: *NBER Working Papers* 17734.

Fernández, C., M.L. Sierra-Huedo, and D. Chinarro (2018). *Climate change-induced migration in Morocco: Sub-saharian and Moroccan migrants*, pp. 177–195. DOI: 10.1007/978-3-319-89632-8_15.

Findley, S.E. (1994). "Does drought increase migration? A study of migration from rural Mali during the 1983-1985 drought". English. In: *International Migration Review* 28.3, pp. 539–553. ISSN: 01979183. DOI: 10.2307/2546820.

Galizzi, G. (2017). "Demographic explosion in Sub-Saharan Africa, subsistence agriculture and the problem of migrants". In: *Rivista Internazionale di Scienze Sociali* 1, pp. 67–86.

Ghimire, R., S. Ferreira, and J.H. Dorfman (2015). "Flood-induced displacement and civil conflict". In: *World Development* 66, pp. 614–628. DOI: 10.1016/j.worlddev.2014.09.021.

Gignoux, J. and M. Menéndez (2016). "Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural Indonesia". In: *Journal of Development Economics* 118, pp. 26–44. DOI: 10.1016/j.jdeveco.2015.08.004.

Goldbach, C. (2017). "Out-migration from coastal areas in Ghana and Indonesia-the role of environmental factors". In: *CESifo Economic Studies* 63.4, pp. 529–559. DOI: 10.1093/cesifo/ifx007.

Grace, K. et al. (2018). "Examining rural Sahelian out-migration in the context of climate change: An analysis of the linkages between rainfall and out-migration in two Malian villages from 1981 to 2009". In: *World Development* 109, pp. 187–196. DOI: 10.1016/j.worlddev.2018.04.009.

Gray, Clark L (2009). "Environment, Land, and Rural Out-migration in the Southern Ecuadorian Andes". In: *World Development* 37.2, pp. 457–468. ISSN: 0305750X. DOI: 10.1016/j.worlddev.2008.05.004.

Gray, Clark L and R. Bilsborrow (2013). "Environmental Influences on Human Migration in Rural Ecuador". In: *Demography* 50.4, pp. 1217–1241. DOI: 10.1007/s13524-012-0192-y.

Gray, Clark L and Valerie Mueller (2012a). "Drought and Population Mobility in Rural Ethiopia". English. In: *World Development* 40.1, pp. 134–145. DOI: 10.1016/j.worlddev.2011.05.023.

— (2012b). "Natural disasters and population mobility in Bangladesh". English. In: *Proceedings of the National Academy of Sciences of the United States of America* 109.16, pp. 6000–6005. DOI: 10.1073/pnas.1115944109.

Gray, Clark L and E. Wise (2016). "Country-specific effects of climate variability on human migration". In: *Climatic Change* 135.3-4, pp. 555–568. DOI: 10.1007/s10584-015-1592-y.

Groen, J.A., M.J. Kutzbach, and A.E. Polivka (2020). "Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term". In: *Journal of Labor Economics* 38.3, pp. 653–685. DOI: 10.1086/706055.

Grogger, Jeffrey and Gordon H Hanson (2011). "Income maximization and the selection and sorting of international migrants". In: *Journal of Development Economics* 95.1, pp. 42–57.

Groschl, J. and T. Steinwachs (2017). "Do natural hazards cause international migration?" In: *CESifo Economic Studies* 63.4, pp. 445–480. ISSN: 1610241X. DOI: 10.1093/cesifo/ifx005.

Groschl, Jasmin (2012). *Climate Change and the Relocation of Population*. Tech. rep. Verein für Socialpolitik / German Economic Association.

Grubel, Herbert G and Peter J Lloyd (1975). *Intra-Industry Trade: The Theory and Measurement of International Trade in Differentiated Products*. Macmillan Press, London.

Gröger, A. and Y. Zylberberg (2016). "Internal labor migration as a shock coping strategy: Evidence from a typhoon". In: *American Economic Journal: Applied Economics* 8.2, pp. 123–153. DOI: 10.1257/app.20140362.

Halliday, TJ (2006). "Migration, risk, and liquidity constraints in El Salvador". In: *Economic Development and Cultural Change* 54.4, pp. 893–925. ISSN: 00130079. DOI: 10.1086/503584.

Halliday, T.J. (2012). "Intra-household labor supply, migration, and subsistence constraints in a risky environment: Evidence from rural El salvador". In: *European Economic Review* 56.6, pp. 1001–1019. DOI: 10.1016/j.euroecorev.2012.04.001.

