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A meta-analysis of climate migration literature

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ABSTRACT

The large literature that aims to find evidence of climate migration delivers mixed findings. This meta-regression analysis i) summarizes direct links between adverse climatic events and migration, ii) maps patterns of climate migration, and iii) explains the variation in outcomes. Using a set of limited dependent variable models, we meta-analyze thus-far the most comprehensive sample of 3,625 estimates from 116 original studies and produce novel insights on climate migration. We find that extremely high temperatures and drying conditions increase migration. We do not find a significant effect of sudden-onset events. Climate migration is most likely to emerge due to contemporaneous events, to originate in rural areas and to take place in middle-income countries, internally, to cities. The likelihood to become trapped in affected areas is higher for women and in low-income countries, particularly in Africa. We uniquely quantify how pitfalls typical for the broader empirical climate impact literature affect climate migration findings. We also find evidence of different publication biases.

Keywords: migration, climate change, meta-analysis
JEL Codes: F22, O15, Q54, Q56

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1 Introduction

Over the past decades, and especially in the context of continued climate change, human migration has increasingly become a matter of vigorous scientific and policy debates. In the assessment reports (AR) by the Intergovernmental Panel on Climate Change (IPCC) for instance, the total number of references with the word *migration* increased from 2 in the AR1 to 185 in the AR5 [Minx et al., 2017]. While one of the reasons behind this increased attention are the striking magnitudes of future migration flows predicted by some studies [Rigaud et al., 2018],[1] the evidence suggests that the association between climate change and migration is not strictly positive [Berlemann and Steinhardt, 2017, Millock, 2015]. To understand the relationship in its complexity, the scientific community has moved away from studying whether people migrate or not as a direct response to climatic effects and how many will do so in the future, towards studying the heterogeneous impacts [Black et al., 2011, Cattaneo et al., 2019]. Greater understanding of *when* and *how* climate change affects migration today and thus could have an influence in the future can importantly guide design and implementation of policy interventions, to avoid or mitigate any present and future welfare losses from climate change-related migration choices.

We contribute to this literature with the most comprehensive meta-regression analysis (MRA) to date, synthesizing all empirical analyses of climate migration published at least in a working format until October 31st, 2018. The broad range of research contexts and designs across original studies enables us to address the following questions: *How do different adverse climatic events affect migration?*, *What are the existing climate migration patterns?* and *What drives the differences in the existing evidence?* We meta-analyze a new, comprehensive and transparently constructed sample of 3,625 estimates retrieved from 116 original papers that examine the direct association between climatic events and human migration, applying regression analysis. Because of the heterogeneity of data and research designs across original studies, we classify the estimated effects by i) the statistical significance, and ii) the direction and statistical significance to estimate probit

[1] Rigaud et al. [2018] forecast that over 143 million people in Sub-Saharan Africa, South Asia, and Latin America, will be forced to move within their own countries by 2050 as a result of slow-onset climate change alone.

and multinational probit models respectively, following the practices, for instance, of Card et al. [2010], Waldorf and Byun [2005] or Wehkamp et al. [2018]. We hypothesize that the variation across findings stems from different migration implications of different climatic events, as well as from factors related to modeling of climatic variables, conceptualizing and modeling of migration, diversity of study contexts and estimation techniques.

This MRA complements several streams of literature. First, we contribute to literature reviews that synthesize direct effects of climatic events on human migration [Berlemann and Steinhardt, 2017, Cattaneo et al., 2019, Hunter et al., 2015, Kaczan and Orgill-Meyer, 2020, Millock, 2015] by providing a quantitative summary with a multivariate regression analysis. We deliver new evidence showing that slow-onset climatic changes, in particular extremely high temperatures and drying conditions (i.e. extreme precipitation decrease or droughts), are more likely to increase migration than sudden-onset events. We also show that sudden-onset events do not significantly affect migration, either because migration is unlikely to serve as an adaptation to these events, or because capturing migration specific to sudden-onset events is challenging.

Second, by synthesizing the evidence from across different contexts, we contribute to the recent efforts to understand heterogeneous implications of climatic events for migration [Cattaneo et al., 2019]. This enables us to identify general patterns of and selection into climate migration. We show that climate migration patterns are strongly determined by budget constraints and climate-related sensitivity of livelihoods at the origin and at the destination. We also find systematic gender differences in climate migration, i.e. that women are generally less likely to self-select into migration to adapt to slow-onset climate change. We do not find, however, any gender differences in migration implications of sudden-onset events. This is an important contribution as these differences have thus-far been poorly understood [Cattaneo et al., 2019], but play a crucial role for climate security.

Third, we complement two recent meta-analyses (i.e. Beine and Jeusette [2019] and Hoffmann et al. [2020]) of climate migration and close important research gaps. Unlike Hoffmann et al.

[2020], who focus exclusively on macro studies at the country level to synthesize larger-scale effects of environmental factors on migration, we consider both micro- and macro-level analyses. By zooming into specific contexts, we reveal important nuances that cannot be found at aggregated levels. For instance, we shed more light on the selection into migration, detail specifics of climate migration patterns within countries' borders, or explore temporal dimensions. We further complement Beine and Jeusette [2019], who provide valuable insights into how modeling of migration and climatic variables, econometric approaches or contextual effects impact climate migration evidence, by uniquely studying potential biases from methodological pitfalls typical for the general climate impact literature, as discussed for example by Auffhammer et al. [2013], or Dell et al. [2014]. Among other things, we show that not addressing spatial correlation of climatic events and correlation among climatic events, over-controlling, or not applying causal inference techniques systematically affects the evidence. The quantification of these biases serves also as an important contribution to the general climate impact literature. In addition, the samples of both aforementioned MRAs are substantially smaller compared to our comprehensive sample of 116 studies, which is representative of the whole literature landscape at the time.[2]

Taken together, this MRA provides key contributions for the policy as well as scientific community, for example by uniquely mapping internal climate migration patterns - the most prevalent climate migration form, addressing longstanding methodological discussions in the climate impact literature, or analyzing biases by authors' disciplines and genders. Our MRA ensures high reliability and quality of the extracted information as every study has been coded by two independent coders. Lastly, we lay the foundation for a best practice of climate migration analysis and highlight important avenues for future research.

In the next section, we detail the construction of the population of original studies. Section 3 provides an overview of a conceptual and methodological approaches. Section 4 presents the meta-analysis outcomes from the aggregate sample and section 5 from sub-samples defined by

[2]The sample by Beine and Jeusette [2019] considers 51 and the sample by Hoffmann et al. [2020] has 30 original studies.

climatic variables. Lastly, section 6 provides concluding remarks and discusses policy and research implications.

2 Assembling the sample of original studies

Studies qualify for our sample if they fulfill the following inclusion criteria: i) they are written in the English language, ii) they apply regression analysis to explain migration by climate-related drivers, iii) they perceive climatic events as push factors, iv) they report the minimum information as suggested by Stanley and Doucouliagos [2012] (i.e. regression coefficients, sample size, standard errors and/or t-statistics and/or p-values), and v) they report direct effects of climate-related variables. As for the last criterion, we exclude all estimates with interactions or polynomial terms. We acknowledge that interaction terms and polynomials provide important contextual information. However, because the original studies often only report the conditional effects, it becomes challenging to calculate the overall marginal effect of a climatic event unless the original data is retrieved and reanalyzed. Given the large number of studies and limited resources, we decided to follow recommendations by Stanley and Doucouliagos [2012] and restrict our sample only to direct effects. Nevertheless, the broad range in coding of climatic events and research contexts in our final sample of studies allows us to capture both the non-linear as well as the heterogeneous implications of climatic impacts for migration. Lastly, we did not impose any geographical or temporal inclusion criteria. Moreover, we considered both published studies and gray literature, which enables us to examine the existence of a publication bias.

To ensure that the construction of our sample of original studies is reproducible and transparent, in Appendix A we detail the flow of articles through the searching and screening process. Here, we followed the RepOrting standards for Systematic Evidence Syntheses in environmental research (ROSES) ensuring that all necessary information is present and described in detail [Haddaway et al., 2018]. Figure 10 then depicts an adaptation of the ROSES flow diagram and Table 4 provides a comprehensive list of the collected papers. Overall, we identified 116 original studies. The main unit of analysis in our study is at the effect-level. One original study may contain several regression models and one regression model may contain more than one estimated effect of climate-related variables on migration. We decided to use all of this information and obtained a comprehensive sample of 3,625 estimated effects.

Figure 1: Number of original studies, by year

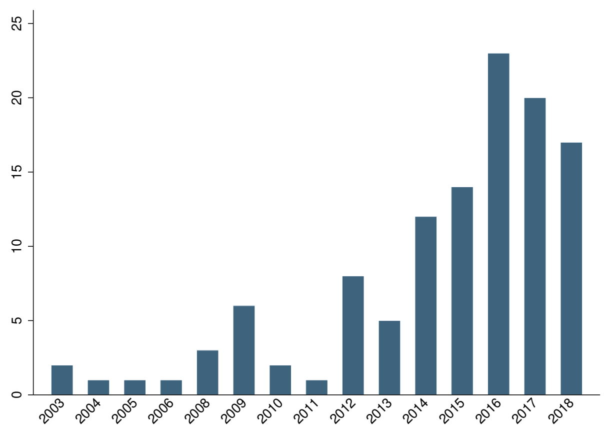


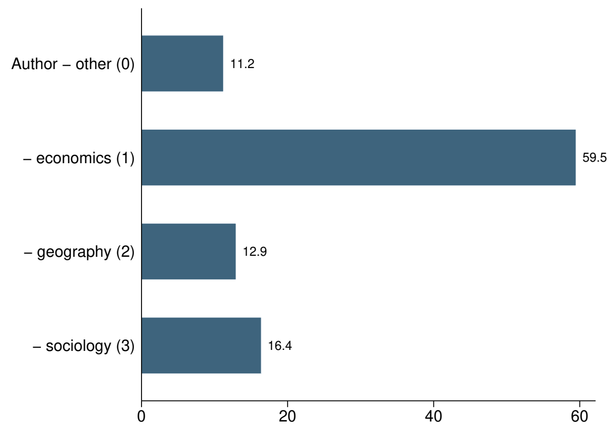
Figure 1 shows that the econometric literature on climate-related migration emerged in the early 2000s and has been growing ever since, with most of the studies published in 2016. Table 1 provides descriptive statistics of the sample of original studies. It shows that the literature is dominated by male authors, since approximately 43% of primary authors of the original studies are female. 75% of the studies are published in peer-reviewed journals. An average study in our sample is cited approximately 50 times according to Google Scholar and published in a journal with an impact factor of 2.5.

Table 1: Summary statistics: sample of original studies

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Year	2014.509	3.427	2003	2018
Author female	0.431	0.497	0	1
Published	0.75	0.435	0	1
Citations	49.5	163.882	0	1659
Impact factor	2.523	5.403	0	41.063
N		116		

Figure 2 further displays the distribution of original studies by disciplines of lead authors. It shows that lead authors of 60% of the studies are economists, 13% are geographers, and almost 16% are sociologists, implying that the econometric climate migration literature is strongly dominated by these three disciplines.

Figure 2: Percent of original studies, by discipline of the primary author



3 Conceptual and methodological approach

In section 3.1, we illustrate the conceptual underpinning that guided the choice of information that we extracted from original studies. In section 3.2, we describe the generated variables. In section 3.3, we present the meta-analytic model.

3.1 Conceptual framework

The conceptual framework and the resulting choice of specific variables are guided by several streams of literature, namely the technical MRA literature, the climate impact literature, and the empirical climate migration literature.

First, the technical MRA literature suggests that a general meta-regression model can be summarized as follows [Nelson and Kennedy, 2009, Stanley and Doucouliagos, 2012]:

$$Y = f(P, X) + e \tag{1}$$

where Y is the dependent variable that captures the estimated effect, P is the focal predictor (i.e. the key independent variable of interest), X covers a set of moderator variables recording different research designs, contexts and study characteristics assumed to systematically affect the evidence and lastly, e is the error term. We follow this structure, when coding variables to be applied in this MRA.

Second, the climate impact literature guided the choice and coding of focal predictors, i.e. adverse climatic events. Climate change involves long-run irreversible changes referred to as slow-onset events, as well as changing likelihoods and intensities of different sudden-onset shocks. As for the slow-onset events, warming climateis accompanied by sea-level rise [Levermann et al., 2013], changes in precipitation patterns [Lehmann et al., 2018], or increasing drought durations and intensities particularly over drying areas [Naumann et al., 2018]. These long-term changes are unlikely to reverse even if we would stop emitting carbon emissions completely [IPCC, 2013, 2018]. In addition, global warming increases intensities and frequencies of sudden-onset shocks such as floods [Hirabayashi et al., 2013, Lehmann et al., 2018], hurricanes [Lin et al., 2012], or tropical cyclones [Knutson et al., 2010]. On aggregate, these climatic changes are linked to severe economic damages [Burke et al., 2015b, Dell et al., 2012, Kalkuhl and Wenz, 2020].

Migration may serve as an important risk management strategy for affected populations to cope with adverse climatic events. At the same time, a stricter budgetary constraint resulting from such events may inhibit costly migration and trap populations in the affected areas. Thus, the association between adverse climatic events and migration depends on initial wealth. This has been formalized by i) Cattaneo and Peri [2016] with respect to slow-onset events, where migration may serve as an adaptation strategy, and ii) by Kleemans [2015] with respect to sudden-onset events, where migration may serve as a survival strategy. In this MRA, we draw on this framework to conceptualize the association between specific climatic events linked to economic losses and human migration. In section 3.2.2, we present the coded climatic variables.

Third, the in-depth analysis of both the empirical climate impact and climate migration literature guided our choice of moderator variables. These variables map the broad range in research foci and designs, data quality as well as information about the characteristics of lead authors and original studies across the empirical climate migration literature [Berlemann and Steinhardt, 2017, Cattaneo et al., 2019, Millock, 2015, Neumann and Hermans, 2017, Piguet et al., 2018]. They capture factors that could potentially impose systematic biases across the estimated findings. The choice of specific variables is discussed in sections 3.2.3 - 3.2.6.

3.2 Sample of coded data

To maintain the highest scientific rigor, information extracted from original studies was double-coded by two independent coders. A third coder reviewed both sets of coding to merge the data and examine potential inconsistencies. Inconsistencies were then discussed among the coders to arrive at a shared understanding and resolution. We code dependent variables and several right hand-side variables categorized into the following five groups: i) climatic variables, ii) study-level variables, iii) sample characteristics, iv) migration-related variables, and v) econometric modeling variables. Appendix C, Table 5 presents the respective summary statistics and Table 6 the weighted summary statistics. For an overview of the distribution of categories of categorical variables, see Figure 11 in Appendix C.

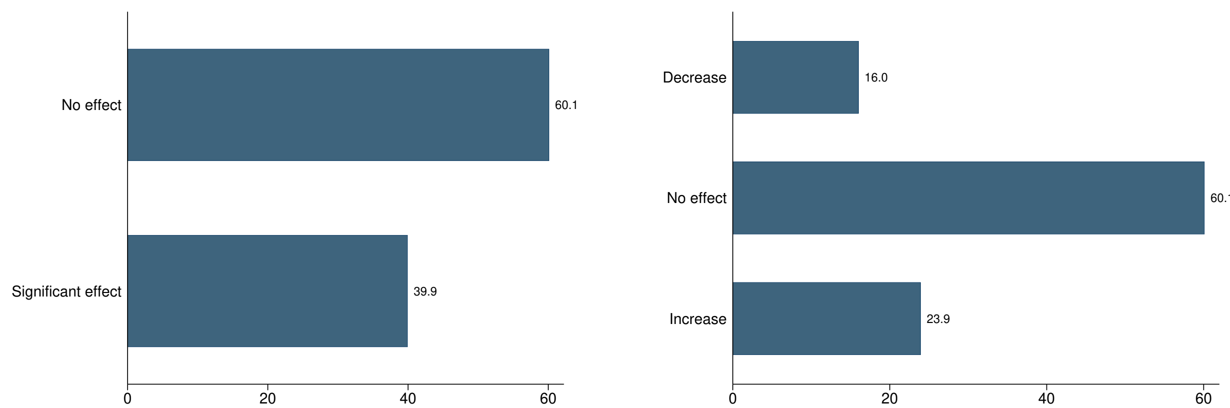
3.2.1 Dependent variable

Ideally, an MRA would extract impact coefficients from original studies that are immediately comparable to estimate the *true* effect of the focal predictor on the dependent variable. Here, estimating the effect size is not possible because of the substantial heterogeneity in research designs and contexts. First, there are significant differences in measurements of migration across the sample of original studies. The measurements include migration of individuals, movements of whole households, urbanization rates or asylum applications. The studies further differ in the level of the analysis, some providing micro- and some more aggregated perspectives. These varying conceptualizations of migration lead to significant differences in coding of the dependent variables (binary, count, continuous etc.). Second, the original studies employ a broad range of estimation techniques. Third, focal predictors, as well es their coding are also very heterogeneous across but also within different types of climate-related events. For example, temperature can be recorded in degrees Celsius, degree days, anomalies or deviations from the location-specific long-run mean. All of these differences impede the direct comparability of the coded effects [Stanley and Doucouliagos, 2012].

Thus, we follow the literature that utilizes limited dependent variable MRA models [Card et al., 2010, Minviel and Latruffe, 2017, Waldorf and Byun, 2005, Wehkamp et al., 2018]. We construct two types of dependent variables. First, a binary variable that takes on a value of one if an adverse climatic event has a significant (at 10% level) effect on migration and zero otherwise. This variable enables us to analyze whether adverse climatic events generally change migration patterns, independent of the effect direction. Second, a categorical variable that takes on a value of one if climate migration significantly decreases, two if there is no significant effect and three if climate migration significantly increases. With this variable, we analyze the direction and the statistical significance of climatic effects on migration. For the distribution of the effects by dependent variable, see Figure 3.

An important aspect of our MRA is the coding of effects from two-stage models. In cases where for instance agricultural output is instrumented by several climate-related variables (see e.g. Feng et al. [2010], Iqbal and Roy [2015], or Viswanathan and Kumar [2015]) we code the effect of each climatic variable separately. As regards the direction and the statistical significance of each climatic variable, we consider them together with the direction and significance of the instrumented variable. If at least one of the two (i.e. instrumental and instrumented) variables is insignificant, we code an insignificant effect. If one of the two variables has a significantly negative and the other a significantly positive effect on the outcome, we code a negative effect. If both of the two variables have simultaneously a significantly negative or positive effect on the outcome, we code a positive effect.

Figure 3: Dependent variable: distribution of climatic effects on migration (percent)



(a) Binary

(b) Categorical

3.2.2 Climatic variables

Climate migration is typically studied according to the type of a climate-related driver. Given the discussion in section 3.1, we generate a binary variable (*Slow (1)*) only distinguishing between slow- (1) and sudden-onset (0) climatic events, to see whether their effects on migration systematically differ. We further generate a set of moderator variables capturing specific climatic events with a sufficient number of observations that are shown to cause economic losses. As regards the slow-onset events, there is evidence that higher temperatures [Burke et al., 2015b, Dell et al., 2012, Kalkuhl and Wenz, 2020], lower precipitation levels [Duflo and Pande, 2007, Jayachandran, 2006, Kleemans, 2015], droughts [Ding et al., 2011, Meyer et al., 2013] and sea-level rise [McAlpine and Porter, 2018, Sušnik et al., 2015] are linked to economic losses. The effects of changing temperature and precipitation are non-linear and mostly felt at the extremes [Bohra-Mishra et al., 2014, Burke et al., 2015b, Carleton and Hsiang, 2016, Schlenker and Roberts, 2009]. Based on this evidence, we code two categorical variables: i) *Temperature increase* and ii) *Precipitation decrease*. Both of them take on three different values: zero if an effect is not related to temperature or precipitation, respectively; one if an effect captures a moderate; and two if it captures an extreme change. We code extreme effects, if models in original studies employ functional forms indicating substantial deviation from normal conditions (i.e. minimum/maximum levels surpassed, conditions above/below two standard deviations from the long run average, warm/cold or dry/wet spell, degree days above optimal temperature, days below/above min./max. and furthermore). We code moderate effects if climatic variables are expressed in e.g. levels, standard deviations or logarithms. Further, we code two binary variables capturing an effect of a *Drought (1)* and *Sea-level rise (1)*. As for sudden-onset events, there are examples of economic damages as a result of floods [Carrera et al., 2015, Haddad and Teixeira, 2015, Meyer et al., 2013] and hurricanes [Strobl, 2011, 2012]. Correspondingly, we code binary variables *Flood (1)* and *Hurricane/cyclone/typhoon (1)*.

To account for the source of climate-related data, we employ a binary variable *Self-reported event (1)*. It takes on a value of one if a study uses self-reported climatic events and zero if more objective data from existing weather products (e.g. weather stations, reanalysis or gridded datasets [Auffhammer et al., 2013, Donaldson and Storeygard, 2016]) is used. Self-reported weather data is often applied in climate impacts studies (e.g. Gray and Mueller [2012a], or Koubi et al. [2016c]). Yet, they may be biased, depending on the motivation or ability of surveyed individuals to accurately report a climatic event.

We further construct a variable capturing the temporal dimension of the association between a climatic event and migration. Researchers use different approaches to define climatic events not only in terms of functional forms but also temporal dimensions. For instance, some studies focusing on low-income countries hypothesize that migration takes place at *t+1* after income from agriculture (determined by weather) is realized at the end of the year *t* [Bazzi, 2017, Gray and Mueller, 2012a]. However, there are also studies that look at the direct association between migration and weather [Beine and Parsons, 2015, Nawrotzki et al., 2015b]. While, these considerations are often guided by a specific theoretical framework, we abstract from their discussion. Rather, we focus on the biases that they cause in practice. We employ a binary variable *Direct event (1)*, which takes on a value of one if a given climatic variable is directly associated with migration and zero if there is a time lag (we do not distinguish between the length of the lag).

Lastly, the coding of specific climatic events varies widely across but also within different event types. We analyze if and how different measures of specific events impact the estimated effects in section 5, when conducting MRA of sub-samples defined by specific climatic events. For temperature- and precipitation related MRAs we differentiate between measures capturing variability (e.g. anomalies or deviations), extremes (see above) and levels (e.g. degrees Celsius, millimeters). For drought-related MRA, we differentiate between binary treatments and measures of intensity. For flood-related MRA, we distinguish between binary treatments, measures capturing economic losses or event counts.