Hanson, G.H. and C. McIntosh (2012). "Birth Rates and Border Crossings: Latin American Migration to the US, Canada, Spain and the UK". In: *Economic Journal* 122.561, pp. 707–726. DOI: 10.1111/j.1468-0297.2012.02509.x.

Harper, S. (2013). "Population-Environment Interactions: European Migration, Population Composition and Climate Change". In: *Environmental and Resource Economics* 55.4, pp. 525–541. DOI: 10.1007/s10640-013-9677-4.

Harzing, A.-W. and S. Alakangas (2016). "Google Scholar, Scopus and the Web of Science: a longitudinal and cross-disciplinary comparison". English. In: *Scientometrics* 106.2, pp. 787–804. ISSN: 01389130. DOI: 10.1007/s11192-015-1798-9.

Head, Keith and Thierry Mayer (2014). "Gravity equations: Workhorse, toolkit, and cookbook". In: *Handbook of international economics*. Vol. 4. Elsevier, pp. 131–195.

Head, Keith and John Ries (2008). "FDI as an Outcome of the Market for Corporate Control: Theory and Evidence". In: *Journal of International Economics* 74.1, pp. 2–20.

Henderson, J.V., A. Storeygard, and U. Deichmann (2017). "Has climate change driven urbanization in Africa?" In: *Journal of Development Economics* 124, pp. 60–82. DOI: 10.1016/j.jdeveco.2016.09.001.

Henry, S., P. Boyle, and E.F. Lambin (2003). "Modelling inter-provincial migration in Burkina Faso, West Africa: The role of socio-demographic and environmental factors". In: *Applied Geography* 23.2-3, pp. 115–136. ISSN: 01436228. DOI: 10.1016/j.apgeog.2002.08.001.

Henry, S., B. Schoumaker, and C. Beauchemin (2004). "The impact of rainfall on the first out-migration: A multi-level event-history analysis in Burkina Faso". In: *Population and Environment* 25.5, pp. 423–460. DOI: 10.1023/B:POEN.0000036928.17696.e8.

Higgins, Julian PT and Simon G Thompson (2002). "Quantifying heterogeneity in a meta-analysis". In: *Statistics in medicine* 21.11, pp. 1539–1558.

Hirsch, J.E. (2005). "An index to quantify an individual's scientific research output". In: *Proceedings of the National Academy of Sciences of the United States of America* 102.46, pp. 16569–16572. DOI: 10.1073/pnas.0507655102.

Hirvonen, K. (2016). "Temperature Changes, Household Consumption, and Internal Migration: Evidence from Tanzania". In: *American Journal of Agricultural Economics* 98.4, pp. 1230–1249. DOI: 10.1093/ajae/aaw042.

Hoffmann, Roman et al. (2020). "A meta-analysis of country-level studies on environmental change and migration". In: *Nature Climate Change* 10.10, pp. 904–912. DOI: 10.1038/s41558-020-0898-6.

Hornbeck, R. (2012). "The enduring impact of the American Dust Bowl: Short- and long-run adjustments to environmental catastrophe". English. In: *American Economic Review* 102.4, pp. 1477–1507. ISSN: 00028282. DOI: 10.1257/aer.102.4.1477.

Hunter, L.M., S. Murray, and F. Riosmena (2013). "Rainfall patterns and U.S. Migration from rural Mexico". In: *International Migration Review* 47.4, pp. 874–909. DOI: 10.1111/imre.12051.

Iqbal, K. and P.K. Roy (2015). "Climate change, agriculture and migration: Evidence from Bangladesh". In: *Climate Change Economics* 6.2. DOI: 10.1142/S2010007815500062.

Jamero, M.L. et al. (2019). "In-situ adaptation against climate change can enable relocation of impoverished small islands". In: *Marine Policy* 108. DOI: 10.1016/j.marpol.2019.103614.

Jennings, J.A. and Clark L Gray (2015). "Climate variability and human migration in the Netherlands, 1865–1937". In: *Population and Environment* 36.3, pp. 255–278. DOI: 10.1007/s11111-014-0218-z.

Jessoe, K., D.T. Manning, and J.E. Taylor (2018). "Climate Change and Labour Allocation in Rural Mexico: Evidence from Annual Fluctuations in Weather". In: *Economic Journal* 128.608, pp. 230–261. DOI: 10.1111/ecoj.12448.