3.2.3 Study-level variables

This group of variables records characteristics of the original studies, as partially introduced in section 2. Specifically, we employ a binary variable capturing the lead authors' gender (*Author - female (1)*), a categorical variable capturing the lead authors' discipline (*Author - discipline*), a continuous variable accounting for the year of publication or latest draft of the original study (*Year of publication/ latest draft*) and lastly a binary variable that captures whether the original study is published in a peer-reviewed journal or not (*Peer-reviewed (1)*), to potentially detect a general publication bias (a similar approach is taken by e.g. Card et al. [2010], or Wehkamp et al. [2018]). Publication bias arises when a certain type of result tends to be published in peer-reviewed journals. It is a well-documented phenomenon in social sciences [Franco et al., 2014, Gerber and Malhotra, 2008]. Selective reporting of scientific findings increases the likelihood that published evidence reflects type I errors rather than true population parameters. It also inhibits assessment of the state of knowledge since a certain type of outcome is not observable [Franco et al., 2014]. As regards climate migration, learning experience impeded by publication bias might directly lead to inefficient resource allocation or programming and thus have direct adverse welfare effects. In addition to the variable *Peer-reviewed (1)*, the remaining study-level variables might detect other forms of a publication bias. For instance, authors of different disciplines, or genders[3] might have different motivations to publish a certain type of results, or due to scientific advances (e.g. in terms of data or methods), newer studies might more accurately capture the true relationship.

3.2.4 Sample characteristics

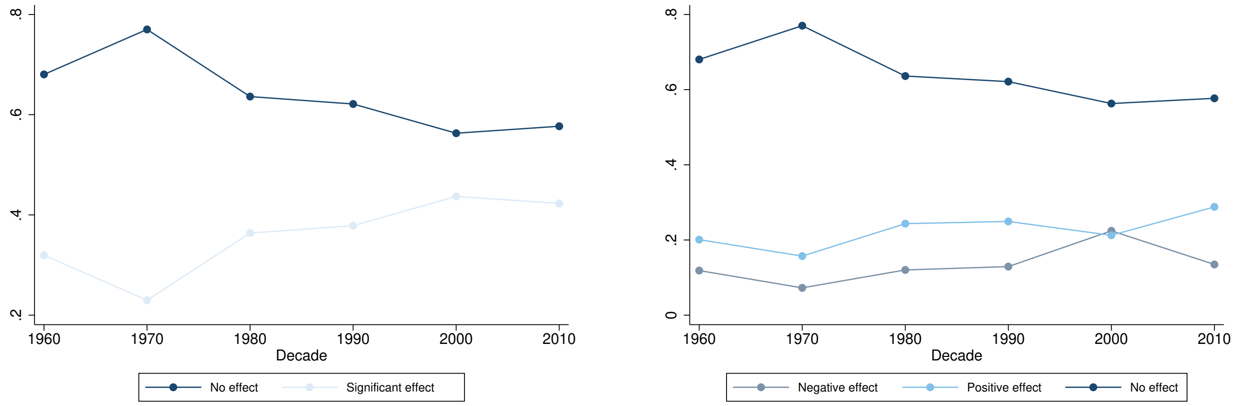
These moderator variables record the framework of a model, from which a specific coefficient is derived. One study usually contains several models and these can be applied to various subsamples of data. The binary variable *Micro-level analysis (1)* takes on a value of one if a coded effect is derived from an analysis conducted at the micro-level and zero for more aggregated analyses. Micro-level analyses provide more detailed information that might get lost in the aggregated perspectives capturing larger-scale trends, and vice versa. Thus, this variable also accounts for any systematic difference in our results compared to Hoffmann et al. [2020] exclusively meta-analyzing macro-level studies. We further employ a set of decadal dummies starting from 1960 onward, capturing whether data-sets cover a specific decade. If a model uses data stretching over several decades, the respective decadal dummies take on a value of one.[4] Figure 4 shows the distribution of significant and insignificant (4a), and significantly positive, significantly negative and insignificant (4b) effects over time using these temporal dummies. The increase in the fraction of significant effects over time suggests that change in migration strategy has been increasingly used as a response to adverse climatic events. Yet, when differentiated by effect direction, we do not observe substantial differences in the distribution of significantly positive and negative effects over time.

Similarly, following Hoffmann et al. [2020], we further generate three binary variables, namely

[3]For instance, men are shown to be more likely to take risks to achieve higher status and engage in questionable research practices [Fang et al., 2013].

[4]Some of the studies consider data covering periods before 1960. Yet, the number of observations is very small. Thus, we abstract from coding decadal dummies from before 1960.

Figure 4: Temporal distribution of estimated effects adverse climatic events on migration



(a) In-/significance (%/year)

(b) Direction and significance (%/year)

Low-income included (1), *Lower-middle income included (1)* and *Higher-middle income included (1)*. Each of them takes on a value of one if an effect is derived from a model covering a sample of low-income, lower-middle-income and/or upper-middle-income countries, as classified by the World Development Indicators dataset [The World Bank, 2020]. If a model uses data covering countries from several income categories, all the respective dummies take on a value of one. This enables us to test the established inverted U-shaped relationship between economic development and climate migration, i.e. a climate-related income decline may depress migration of the very poor, but provide incentives to move to the less poor populations [Cattaneo and Peri, 2016]. We further code a binary variable *Multiple countries (1)* that takes on a value of one if a given coefficient is derived from a model using a sample covering several countries. Such analyses might reveal completely different trends than country-specific studies. For instance, they might fail to reveal certain patterns if countries from different economic groups are considered.

Lastly, we code a set of continent-specific dummies to map the literature visually. Figure 5 displays the number of estimated coefficients by countries and continents as well as their continent-wise distribution among negative, positive and insignificant effects.[5] Most of the evidence covers Asia, Africa and North America. Obvious geographical research gaps are well documented by the

[5]The figure at the continent-level does not display effects derived from multi-continent models. Similarly, the figure at the country-level does not display effects derived from multi-country models.

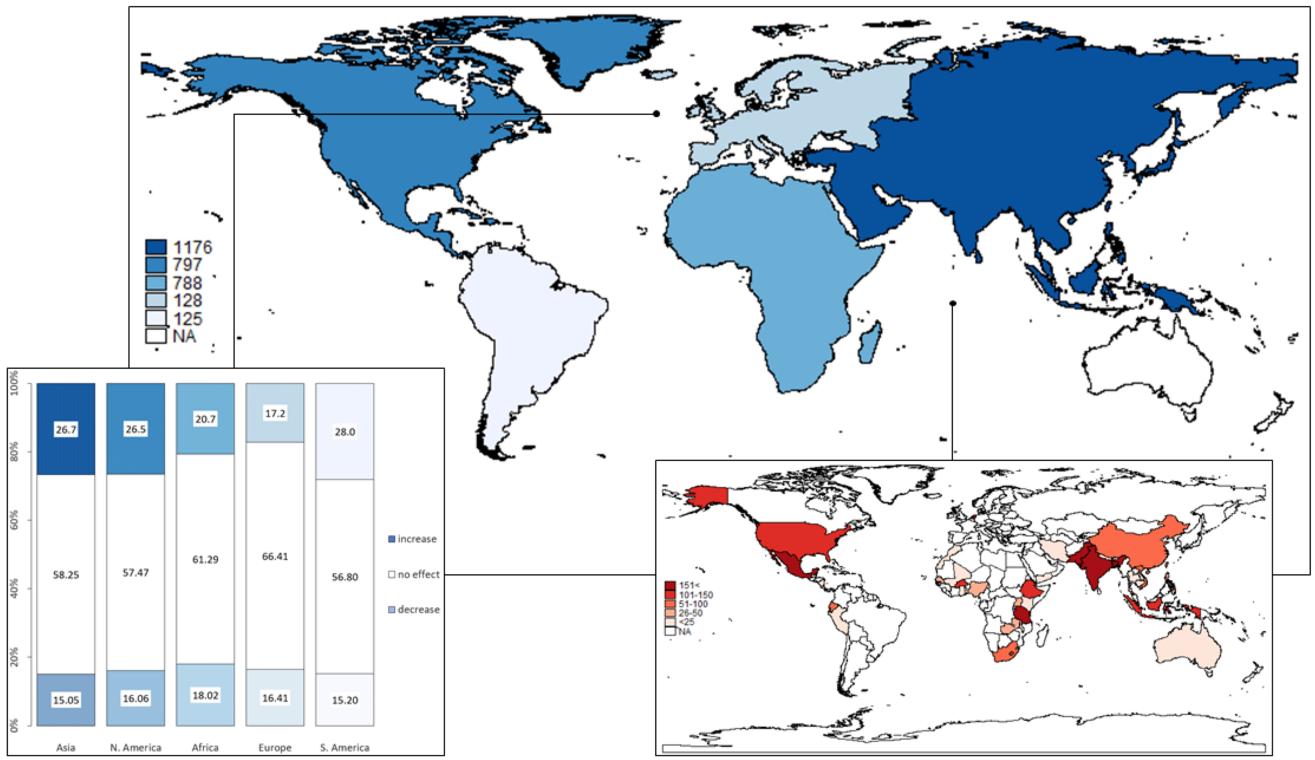
country-specific map. For instance, as regards Europe we only have evidence of climate migration from the Netherlands. The stacked bar chart suggests that the likelihood to become trapped (i.e. decrease in migration) in response to adverse climatic events is the largest on the African continent in line with Millock [2015]. On the contrary, migration is most likely to be positively associated with adverse climatic events in Asia, North and South America, with 27-28% of significantly positive effects. The chart does not cover Australia, since we only have very few (i.e. 25 effects) respective observations and so the effect distribution could provide a biased picture of climate migration trends.[6]

3.2.5 Migration-related variables

We code several moderator variables to cover the heterogeneity in modeling migration. We distinguish between temporal, as well as spatial dimensions related to the origin and the destination of migrants. The categorical variable *Origin* records whether the model considers out-migration from rural (0) or urban (1) areas or whether the origin is not defined (2). Figure 11 in Appendix C suggests that we only have very few observations of climate migration from urban areas. The variable *Destination 1* distinguishes between internal (0), international (1) or undefined (2) destination choices. The variable *Destination 2* captures whether the model considers migration to rural (0) or urban (1) destinations or whether the destination is not defined at this scale (2). The binary variable takes on a value of one, if an original model explicitly considers temporary migration of less than a year. Further, the binary variable *Measurement (1)* indicates whether the migration measure accounts for out-migration only (unilateral (0)), or both out- and in-migration (bilateral (1)). By employing the variable *Migrants*, we also analyze the effect of the migration domain, i.e. what group of potential migrants does the study look at. In the original studies, these different domains are typically captured by using specific sample compositions. We distinguish between migration of women (0), men (1), whole households (2), overall (3) migration and other (4) categories. For all

[6]At the time we finalized the literature search for our MRA, we could not identify more studies with this geographical focus, fitting the inclusion criteria. However, recently new evidence from Australia emerged importantly contributing to filling this gap, see for instance Zander and Garnett [2020], Zander and Garnett.

Figure 5: Number and distribution of estimated effects of adverse climatic events on migration (effects from multi-continent or multi-coutnry models are not included)



Distribution of estimated adverse climatic effects on migration by continents

Number of estimated adverse climatic effects on migration by countries (742 effects from multi-country models not included) variables, we abstract from the interpretation of these *undefined* effects, but include the categories for the sake of sample completeness.

3.2.6 Econometric modeling variables

Literature points out common mistakes from specific analytic choices, when studying climatic impacts using econometric methods (see e.g. Auffhammer et al. [2013], Berlemann and Steinhardt [2017] or Dell et al. [2014]). To quantify the resulting biases, we employ a set of moderator variables as presented below.

The categorical variable *Approach* distinguishes between different estimation techniques applied in climate migration literature. It takes a value of zero, if a coefficient is derived from a cross-sectional analysis, where the identification comes from geographical variation in climatic conditions at one point in time (- *cross-section (0)*). The variable takes on a value of one, if the applied econometric approach draws on longitudinal data, as well as time- and unit of observation-specific fixed-effects (- *panel - causal (1)*). Here, the identification of climatic responses comes via deviation from the mean over time, comparing a given entity under different climatic conditions. The estimates can thus be interpreted causally. Further, the variable takes on a value of two if an effect is derived using instrumental variable approach (- *IV (2)*), as explained in section 3.2.1. Lastly, *Approach* takes on a value of three (- *panel-other/pool (3)*), if the coefficient is derived from an analysis that uses pooled data or panel data, where the coefficients might suffer from an omitted variable bias (i.e. models do not simultaneously apply unit of observation- and time-specific fixed effects).

This moderator variable directly addresses longstanding academic debates in the climate impact literature on how to estimate agents' responses to the changing climate [Dell et al., 2014]. Notably, panel data analyses are often compared to classical cross-sectional studies. The cross-sectional approach may suffer from an omitted variable bias, because the climatic variable of interest as well as the outcome variable may both be correlated with other factors which cannot always be adequately controlled for. Compared to cross-sectional techniques that typically analyze effects of long-run temperature and/ or precipitation averages, panel studies have been criticized for poorly capturing the effect of climate since the responses are derived from short-term weather variations. Nevertheless, due to omitted variable concerns it has been the preferred approach established as a quality standard in the literature. For instance, other meta-analyses from climate impact literature such as Hoffmann et al. [2020], or Hsiang et al. [2013] use these standards as inclusion criteria for their sample of original studies. Our intention differs from these efforts. By including analyses using different econometric designs, we aim to examine whether applying causal inference techniques produces systematically different outcomes. We also conduct a sensitivity test only considering sub-sample of studies using causal inference to see whether not applying these quality standards affects our main conclusions (see Appendix Table 12).

Another recently raised concern by climate impact scholars addressed with the variable *Approach* is the application of climatic variables as instruments to study their effect through a particular intermediary variable [Burke et al., 2015a, Koubi, 2019]. Climatic events have been shown to significantly impact a variety of socio-economic outcomes [Carleton and Hsiang, 2016, Dell et al., 2014], which might plausibly also affect the decision to stay or leave [Black et al., 2011], such as conflict [Hsiang et al., 2013], mortality [Deschenes and Moretti, 2009] or agricultural income [Schlenker and Roberts, 2009]. Thus, the exclusion restriction (i.e. climate only affects migration through its effect on the instrumented variable) necessary for the validity of climatic variables as instruments might be violated [Angrist and Pischke, 2009] and systematically bias the evidence.

Spatial correlation of weather is another important issue in the climate impact literature. Unless this spatial correlation is addressed, produced standard errors might be biased. Clustering of standard errors at the level of the geographical aggregation of the treatment is most commonly applied to address this issue [Auffhammer et al., 2013]. Hence, we employ a respective binary moderator variable *Clustered std. errors (1)*.

Further, the specification of econometric models is non-trivial. Climatic events are correlated.

If a model only accounts for one climatic variable, this causes an omitted variable bias [Auffhammer et al., 2013, Berlemann and Steinhardt, 2017]. Thus, there are good reasons to believe that the number of climatic controls could systematically affect the estimated outcomes. The variable *Nr. of climatic variables*, which captures the model-specific number of additional climatic variables controlled for, allows us to examine these potential biases.

Moreover, econometric models often include controls (e.g. income or conflict), which have been shown to be direct outcomes of climatic events and to also have an impact on the outcome variable (i.e. migration). This causes the *over-controlling* problem [Dell et al., 2014], also referred to as the *bad controls* problem [Angrist and Pischke, 2009]. To analyze whether and how these specification choices affect the derived estimates, we employ three moderator variables. The count variable *Nr. of controls* records the total number of controls that an econometric model includes in addition to the considered climatic event. The binary variables *Income-related controls (1)* and *Polit. stability controls (1)* take on a value of one if a given econometric model controls for an income-related variable (e.g. agricultural income, household wealth), and/or a variable capturing political situation, respectively. These are the most common controls included in the climate migration models that contribute to the *over-controlling/bad controls* problems.

Lastly, the binary variable *Main model (1)* takes on a value of one if a derived effect is presented in the main model of the original study and zero otherwise. It shows whether authors have a bias towards publishing a certain type of result in the main model. Thus, similar to the variable *Peer-reviewed*, this variable is typically employed in meta-analyses to detect the presence of a publication bias.

3.3 Meta-analytic models

We employ two types of limited dependent variable models. Firstly, we estimate a probit model, whereby the binary dependent variable takes on a value of one if a given climatic variable has a significant effect on migration and zero otherwise. Among other things, this model enables us to understand in which contexts climatic variables have a significant effect on migration. The probability of obtaining a positive outcome is given by [Maddala, 1986, Wooldridge, 2010]:

$$P(y_i = 1|x_{ims}, \beta) = \int_{-\infty}^{-x_{ims}\beta} \phi(z)dz \tag{2}$$

where $\phi(z)$ denotes the standard normal density and y captures the (in)significance of the estimated effect i. For simplicity, x summarizes the focal predictors, as well as the set of moderator variables at the effect-, model- (m) or study-level (s) and β covers the respective parameters to be estimated.

Secondly, we estimate a series of multinomial probit models (MNPs). MNPs are random utility models with a discrete dependent variable with more than two outcomes that have no natural ordering. We code a categorical dependent variable accounting for the significance and direction of the estimated migration effect. It takes on a value of one if migration decreases, two if there is no significant change in migration and three if migration increases in response to a given climatic variable. Among other things, this model enables us to examine the direction in which specific climatic events affect migration. The dependent variable y_i for the ith effect takes on a value $j = 1, 2$ or 3 and is associated with an underlying latent variable $y^\star_{ij}$, such that:

$$y^\star_{ij} = x_{ims}\beta + \epsilon_{ij} \tag{3}$$

where ϵ_{ij} have independent standard normal distributions. The outcome $y^\star_{ia}$ is chosen if $y^\star_{ia} > y^\star_{ib}$ for $a \neq b$. Hence, the probability of observing, for instance, the first effect category (i.e. $j = 1$) is given as follows:

$$P(y_{i1}) = P[y^\star_{i1} > y^\star_{i2}] \;\&\; P[y^\star_{i1} > y^\star_{i3}] \tag{4}$$

Similar expressions can be derived for $P(y^\star_{i2})$ and $P(y^\star_{i3})$. We choose MNP rather than a multinomial logit model (MNL). The MNL model imposes strict assumptions on the error terms as it restricts the correlation between each pair of errors in the model to be zero. This causes the Independence of Irrelevant Alternatives (IIA) problem, i.e. the multinomial logit assumes that the relative probabilities of any two outcomes are unaffected by the addition of another outcome. MNP, on the contrary, allows for all possible correlations among error terms [Maddala, 1986, Hausman and Wise, 1978].

As suggested by Nelson and Kennedy [2009], a complete meta-analysis should address heterogeneity, heteroscedasticity and correlation of the observations. The term heterogeneity implies that the estimates from the original studies do not measure the same effect. To address this issue, we employ a set of moderator variables (X in model 1) that capture the potential sources of heterogeneity.

As a result of different primary sample sizes, sample observations and estimation techniques, the estimated effects have non-homogeneous variances, i.e. suffer from heteroscedasticity. As a consequence, some estimates are more reliable (smaller variance, or larger sample size) than the others (larger variance, smaller sample size). Typically, the inverse of variances is used to control for such robustness differences. However, numerous original studies in our sample do not report this information. Alternatively, the sample size can also be used as a weight since it is inversely related to the variance [Waldorf and Byun, 2005]. Following the MRA literature (e.g. Horowitz and McConnell [2002], Waldorf and Byun [2005], Nelson and Kennedy [2009], Wehkamp et al. [2018]) we use this approach to maximize the statistical efficiency of the meta-analysis. As regards the functional form of the weights we follow Wehkamp et al. [2018] and apply a log of square root of the sample sizes. The square root gives higher weight to the effects from models with more observations, but at a decreasing rate. We utilize the log-transformation, since the wide range of the square root sample size values (min. 6.24; max. 14541.7) could lead to over-correction for robustness differences when weighting.

Further, since we use multiple estimates per primary study, these observations may be correlated within studies. To account for this potential within-study dependence, we follow Nelson and Kennedy [2009], Card et al. [2010], Wehkamp et al. [2018] and apply robust standard errors clustered at the study-level.

4 Results from an aggregate MRA

Here, we report outcomes from MRAs of the full sample of reported effects. Table 2 shows average marginal effects from probit (i.e. model (1) according to equation 2), and multinomial probit (i.e. model (2) according to equation 3) models. In the interest of space, we do not report standard errors (for the comprehensive outcomes, see Appendix D, Table 7). We find that extreme temperatures unlikely reduce migration and the positive, at conventional levels insignificant effect on migration increase is an indication of a generally positive association. This evidence underlines the non-linear impacts of temperature mostly felt in the extremes [Burke et al., 2015b, Schlenker and Roberts, 2009]. Moderate precipitation decrease is not likely to reduce migration, but rather suggests to have no effect. While both extreme precipitation reduction and droughts unlikely reduce migration, their positive, yet insignificant effects on migration increase further support broader conclusions from the literature (see e.g. Cattaneo et al. [2019]) that drier conditions are linked to departures. Sea-level rise is likely to have an insignificant effect, contradicting conclusions by Perch-Nielsen et al. [2008] that sea-level rise is positively associated with migration. A possible explanation of our rather counter-intuitive findings is that the historical sea-level rise has not yet crossed the critical magnitudes that would trigger out-migration. At the same time, our sample only has a very small number of observations (less than 3%) capturing sea-level rise effects. Both of these factors hinder drawing meaningful conclusions and imply that more evidence in this direction is needed. Floods are likely to have an insignificant migration effect as also suggested by Perch-Nielsen et al. [2008], who indicate that floods prompt adaptive responses other than moving. We further find that hurricanes are unlikely to reduce migration and an indication (yet the effect is insignificant) that they are likely to have an insignificant effect.

Overall, these patterns have two possible explanations. Firstly, change in migration behavior is more likely to serve as an adaptation to slow-onset events that have irreversible implications possibly by allowing more time to gather resources to migrate. In contrast, sudden-onset events rapidly deplete resources, reducing the ability to move [Kaczan and Orgill-Meyer, 2020]. Alternatively, sudden-onset events tend to be associated with a type of moves that are difficult to capture, such as short-distance or irregular migration [Cattaneo et al., 2019, Ponserre and Ginnetti, 2019]. To resolve this, more research on migration responses to rapid-onset events and possible mechanisms behind them is needed. We further compare this evidence with conclusions of the other two MRAs of climate migration. Our findings that extreme temperature and precipitation changes induce migration are in line with Hoffmann et al. [2020], but contrast Beine and Jeusette [2019], who show that extreme temperatures do not affect mobility. Our conclusions on the implications of floods are in line with Beine and Jeusette [2019], but contrast Hoffmann et al. [2020] who suggest that rapid-onset events induce migration. Overall, differences in results can likely be explained by diverging samples considered in the respective MRAs.