Joseph, G. and Q. Wodon (2013). "Is internal migration in yemen driven by climate or socio-economic factors?" In: *Review of International Economics* 21.2, pp. 295–310. DOI: 10.1111/roie.12037.

Joseph, George et al. (2014). "Is Climate Change Likely to Lead to Higher Net Internal Migration? The Republic of Yemen's Case". In.

JRC (2021). *INFORM Trend 2012-2021*. data retrieved from https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Risk.

Kabir, M.E. et al. (2017). *Seasonal drought thresholds and internal migration for adaptation: Lessons from northern Bangladesh*, pp. 167–189. DOI: 10.1007/978-3-319-67702-6_10.

Kawawaki, Y. (2018). "Economic analysis of population migration factors caused by the great East Japan earthquake and tsunami". In: *Review of Urban and Regional Development Studies* 30.1, pp. 44–65. DOI: 10.1111/rurd.12075.

Kessler, Maxwell Mirton (1963a). "An Experimental Study of Bibliographic Coupling Between Technical Papers". In: *IEEE Transactions on Information Theory* 9.1, pp. 49–51. DOI: 10.1109/TIT.1963.1057800.

— (1963b). "Bibliographic coupling between scientific papers". In: *American documentation* 14.1, pp. 10–25.

Khamis, M. and X. Li (2020). “Environment matters: new evidence from Mexican migration”. In: *Applied Economics Letters* 27.3, pp. 168–173. DOI: 10.1080/13504851.2019.1612026.

Klaiber, H.A. (2014). “Migration and household adaptation to climate: A review of empirical research”. In: *Energy Economics* 46, pp. 539–547. DOI: 10.1016/j.eneco.2014.04.001.

Klavans, R. and K.W. Boyack (2006). “Identifying a better measure of relatedness for mapping science”. In: *Journal of the American Society for Information Science and Technology* 57.2, pp. 251–263. DOI: 10.1002/asi.20274.

— (2017). “Which Type of Citation Analysis Generates the Most Accurate Taxonomy of Scientific and Technical Knowledge?” In: *Journal of the Association for Information Science and Technology* 68.4, pp. 984–998. DOI: 10.1002/asi.23734.

Kolaczyk, Eric D and Gábor Csárdi (2014). *Statistical analysis of network data with R*. Vol. 65. Springer.

Koubi, V. et al. (2016a). “Environmental Stressors and Migration: Evidence from Vietnam”. In: *World Development* 79, pp. 197–210. DOI: 10.1016/j.worlddev.2015.11.016.

Koubi, V. et al. (2016b). “The role of environmental perceptions in migration decision-making: evidence from both migrants and non-migrants in five developing countries”. In: *Population and Environment* 38.2, pp. 134–163. DOI: 10.1007/s11111-016-0258-7.

Kruskal, Joseph B (1956). “On the shortest spanning subtree of a graph and the traveling salesman problem”. In: *Proceedings of the American Mathematical society* 7.1, pp. 48–50.

Kubik, Z. and M. Maurel (2016). “Weather Shocks, Agricultural Production and Migration: Evidence from Tanzania”. In: *Journal of Development Studies* 52.5, pp. 665–680. DOI: 10.1080/00220388.2015.1107049.

Lee, J and A Nobi (2018). “Structural transformation of minimal spanning trees in world commodity market”. In: *Acta Physica Polonica A* 133.6, pp. 1414–1416.

Leicht, Elizabeth A and Mark EJ Newman (2008). “Community structure in directed networks”. In: *Physical review letters* 100.11, p. 118703.

Leone Sciabolazza, Valerio (2018). “Moving people: network analysis of international migration”. In: *Networks of International Trade and Investment: Understanding globalisation through the lens of network analysis*, p. 249.

Lewin, P.A., M. Fisher, and B. Weber (2012). “Do rainfall conditions push or pull rural migrants: Evidence from Malawi”. In: *Agricultural Economics* 43.2, pp. 191–204. DOI: 10.1111/j.1574-0862.2011.00576.x.

Liberati, Alessandro et al. (2009). “The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration”. In: *Journal of clinical epidemiology* 62.10, e1–e34. DOI: 10.1371/journal.pmed.1000100.