Table 2 further shows that direct adverse climatic events are by 7 p.p. less likely to decrease migration compared to lagged events. Even though insignificant, the impact on the migration increase further implies that this association might generally be positive. Kleemans [2015] provides a possible explanation suggesting that contemporaneous income decrease triggers survival migration. This contrasts the insignificant effect of a time lag between environment-migration association revealed by Hoffmann et al. [2020].

As regards study properties, we find evidence of various biases. Authors from disciplines of economics and geography are likely to report an increase in climate migration. We further reveal that newer studies are likely to find an insignificant effect (2 p.p./year), possibly reflecting advances in data availability and quality or methodological advances, which enable more precise estimations. This finding contrasts Beine and Jeusette [2019], who find no systematic differences based on the year of publication. Moreover, in contrast to Beine and Jeusette [2019] and Hoffmann et al. [2020] we find evidence of publication bias in the aggregate climate migration literature, i.e. peer-reviewed journals are likely to report a significant decrease in migration in response to adverse climatic events.

As for sample characteristics, we reveal that in low-income countries climatic events do not significantly affect migration. However, we find an indication of a positive association in lower-middle income countries. We find a clearly positive relationship between climatic events and migration in upper-middle income countries. This evidence is suggestive of the inverted U-shaped relation between economic development and migration as discussed in section 3.2.4 and is in line with findings by Hoffmann et al. [2020].

As regards migration-specific moderator variables, studies where the origin of migration is urban are more likely to find an insignificant effect of adverse climatic events on migration compared to studies that analyze rural out-migration. A potential explanation is that in rural contexts, where livelihoods are more dependent on climate-sensitive activities (e.g. agriculture), migration serves as an important adaptation strategy [Cai et al., 2016, Feng et al., 2010, Šedová and Kalkuhl, 2020]. Yet, we only have a few observations in the category *Origin - urban* (see Appendix C, Figure 11) and more evidence in this direction is needed to verify the validity of these outcomes. Studies that use a bilateral measure of migration are unlikely to find evidence of climate migration, compared to studies that use a unilateral measure. The explanation is rather intuitive, since migration rates captured by bilateral measures are lower than unilateral measures as they are reduced by the number of in-migrants. Further, females are generally less likely to significantly adapt their migration strategy in response to adverse climatic events, possibly because male household members typically migrate in search of alternative livelihoods [Chindarkar, 2012].

Lastly, we show that differences across estimation techniques and model specifications significantly affect the estimated outcomes. Estimates derived using causal inference are by 9 p.p. less likely to find a significant increase in climate migration compared to cross-sectional analyses. Thus, cross-sectional analyses likely overestimate the positive effect of climatic events on migration, if we assume that causal inference techniques more accurately captures the climate-migration association. Models that control for more climatic variables are less likely to find a significant effect, with a decrease in likelihood by almost 2 p.p. per an additional climatic control included. Because climatic events are correlated, an additional climatic event controls out the variation of already included climatic variables and increase the likelihood of their insignificance. Further, an additional control included reduces the likelihood of finding a decrease in climate migration. Moreover, controlling for variables approximating income or political situation are less likely to find a significantly positive association between migration and adverse climatic events. These outcomes support the conclusions derived by Cattaneo et al. [2019] that wealth and political stability are important mechanisms through which climatic events have an effect on migration. Including them in econometric models controls out an important part of the variation of climatic events and causes the over-controlling problem. The remaining residual effect tends to be biased downwards.

In Appendix E, we show a series of sensitivity tests examining whether and how the derived conclusions depend on our research design choices. First, in Table 8, we analyze whether there is generally a difference in implications of slow- and sudden-onset climatic events. Second, in Tables 9, 10 and 11 we employ alternative weighting strategies. Third, in Table 12 we meta-analyze a sub-sample of effects derived from analyses using causal inference techniques (see section 3.2.6). Fourth, in Table 13 we meta-analyze a sub-sample of effects with focus on international migration to understand whether there are different climatic drivers of internal and international moves. Overall, these tests provide strong support for the outcomes from the main analysis. New, notable evidence is i) a clear positive effect of extremely high temperatures and extremely dry conditions, ii) that when applying an instrumental variable approach, researchers are unlikely to find an insignificant effect, and iii) climate migration mostly takes place internally. For a more detailed discussion, see Appendix E.

5 Results from MRAs by climatic events

Here, we present outcomes from several MRAs of climate migration direction for sub-samples defined by climatic events with the highest number of reported effects. The outcomes are reported as mean marginal effects of moderator variables and are presented visually in four different sub-sections, by the following four climatic events: temperature increase (section 5.1, Figure 6),

Table 2: Meta-analytic probit (1) and multinomial probit (2) models

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.015	-0.050	-0.009	0.059
- extreme (2)	0.037	-0.134***	-0.064	0.198
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.109	-0.092**	0.111	-0.019
- extreme (2)	-0.048	-0.131***	0.044	0.087
Drought (1)	-0.023	-0.140***	-0.023	0.163
Sea level rise (1)	-0.282***	-0.149***	0.249***	-0.100
Flood (1)	-0.192***	-0.075**	0.208***	-0.133**
Hurricane/cyclone/typhoon (1)	-0.133	-0.092**	0.127	-0.034
Self-reported event (1)	-0.056	-0.001	0.041	-0.040
Direct effect (1)	-0.036	-0.074***	0.034	0.040
Study-level variables				
Author: female (1)	0.026	-0.037	-0.022	0.060
Author - economics (1)/ref.: other (0)	0.085	-0.076	-0.071	0.147***
- geography (2)	-0.042	-0.171***	0.027	0.144**
- sociology (3)	-0.098	-0.083	0.095	-0.012
Year of publication/ latest draft	-0.021**	-0.013***	0.021***	-0.008
Peer-reviewed: yes (1)	-0.002	0.045*	0.009	-0.054
Sample characteristics				
Micro-level analysis (1)	-0.040	0.012	0.045	-0.057
Multiple countries (1)	-0.022	-0.037	0.032	0.005
Low income included (1)	-0.000	-0.014	0.001	0.013
Lower-middle income included (1)	-0.052*	-0.052**	0.049	0.003
Higher-middle income included (1)	0.066**	0.006	-0.065**	0.058**
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.199**	-0.119***	0.198**	-0.080
- undefined (2)	0.021	-0.000	-0.010	0.011
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.010	-0.021	-0.003	0.023
- undefined (2)	-0.001	-0.000	0.002	-0.002
Dest. 2 - urban (1)/ ref.: rural (0)	-0.069	-0.091	0.081	0.010
- undefined (2)	-0.014	-0.074	0.019	0.055
Temporary (1)	0.097	0.010	-0.088	0.077
Measurement - bilateral (1)	-0.107**	-0.001	0.106**	-0.105***
Migrants - male (1)/ ref.: female (0)	0.057	0.044	-0.056	0.012
- households (2)	0.216***	0.146***	-0.205***	0.059
- overall (3)	0.198***	0.073*	-0.198***	0.125***
- other (4)	0.269***	0.081*	-0.267***	0.186***
Econometric modeling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.076	0.020	0.066	-0.087*
- IV (2)	0.071	0.106	-0.097	-0.009
- panel-other /pool (3)	0.034	0.034	-0.038	0.004
Clustered std. errors (1)	0.033	0.002	-0.019	0.017
Nr. of climatic variables	-0.016**	-0.004	0.015**	-0.011*
Nr. of controls	-0.002	-0.003**	0.002	0.001
Income-related controls (1)	-0.038	0.041*	0.037	-0.078**
Polit. stability-related controls (1)	-0.009	0.072*	0.004	-0.076*
Main model (1)	0.015	0.005	-0.011	0.006
Observations	3625	3625	3625	3625

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level. Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. For the full model specification with std. errors, see Appendix Table 7). * p<0.10, ** p<0.05, *** p<0.01.

precipitation decrease (section 5.2, Figure 7), droughts (section 5.3, Figure 8) and floods (section 5.4, Figure 9).These analyses enable us to examine systematic biases that may stem from the unique approaches to studying implications of specific climatic events (e.g. modeling droughts or floods, discipline-specific biases) and particular migration patterns they induce. The set of moderator variables in each of the following sections might differ from the comprehensive list employed in the main analysis (section 4), as some of the variables were causing multicollinearity in these more restricted samples. Differences in model specifications are discussed in Appendix F.

5.1 Temperature increase

We show that studies drawing on self-reported events are likely to find an insignificant association between higher temperatures and migration. As suggested in section 3.2.2, self-reported data may be biased. Our findings imply that these less objective measures distort the climate migration evidence. We find a clear positive association between direct, as well as extreme effects of temperature and migration, amplifying the weak evidence from the main analysis.

We reveal that female authors are unlikely to report a negative effect of a temperature increase on migration. A plausible explanation is that female authors are less likely to take risks and present new findings that do not match the conventional narrative [Fang et al., 2013] that climatic hazards induce migration. We only find a weak evidence that economists and geographers are likely to report a significant increase in climate migration. We reveal that sociologists tend to find an insignificant effect of temperatures.

We show that studies conducted at the micro-level are likely to find a decrease in migration in response to higher temperatures. This emphasizes the necessity of conducting both micro- and macro-level studies as they seemingly capture different trends in climate migration. It also underlines that this MRA complements Hoffmann et al. [2020], who exclusively focus on macro analyses. Moreover, we find additional evidence for the inverted U-shaped relation between economic development and climate migration.

The outcomes further indicate that higher temperatures are unlikely to reduce temporary migration and the insignificant coefficients suggest a generally positive association. This is in line with Call et al. [2017], who show that temporary migration is an important adaptation strategy if local yields decrease due to higher temperatures. We find additional evidence that women are generally less likely to respond to climatic stress. These gender effects are reinforced by the new, explicit evidence that men are more likely to significantly respond to temperature-related events by adjusting their migration strategy.

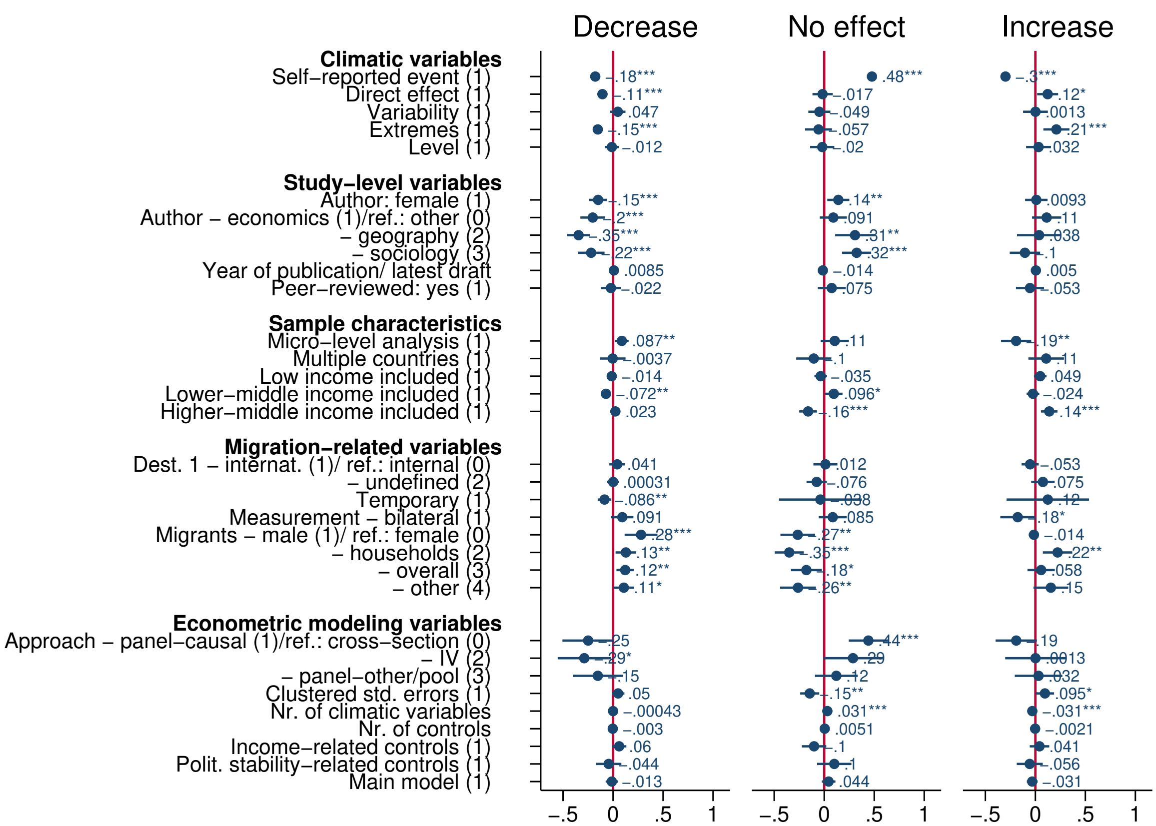
Lastly, our results explicitly suggest that estimates derived from causal inference are likely to find insignificant effect of higher temperatures on migration, validating the suggestive outcomes from the main analysis. We further show that using instrumental variable analyses unlikely produces a decrease in climate migration. This systematic bias reinforces concerns about the validity of using climatic variables as instruments, discussed in section 3.2.6. We also show that accounting for spatial correlation of climatic events by clustering standard errors likely produces a positive coefficient of higher temperature on migration. Finally, we validate the main findings, i.e. that including more climatic controls reduces the likelihood of finding a significant effect.

5.2 Precipitation decrease

We reveal that female lead authors are likely to report an increase in migration due to less precipitation. Similarly as in section 5.1, possibly this is because female authors might be more likely to present findings that match the conventional narrative that climatic hazards induce migration [Fang et al., 2013]. We find additional evidence that newer studies are likely to report insignificant effect of climatic events on migration, as in the main analysis.

As for climate migration patterns, we find further outcomes indicating that it serves as an adaptation primarily in rural areas. We reveal that if precipitation decreases, international migration is less likely to decrease than internal migration. This suggests that i) decrease in precipitation might trap people in the affected areas, who would have migrated internally and ii) engagement into inter-

Figure 6: Multinomial probit model for effect direction of temperature on migration

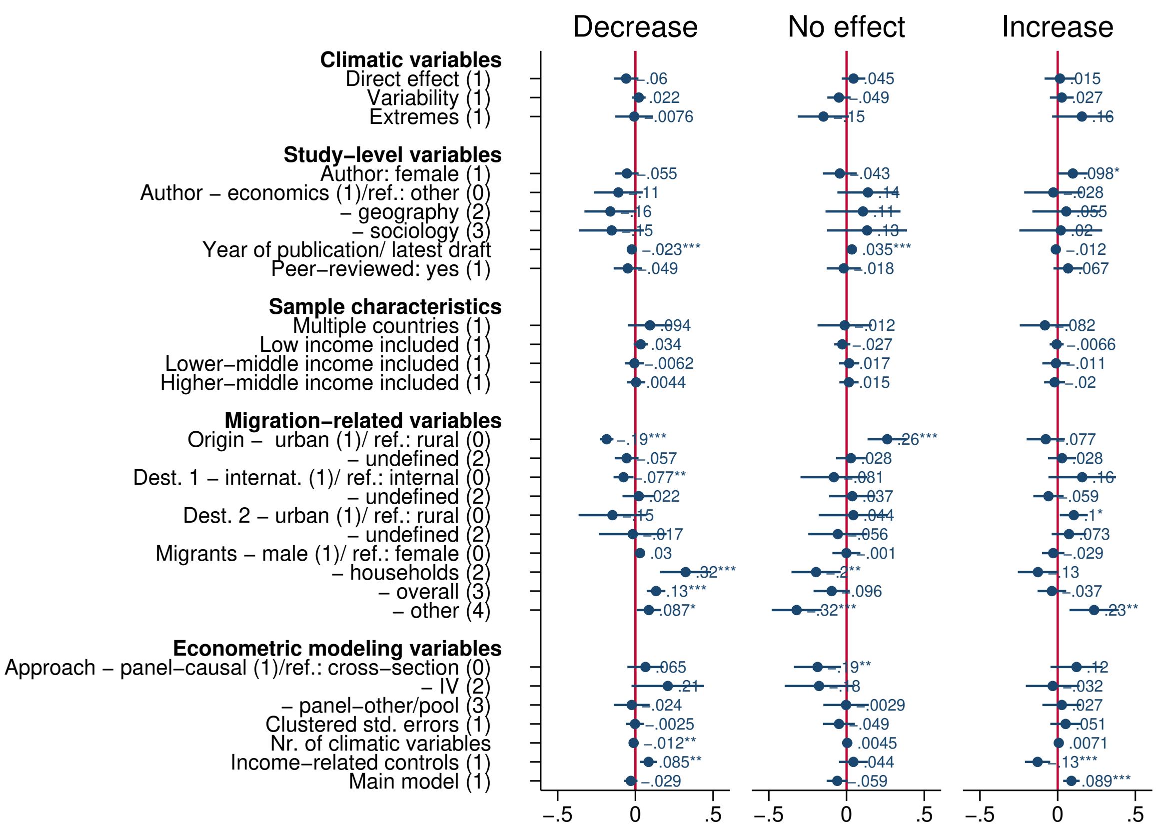


national migration might not be determined by climatic conditions. Migration in response to less precipitation takes place to urban areas, which are less likely to be dependent on climate-sensitive activities such as agriculture. This validates the general notion that climate change accelerates urbanization [Adger et al., 2020]. As in the previous sections, we show that women are generally less likely to adapt their migration strategy in response to climatic stress.

We reveal that models using causal inference are less likely to find an insignificant effect of precipitation decrease on migration. This bias goes in the opposite direction compared to the one revealed for the temperature-related sub-sample. Even though directions of these biases are not straightforward to interpret, they ultimately imply that using causal inference techniques produces systematically different outcomes compared to approaches that might suffer from the omitted variable bias. We further show that the number of climatic controls is unlikely to produce a negative effect and an indication (even though insignificant) that it likely produces insignificant coefficients, similar to the main analysis. We find further evidence that models that include income-related controls are not likely to report an increase in climate migration (for intuition, see the main analysis). Lastly, we reveal that authors are more likely to report an increase in migration in response to precipitation decrease in the main model. This contrasts findings by Beine and Jeusette [2019], who largely find no evidence of such a reporting bias.

It is important to note that generally the reliability of precipitation data is perceived to be problematic, which could explain why in this sub-sample analysis, we often do not find further evidence for the main results. Even though weather products tend to agree on long-run averages, particularly in the case of precipitation they do not necessarily agree on anomalies [Auffhammer et al., 2013]. Since often deviations from the mean are the main source of identification (especially in causal inference), the choice of weather products is non-trivial and could produce inconsistent evidence. For these and other reasons, recent trend in the climate impact literature is to focus primarily on the implications of temperature demonstrating more consistency across data products, while controlling for precipitation [Burke et al., 2009, Missirian and Schlenker, 2017].

Figure 7: Multinomial probit model for effect direction of precipitation decrease on migration



5.3 Droughts

We show that in response to self-reported droughts, migration is likely to increase. The bias goes in the opposite direction than in the temperature-related sub-sample, which is not straightforward to interpret. However, it further emphasizes that using subjective measures of climatic events systematically affects the evidence. Consistent with outcomes from other sections, measurement of climatic events matters for what results original analyses produce. If droughts are captured as binary treatments, studies likely find a decrease in migration. Drought intensity measures, however, increases the likelihood of finding a significant effect. This latter outcome is quite intuitive, implying that their intensity rather than mere occurrence enables researchers to better capture droughts' migration implications. It, however, contrasts evidence delivered by Beine and Jeusette [2019], who show just the opposite.

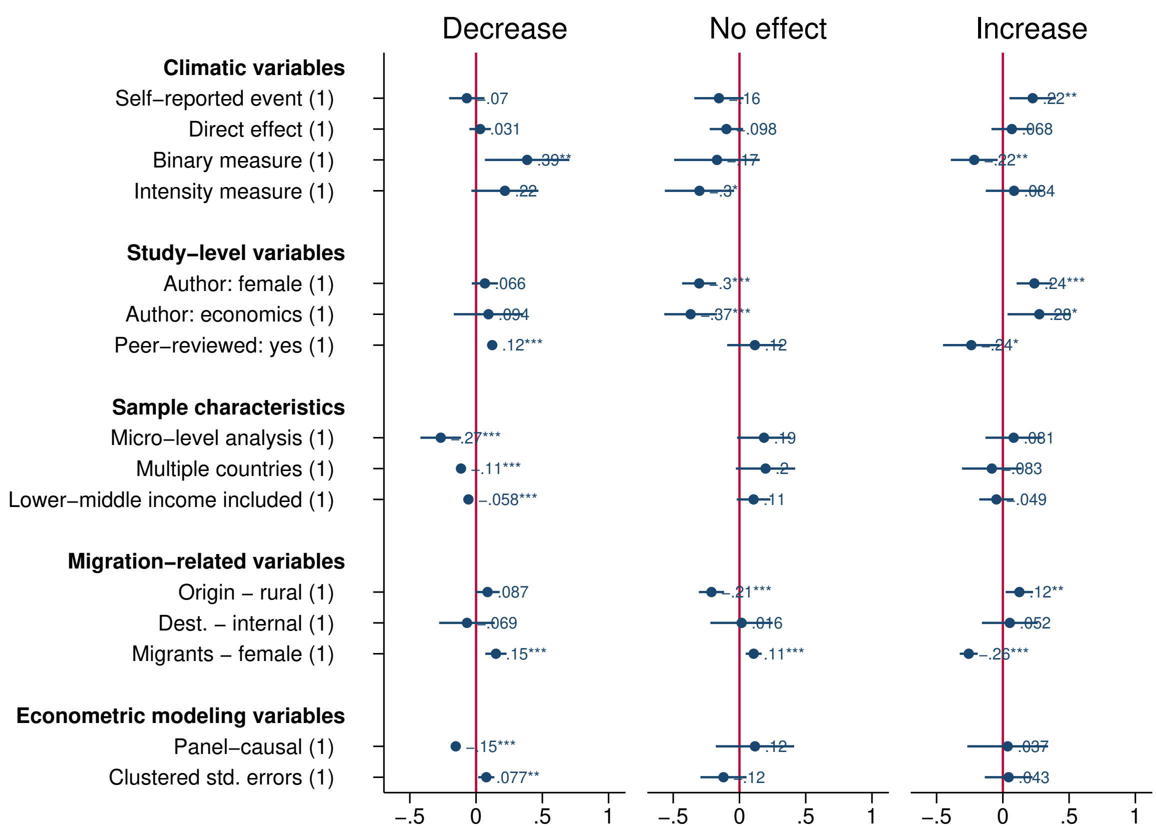
Consistent with section 5.2, we find that female lead authors are likely to publish an increase in climate migration in line with the more conventional narrative (for intuition, see section 5.1). Additionally, we reveal stronger evidence of publication biases suggested by the main analysis; studies led by economists are likely to report an increase and studies published in peer-reviewed journals are likely to report a decrease in climate migration.