Maeng, Seong Eun, Hyung Wooc Choi, and Jae Woo Lee (2012). “Complex networks and minimal spanning trees in international trade network”. In: *International Journal of Modern Physics: Conference Series*. Vol. 16. World Scientific, pp. 51–60.

Mahajan, P. and D. Yang (2020). “Taken by storm: Hurricanes, Migrant networks, and US immigration”. In: *American Economic Journal: Applied Economics* 12.2, pp. 250–277. DOI: 10.1257/app.20180438.

Marchiori, L., J.-F. Maystadt, and I. Schumacher (2012). “The impact of weather anomalies on migration in sub-Saharan Africa”. In: *Journal of Environmental Economics and Management* 63.3, pp. 355–374. ISSN: 00950696. DOI: 10.1016/j.jeem.2012.02.001.

Marchiori, L., J.F. Maystadt, and I. Schumacher (2017). “Is environmentally induced income variability a driver of human migration?” In: *Migration and Development* 6.1, pp. 33–59. DOI: 10.1080/21632324.2015.1020106.

Marchiori, L. and I. Schumacher (2011). “When nature rebels: International migration, climate change, and inequality”. In: *Journal of Population Economics* 24.2, pp. 569–600. DOI: 10.1007/s00148-009-0274-3.

Marin-Ferrer, M., L. Vernaccini, and K. Poljansek (2017). *Index for Risk Management INFORM Concept and Methodology Report - Version 2017*. EUR 28655 EN. DOI: 10.2760/094023.

Mason, C.F. (2017). “Climate change and migration: A dynamic model”. In: *CESifo Economic Studies* 63.4, pp. 421–444. DOI: 10.1093/cesifo/ifx003.

Mastrorillo, M. et al. (2016). “The influence of climate variability on internal migration flows in South Africa”. In: *Global Environmental Change* 39, pp. 155–169. DOI: 10.1016/j.gloenvcha.2016.04.014.

Maurel, M. and M. Tuccio (2016). “Climate Instability, Urbanisation and International Migration”. In: *Journal of Development Studies* 52.5, pp. 735–752. DOI: 10.1080/00220388.2015.1121240.

Maurel, Mathilde and Kubik Zaneta (2014). *Climate Variability and Migration: Evidence from Tanzania*. Working Paper P104. FERDI.

Mbaye, L.M. and K.F. Zimmermann (2016). “Natural disasters and human mobility”. In: *International Review of Environmental and Resource Economics* 10.1, pp. 37–56. DOI: 10.1561/101.00000082.

McFadden, Daniel (1974). “Conditional Logit Analysis for Qualitative Choice Behaviour”. In: Academic Press.

Melitz, Jacques (2008). "Language and foreign trade". In: *European Economic Review* 52.4, pp. 667–699. ISSN: 0014-2921.

Millock, K. (2015). "Migration and environment". In: *Annual Review of Resource Economics* 7.1, pp. 35–60. DOI: 10.1146/annurev-resource-100814-125031.

Missirian, A. and W. Schlenker (2017). "Asylum applications respond to temperature fluctuations". In: *Science* 358.6370, pp. 1610–1614. DOI: 10.1126/science.aao0432.

Mueller, Valerie, Clark L Gray, and K. Kosec (2014). "Heat stress increases long-term human migration in rural Pakistan". In: *Nature Climate Change* 4.3, pp. 182–185. ISSN: 1758678X. DOI: 10.1038/nclimate2103.

Mueller, Valerie et al. (2020). "Temporary migration and climate variation in eastern Africa". English. In: *WORLD DEVELOPMENT* 126. DOI: {10.1016/j.worlddev.2019.104704}.

Naqvi, A. (2017). "Deep Impact: Geo-Simulations as a Policy Toolkit for Natural Disasters". In: *World Development* 99, pp. 395–418. DOI: 10.1016/j.worlddev.2017.05.015.

Naqvi, A.A. and M. Rehm (2014). "A multi-agent model of a low income economy: simulating the distributional effects of natural disasters". In: *Journal of Economic Interaction and Coordination* 9.2, pp. 275–309. DOI: 10.1007/s11403-014-0137-1.

Naudé, W (2009). "Natural Disasters and International Migration from Sub-Saharan Africa". In: *MIGRATION LETTERS* 6.2, SI, pp. 165–176. ISSN: 1741-8984. DOI: 10.33182/ml.v6i2.75.

Naudé, Wim (2008). *Conflict, Disasters, and No Jobs: Reasons for International Migration from Sub-Saharan Africa*. WIDER Working Paper Series RP2008-85. World Institute for Development Economic Research (UNU-WIDER).

— (2010). "The determinants of migration from sub-saharan african countries". In: *Journal of African Economies* 19.3, pp. 330–356. DOI: 10.1093/jae/ejq004.

Nawrotzki, R.J. and M. Bakhtsiyarava (2017). "International Climate Migration: Evidence for the Climate Inhibitor Mechanism and the Agricultural Pathway". In: *Population, Space and Place* 23.4. DOI: 10.1002/psp.2033.

Nawrotzki, R.J., F. Riosmena, and L.M. Hunter (2013). "Do Rainfall Deficits Predict U.S.-Bound Migration from Rural Mexico? Evidence from the Mexican Census". In: *Population Research and Policy Review* 32.1, pp. 129–158. DOI: 10.1007/s11113-012-9251-8.

Newman, Mark EJ and Michelle Girvan (2004). "Finding and evaluating community structure in networks". In: *Physical review E* 69.2, p. 026113.

Ng'ang'a, S.K. et al. (2016). "Migration and Self-Protection Against Climate Change: A Case Study of Samburu County, Kenya". In: *World Development* 84, pp. 55–68. DOI: 10.1016/j.worlddev.2016.04.002.

Noy, I. (2017). "To leave or not to leave? Climate change, exit, and voice on a Pacific Island". In: *CESifo Economic Studies* 63.4, pp. 403–420. DOI: 10.1093/cesifo/ifx004.

Oliveira, J. and P. Pereda (2020a). "The impact of climate change on internal migration in Brazil". In: *Journal of Environmental Economics and Management* 103. DOI: 10.1016/j.jeem.2020.102340.

Oliveira, Jaqueline and Paula Pereda (2020b). "The impact of climate change on internal migration in Brazil". In: *Journal of Environmental Economics and Management* 103, p. 102340.

Olper, Alessandro, Chiara Falco, and Marzio Galeotti (2018). *Climate Change, Agriculture and Migration: Is there a Causal Relationship?* Conference paper 277488. International Association of Agricultural Economists.

Ortega, Francesc and Giovanni Peri (2009). *The Causes and Effects of International Migrations: Evidence from OECD Countries 1980-2005*. NBER Working Papers 14833. National Bureau of Economic Research, Inc.

Ouattara, B. and E. Strobl (2014). "Hurricane strikes and local migration in US coastal counties". In: *Economics Letters* 124.1, pp. 17–20. DOI: 10.1016/j.econlet.2014.03.025.

Owen, P.D. and D. Wesselbaum (2020). "On thresholds in the climate–migration relationship". In: *International Review of Applied Economics* 34.3, pp. 400–412. DOI: 10.1080/02692171.2020.1749242.

Özden, Çağlar et al. (2011). "Where on earth is everybody? The evolution of global bilateral migration 1960–2000". In: *The World Bank Economic Review* 25.1, pp. 12–56.

Page, Matthew J et al. (2021). "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews". In: *Bmj* 372. DOI: 10.1136/bmj.n71.

Pajaron, M.C. and G.N.A. Vasquez (2020). "Weathering the storm: weather shocks and international labor migration from the Philippines". In: *Journal of Population Economics* 33.4, pp. 1419–1461. DOI: 10.1007/s00148-020-00779-1.

Paldam, Martin (2015). "Meta-analysis in a nutshell: Techniques and general findings". In: *Economics: The Open-Access, Open-Assessment E-Journal* 9.2015-11, pp. 1–14. DOI: 10.5018/economics-ejournal.ja.2015-11.

Pan, C.-Y. (2020). "Protections from natural disasters as local public goods: Migration and local adaptations". In: *Regional Science and Urban Economics* 85. DOI: 10.1016/j.regsciurbeco.2020.103592.

Peri, Giovanni and Akira Sasahara (2019). *The Impact of Global Warming on Rural-Urban Migrations: Evidence from Global Big Data*. Working Papers 25728. National Bureau of Economic Research, Inc.

Perkiss, S. and L. Moerman (2018). "A dispute in the making: A critical examination of displacement, climate change and the Pacific Islands". In: *Accounting, Auditing and Accountability Journal* 31.1, pp. 166–192. DOI: 10.1108/AAAJ-06-2016-2582.