We show that analyses conducted at the micro-level are unlikely to find a significant decrease in drought-related migration. This bias goes into an opposite direction as compared to section 5.1. Similarly, we reveal that studies covering multiple countries are less likely to report a decrease in climate migration than country-specific analyses. While these bias directions are not straightforward to interpret, they emphasize the importance to consider both i) micro- and macro-level , as well as ii) multi-country and country-specific analyses, because ultimately all of them provide different, likely complementary insights on climate migration dynamics. We further find that lower-middle income countries are less likely to report a decrease in drought-related migration and an indication of a positive association, similar to the main analysis.

We amplify findings from the main analysis, by further showing that migration in response to climatic hazards likely increases from rural areas and is less likely to be undertaken by women.

As for econometric modeling we reveal that studies using causal inference are unlikely to report a decrease in drought-related migration. Even though the bias direction differs from previous sections and it is not straightforward to interpret it, this evidence further emphasizes that the choice of the econometric approach may systematically affect climate migration evidence. Lastly, we show that studies, which apply clustered standard errors are more likely to report a decrease in climate migrations, whereby this bias goes in the opposite direction as the one revealed in section 5.1. Also here the bias direction is not easy to interpret. Yet, it suggests that not accounting for spatial correlation of climatic events is important as it systematically produces different evidence.

Figure 8: Multinomial probit model for effect direction of drought on migration



5.4 Floods

Consistent with other sections we find that how climatic events are measured systematically affects the evidence. If floods are captured as losses or binary treatments, researchers are likely to find a positive association with migration.

We reveal that studies led by female authors are likely to report no effect. This contrasts the bias of female lead authors to publish an increase in migration in response to climatic stress as revealed for instance in sections 5.2 and 5.3. However, since in the main analyses we show that floods are unlikely to induce migration, the explanation for this finding remains as in previous sections. Female lead authors are more likely to report evidence in line with the conventional narrative. We further show that studies published in peer-reviewed journals are likely to report an insignificant effect and less likely to report a decrease in flood-related migration. This bias differs from the one revealed in the main analysis when pooling all estimates together.

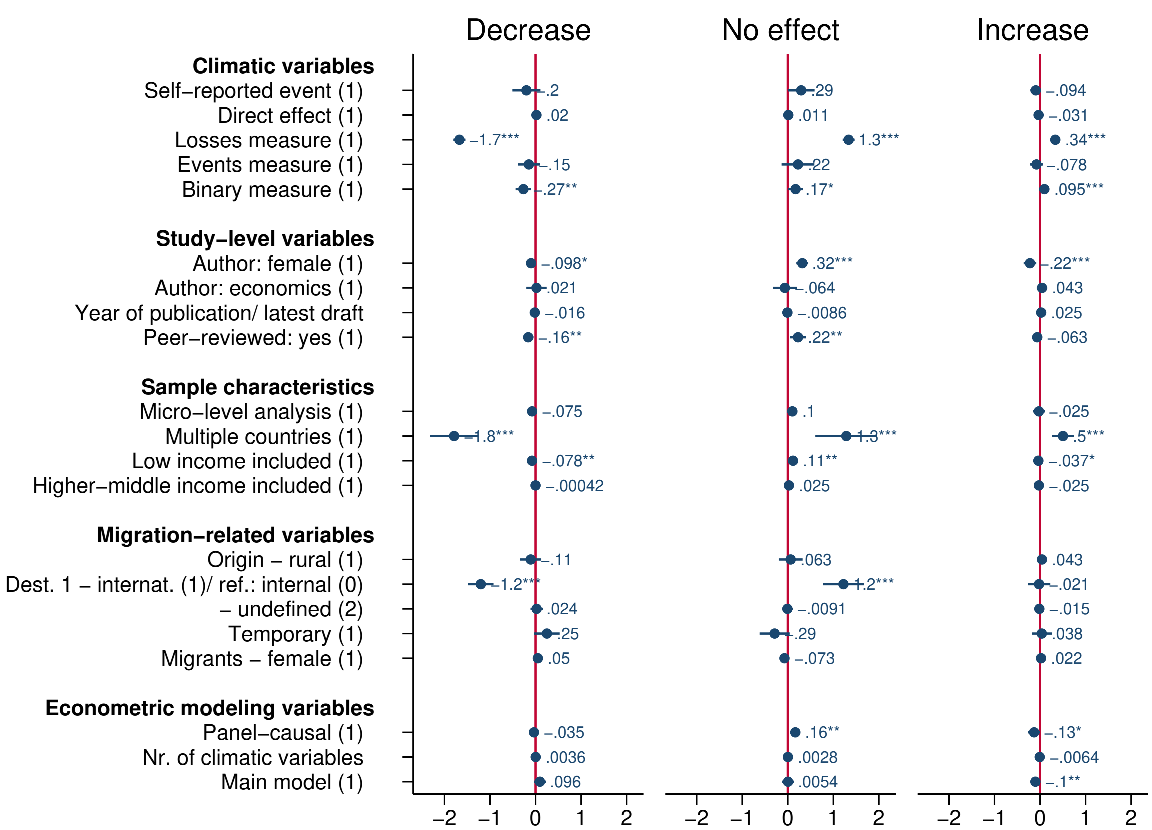
Similarly as in section 5.3, samples covering multiple countries are unlikely to report a decrease in flood-related migration than country-specific studies. This further emphasizes that both types of studies are complementary as they reveal different climate migration patterns. We further validate outcomes from the main analysis that low income populations are less likely to significantly respond to climatic hazards, plausibly due to lack of their adaptive capacity.

In contrast to the main outcomes, we fail to find systematic differences in flood-related migration with respect to the migrants' origin. A possible explanation is that floods cause disruptions both in rural areas and cities, in comparison to impacts of slow-onset events that are importantly channeled through agricultural production and thus primarily felt in rural areas. We also find that changes in internal rather than international migration serve as an adaptation to floods as it is less costly [Bazzi, 2017, Cattaneo and Peri, 2016], in line with findings from section 5.2. In contrast to the findings form previous sections, we do not find gender-specific differences in flood-related migration. This is in line with Call et al. [2017], who show that vulnerable populations such as women are not consistently more/less likely to be displaced by floods. A plausible explanation is that while slow-onset events trigger migration in search of alternative livelihoods, which is more often picked up by men [Chindarkar, 2012], floods are more likely to lead to displacement affecting both genders equally.

In terms of econometric modeling, we further show that applying causal inference techniques systematically affects the evidence, whereby the bias direction is the same as in section 5.1. Lastly, outcomes presented in the main models are unlikely to report an increase in flood-related migration.

Taken together, the evidence of the flood-related sub-sample differ the most from the main analysis. This is plausibly because sudden-onset events trigger different adaptive responses than slow-onset events. Thus, the outcomes as found in the main analysis seem to be mainly driven by the slow-onset events, prevalent in our sample.

Figure 9: Multinomial probit model for effect direction of flood on migration



6 Discussion and conclusion

This meta-analysis has considered all relevant econometric studies across multiple disciplines that analyze implications of climate-related events for human migration. By summarizing the mixed outcomes and providing explanations for the sources of heterogeneity in derived conclusions across this rapidly growing literature, we have been able to address a number of remaining open questions. The main findings are summarized in Table 3.

We show that slow-onset climatic events (particularly temperature extremes and drying conditions) are generally more likely to increase migration than sudden-onset events (i.e. floods and hurricanes). This evidence has two possible explanations. Firstly, migration likely serves as an adaptation to slow-onset events by allowing more time to gather resources to migrate, whereas sudden-onset events hinder people's ability to move by depleting their resources. Alternatively, sudden-onset events tend to be associated with a type of moves that are more difficult to capture. Given the increasing yearly estimates number of people displaced due to natural disasters, the latter explanation seems more plausible.[7] However, to resolve this, future research should aim to improve the understanding of migratory patterns in the aftermath of sudden-onset events.

We find evidence of different biases prevalent in the literature indicating how both the academic and public discourse on climate migration is distorted. For illustration, we show that peer-reviewed journals are likely to report a significant decrease in climate migration. This contrasts findings by Beine and Jeusette [2019] and Hoffmann et al. [2020], who do not find evidence of a publication bias in the overall climate migration literature. We also find a publication bias for effects of specific climatic events, as well as gender-, discipline- and time-specific biases. These biases are often a result of researchers or editors making decisions about publishing evidence on the basis of the direction or strength of findings. Yet, they adversely affect our learning experience inhibiting effective policy responses. To combat these practices, an important step for social sciences would entail

[7] The estimates show that in 2019 alone, 17.2 million people were displaced due to natural disasters [NRC and IDMC, 2019].

measures such as pre-registration of studies with journals and incentives to also report insignificant results [Franco et al., 2014]. When it comes to policy-making, we recommend to consider the grey literature in addition to peer-reviewed journals in order to amass a more accurate evidence base.

This analysis further enables us to summarize the patterns of climate migration that are seemingly strongly determined by budget constraints and climate-related sensitivity of livelihoods. In line with Hoffmann et al. [2020], our findings indicate an inverted U-shaped relationship between countries' income levels and climate migration. We further show that migration responds to slow-onset climatic events particularly in rural areas. Additionally, climate migration is likely to increase in response to contemporaneous rather than lagged adverse climatic events. As regards the destination choices, climate migration likely takes place in middle income countries, internally, and to destinations with lower dependence on the agricultural sector (i.e. cities). The likelihood of becoming trapped in adversely affected areas is higher in low-income countries, on the African continent in particular. Lastly, we show that while women are less likely to adapt to slow-onset climate change by migration, effects of sudden-onset events do not differ by gender. By making migratory responses to climatic events more predictable, this evidence is of high relevance for policy makers. If combined with i) future climate change scenarios indicating which areas are likely to be more severely affected by e.g. temperature extremes (e.g. Xu et al. [2020]) or water scarcity (e.g. Schewe et al. [2014]), and ii) socio-economic forecasts, our outcomes might enable the identification of hot-spots of future out- and in-migration and locations where people are likely to become trapped. Such information serves as an important entry point for policies, which aim to minimize welfare losses from migration choices in a changing climate.

Lastly, this study also seeks to inspire future research on climate migration and suggests how to move the scientific agenda forward. First, there are some obvious research gaps. Thus-far, research has primarily focused on climate-related out-migration from rural areas, yet we still lack evidence from cities. Further, as presented in Figure 5, we need evidence of climate migration from Europe as well as from countries that are likely to be disproportionately affected by climate change such as small islands located in the Pacific Ocean or many land-locked countries on the African continent. More evidence is further needed on migratory responses to sea-level rise, sudden-onset events or in response to distant climatic shocks transmitted e.g. via international commodity prices. Second, as a result of the heterogeneity of estimation techniques as well as approaches to measure migration and climate-related events, this meta-analysis cannot estimate the effect size. This is an important limitation. Yet, this limitation also provides a space to reflect on what the best practices in the climate migration literature are or should be. A methodological guidebook that would bring subsequent studies to a common denominator, would enable a meta-analysis of the effect size of climate change impacts on migration and would hence be an important next step in the field. This would substantially improve the learning experience for policy makers, thus facilitating more efficient policy responses to migration challenges in a changing climate. This is key, as we can ultimately expect that the adverse effects of climate change will be felt across many regions, forcing people in the most affected areas to make the hard decision of whether to stay or to go, with potentially far-reaching implications.