Pismennaya, E.E. et al. (2015). "Impact of climate change on migration from Vietnam to Russia as a factor of transformation of geopolitical relations". In: *Mediterranean Journal of Social Sciences* 6.3, pp. 202–207. DOI: 10.5901/mjss.2015.v6n3s2p202.

Plotnikova, Maria and Magdalena Ulceluse (2021). "Inequality as a driver of migration: A social network analysis". In: *Population, Space and Place*, e2497.

Radel, C. et al. (2018). "Toward a Political Ecology of Migration: Land, Labor Migration, and Climate Change in Northwestern Nicaragua". In: *World Development* 108, pp. 263–273. DOI: 10.1016/j.worlddev.2017.04.023.

Ragazzi, Pamela (2012). *Climate Change and Migration: A Gravity Model Approach*. Tech. rep. 2012031. University of Ferrara, Department of Economics.

Rao, Nitya et al. (2020). "Managing risk, changing aspirations and household dynamics: Implications for wellbeing and adaptation in semi-arid Africa and India". English. In: *WORLD DEVELOPMENT* 125. ISSN: 0305-750X. DOI: {10.1016/j.worlddev.2019.104667}.

Ravenstein, Ernest George (1885). "The laws of migration". In: *Journal of the statistical society of London* 48.2, pp. 167–235.

— (1889). "The laws of migration". In: *Journal of the royal statistical society* 52.2, pp. 241–305.

Reuveny, R. and W.H. Moore (2009). "Does environmental degradation influence migration? Emigration to developed countries in the late 1980s and 1990s". In: *Social Science Quarterly* 90.3, pp. 461–479. ISSN: 00384941. DOI: 10.1111/j.1540-6237.2009.00569.x.

Robalino, J., J. Jimenez, and A. Chacón (2015). "The Effect of Hydro-Meteorological Emergencies on Internal Migration". In: *World Development* 67, pp. 438–448. DOI: 10.1016/j.worlddev.2014.10.031.

Roy, Andrew Donald (1951). "Some thoughts on the distribution of earnings". In: *Oxford economic papers* 3.2, pp. 135–146.

Ruiz, V. (2017). *Do climatic events influence internal migration? Evidence from Mexico*. Working Papers WP 2017.19. FAERE - French Association of Environmental and Resource Economists.

Ruyssen, I. and G. Rayp (2014). "Determinants of Intraregional Migration in Sub-Saharan Africa 1980-2000". In: *Journal of Development Studies* 50.3, pp. 426–443. DOI: 10.1080/00220388.2013.866218.

Saldaña-Zorrilla, S.O. and K. Sandberg (2009). "Impact of climate-related disasters on human migration in Mexico: A spatial model". In: *Climatic Change* 96.1, pp. 97–118. DOI: 10.1007/s10584-009-9577-3.

Sedova, B. and M. Kalkuhl (2020). "Who are the climate migrants and where do they go? Evidence from rural India". In: *World Development* 129. DOI: 10.1016/j.worlddev.2019.104848.

Silva, JMC Santos and Silvana Tenreyro (2006). "The log of gravity". In: *The Review of Economics and statistics* 88.4, pp. 641–658.

Simonelli, A.C. (2018). *Migration and climate change*, pp. 695–710. DOI: 10.1016/B978-0-12-814104-5.00023-5.

Small, H. (1973). "Co-citation in the scientific literature: A new measure of the relationship between two documents". In: *Journal of the American Society for Information Science* 24.4, pp. 265–269. DOI: 10.1002/asi.4630240406.

Spencer, N. and M.-A. Urquhart (2018). "Hurricane strikes and migration: Evidence from storms in central America and the caribbean". In: *Weather, Climate, and Society* 10.3, pp. 569–577. DOI: 10.1175/wcas-d-17-0057.1.

Spitzer, Yannay, Gaspare Tortorici, and Ariell Zimran (2020). *International Migration Responses to Natural Disasters: Evidence from Modern Europe's Deadliest Earthquake*. Tech. rep. National Bureau of Economic Research, Inc.

Stanley, Tom D and Hristos Doucouliagos (2012). *Meta-regression analysis in economics and business*. Vol. 5. routledge.

— (2014). "Meta-regression approximations to reduce publication selection bias". In: *Research Synthesis Methods* 5.1, pp. 60–78.

— (2017). "Neither fixed nor random: weighted least squares meta-regression". In: *Research synthesis methods* 8.1, pp. 19–42.

Stanley, Tom D, Hristos Doucouliagos, and Piers Steel (2018). "Does ICT generate economic growth? A meta-regression analysis". In: *Journal of Economic Surveys* 32.3, pp. 705–726. DOI: 10.1111/joes.12211.

Sternitzke, Christian and Isumo Bergmann (2009). "Similarity measures for document mapping: A comparative study on the level of an individual scientist". eng. In: *Scientometrics* 78.1, pp. 113–130. ISSN: 0138-9130.

Suliman, S. (2016). "Rethinking about Civilizations: The Politics of Migration in a New Climate". In: *Globalizations* 13.5, pp. 638–652. DOI: 10.1080/14747731.2016.1204129.

Sutton, Alex J et al. (2000). *Methods for meta-analysis in medical research*. Vol. 348. Wiley Chichester.

Thiede, B., Clark L Gray, and Valerie Mueller (2016). "Climate variability and inter-provincial migration in South America, 1970–2011". In: *Global Environmental Change* 41, pp. 228–240. DOI: 10.1016/j.gloenvcha.2016.10.005.

Thiede, B.C. and Clark L Gray (2017). "Heterogeneous climate effects on human migration in Indonesia". In: *Population and Environment* 39.2, pp. 147–172. DOI: 10.1007/s11111-016-0265-8.

Thijs, B., L. Zhang, and W. Glänzel (2015). "Bibliographic coupling and hierarchical clustering for the validation and improvement of subject-classification schemes". In: *Scientometrics* 105.3, pp. 1453–1467. DOI: 10.1007/s11192-015-1641-3.

Tinbergen, Jan (1962). "Shaping the world economy; suggestions for an international economic policy". In.

Tranos, Emmanouil, Masood Gheasi, and Peter Nijkamp (2015). "International migration: a global complex network". In: *Environment and Planning B: Planning and Design* 42.1, pp. 4–22.

UNDESA (2019). *International Migrant Stock 2019*.

UNDRR (2019). *Global Assessment Report on Disaster Risk Reduction*. United Nations Office for Disaster Risk Reduction (UNDRR).

Valsson, T. and G.F. Ulfarsson (2012). "Megapatterns of global settlement: Typology and drivers in a warming world". In: *Futures* 44.1, pp. 91–104. DOI: 10.1016/j.futures.2011.09.001.

Viswanathan, B. and K.S.K. Kumar (2015). "Weather, agriculture and rural migration: Evidence from state and district level migration in India". In: *Environment and Development Economics* 20.4, pp. 469–492. DOI: 10.1017/S1355770X1500008X.

Vogler, Michael and Ralph Rotte (2000). "The effects of development on migration: Theoretical issues and new empirical evidence". In: *Journal of Population Economics* 13.3, pp. 485–508.

Waldinger, M (2015). *The effects of climate change on internal and international migration: implications for developing countries*. Tech. rep. Grantham Research Institute on Climate Change and the Environment.

Weinberg, B.H. (1974). "Bibliographic coupling: A review". In: *Information Storage and Retrieval* 10.5-6, pp. 189–196. DOI: 10.1016/0020-0271(74)90058-8.

Weinthal, E., N. Zawahri, and J. Sowers (2015). "Securitizing Water, Climate, and Migration in Israel, Jordan, and Syria". In: *International Environmental Agreements: Politics, Law and Economics* 15.3, pp. 293–307. DOI: 10.1007/s10784-015-9279-4.

Wesselbaum, D. and A. Aburn (2019). "Gone with the wind: International migration". In: *Global and Planetary Change* 178, pp. 96–109. DOI: 10.1016/j.gloplacha.2019.04.008.

Wyett, K. (2014). "Escaping a Rising Tide: Sea Level Rise and Migration in Kiribati". In: *Asia and the Pacific Policy Studies* 1.1, pp. 171–185. DOI: 10.1002/app5.7.

Yotov, Yoto V et al. (2016). *An advanced guide to trade policy analysis: The structural gravity model*. World Trade Organization Geneva.

Yuan, H. and C. Zhu (2016). "Shock and roam: Migratory responses to natural disasters". In: *Economics Letters* 148, pp. 37–40. DOI: 10.1016/j.econlet.2016.09.020.

Zhou, J. (2011). "Climate change, health and migration in urban China". In: *Frontiers of Economics in China* 6.4, pp. 592–615. DOI: 10.1007/s11459-011-0149-x.