Table 3: Summary of the main findings

How do different adverse climatic events affect migration?

- Slow-onset events, i.e. temperature extremes, extreme precipitation decrease, and droughts increase migration
- Sudden-onset events, i.e. floods and hurricanes, do not have a significant effect

What are the existing climate migration patterns?

- Climate migration is likely to: originate in rural areas, take place in middle income countries and internally to destinations with low agricultural dependence, and increase in response to contemporaneous rather than lagged adverse climatic events
- The likelihood to become trapped is higher for women and in low-income countries, on the African continent in particular
- Temporary migration likely to increase in response to higher temperatures

What drives the differences in the existing evidence?

- Biases resulting from conceptualization of climatic events
  - Temperature increase: measures of extremes linked to climate migration increase
  - Precipitation decrease: measures of extremes linked to climate migration increase
  - Droughts: measures of intensity linked to significant effects, binary treatments linked to climate migration decrease
  - Floods: measures of losses and binary treatments linked to climate migration increase
- Data quality and sample characteristics:
  - Micro-level analyses: different biases for different sub-samples defined by climatic events
  - Multiple countries: different biases for different sub-samples defined by climatic events
  - Bilateral migration flows: bias towards an insignificant effect
  - Self-reported climatic events: different biases for different sub-samples defined by climatic events
- Biases resulting from attributes at the study-level:
  - Female authors: bias to publish more conventional narratives
  - Authors from disciplines of Economics and Geography: bias towards reporting an increase in climate migration
  - Newer studies: bias towards an insignificant effect
  - Peer-reviewed journals: bias to report a decrease in climate migration, especially of droughts and insignificant effects of floods
- Biases resulting from econometric modeling:
  - Causal inference: different biases for different sub-samples defined by climatic events
  - Instrumental variable approach: different biases for different sub-samples defined by climatic events
  - Clustered standard errors: different biases for different sub-samples defined by climatic event
  - Number of climatic controls: bias towards decrease in migration
  - Number of controls: bias towards an insignificant effect
  - Inclusion of income-related and political stability-related controls: bias towards a decrease in climate migration
  - Main models: different biases for different sub-samples defined by climatic events

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Appendices

A Assembling the sample of original studies: a detailed description

To build the initial sample of original studies, we drew on a series of prominent literature reviews on environmental migration (Millock [2015], Berlemann and Steinhardt [2017], Cattaneo et al. [2019], Neumann and Hermans [2017], Piguet et al. [2011]) and an additional literature review conducted by a research assistant.[8] Next, following Ringquist [2013], we developed a search profile by using keywords related to the outcome variable (migration), focal predictor (climat*, environment*, natural disasters) and methodology (regression, econometric). We tested different types of boolean connectors and developed the following final query: migration AND (climat* OR environment* OR natural disaster) AND (regression OR econometric). The last search was carried out on October 31st, 2018 using a scoping review helper developed by the Mercator Research Institute on Global Commons and Climate Change (MCC) [Callaghan et al., 2020] and Google Scholar. Via MCC's scoping helper, we accessed the database of Web of Science and Scopus and identified 1,157 studies. Further, we reviewed the first 50 pages of results returned by Google Scholar. We also conducted a backward search and analyzed Google Scholar profiles and (if existing) other personal or professional websites of corresponding authors of every acceptable study in our sample and contacted them for the approval of the final list of studies.

Applying the approach suggested by Ringquist [2013], after the analysis of the titles of the original studies applying generous inclusion criteria, we narrowed down 457 potentially relevant studies. A closer examination of abstracts, summaries and in some cases of full texts enabled us to refine the sample to 176 relevant studies. At this stage we excluded studies that i) do not apply

[8] This literature review is summarized in a Masters' thesis "On the empirical evidence on environmental. migration -a systematic literature review" by our research assistant at the time, Ms. Ramlah Abbas.

econometric methods, ii) do not measure effect of climatic events[9] on migration,[10] iii) only reported interactions/polynomials, or iv) we were not able to access.[11] We then conducted a full text analysis of the relevant studies to further exclude 60 papers based on the duplication and relevance criteria,[12] or if studies do not report minimum information such as sample size, or significance. This left us with a final sample of 116 original studies. The main unit of analysis in our study is at the effect-level, corresponding to 3,625 estimated effects.

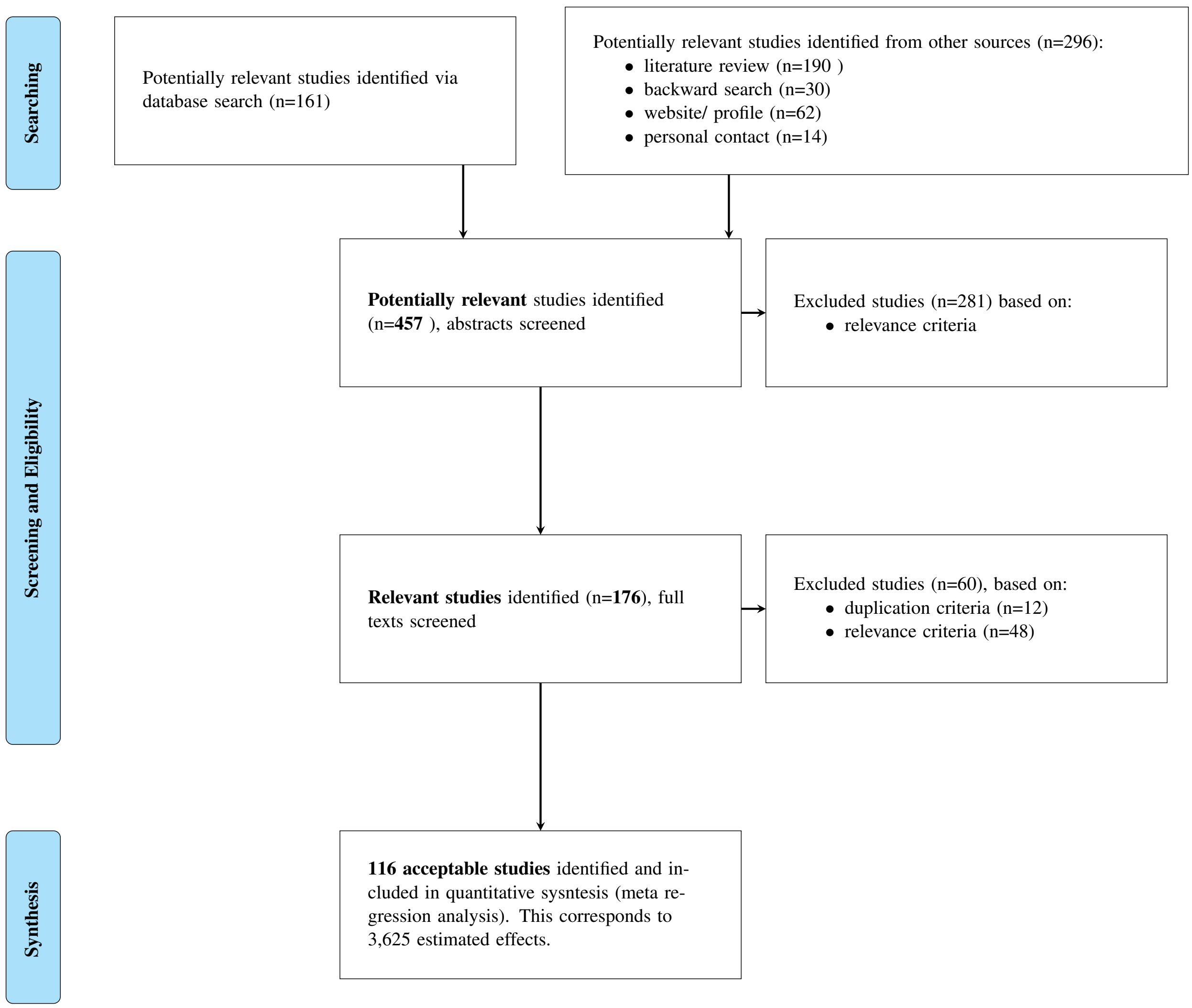
[9]Some studies examined effects of other environmental disasters (e.g. landslides) or geological disasters (e.g. Tsunami) rather than climatic events.

[10]In some cases, it was not clear from the title of the study what the outcome variable was.

[11]In these cases, study authors were contacted but were not responsive.

[12]We excluded studies based on the relevance criteria, if they perceived climate migration through the amenity channel. In such settings, climatic factors attract in-migration (thus are not the push factors) enabling populations, e.g. to escape hotter summers or experience warmer winters. Further, we also excluded studies where, the dependent variable only captures intention to migrate and not actual migration, or independent variables do not capture focal predictors of interest (i.e. climatic effects).

Figure 10: ROSES flow diagram for systematic reviews



B List of original studies

Table 4: Summary statistics: list of original studies

	Number of estimates	Author female	Published
Adoho and Wodon [2014]	32	0	0
Afifi et al. [2008]	1	0	0
Alem et al. [2016]	6	0	0
Asrat [2017]	4	0	0
Backhaus et al. [2015]	18	0	1
Badiani and Abla [2008]	2	1	0
Baez et al. [2017]	2	1	1
Bakar and Jin [2018]	21	0	1
Barassi et al. [2018]	60	0	1
Baronchelli and Ricciuti [2018]	25	1	0
Barrios et al. [2006]	4	0	1
Bazzi [2017]	15	0	1
Beine and Parsons [2015]	55	0	1
Beine and Parsons [2017]	48	0	1
Bettin and Nicolli [2012]	36	1	0
Bhattacharya and Innes [2008]	32	1	1
Bohra-Mishra et al. [2014]	60	1	1
Bohra-Mishra et al. [2017]	40	1	1
Bosetti et al. [2018]	4	1	0
Bylander [2016]	3	1	0
Cai et al. [2016]	5	0	1
Call et al. [2017]	15	1	1
Carvajal and Medalho Pereira [2009]	1	1	0
Castañer et al. [2017]	2	1	1
Cattaneo and Peri [2016]	50	1	1
Chen and Mueller [2018]	94	1	0
Chen et al. [2017]	32	1	1
Chort and De La Rupelle [2016]	58	1	1
Chort and De La Rupelle [2017]	281	1	0
Coniglio and Pesce [2015]	27	0	1
Curran and Meijer-Irons [2014]	8	1	1
Dallmann and Millock [2017]	94	1	0
Deschenes and Moretti [2009]	1	0	1
Dillon et al. [2011]	9	0	1
Drabo and Mbaye [2014]	106	0	1
Duda et al. [2018]	2	1	1
Feng et al. [2015]	32	0	0
Fussell et al. [2017]	32	1	1
Gao and Sam [2017]	24	1	1
Goldbach [2017]	42	1	1
Grace et al. [2018]	16	1	1
Gray [2009]	3	0	1
Gray [2010]	4	0	1
Gray and Bilsborrow [2013]	72	0	1
Gray and Mueller [2012a]	116	0	1
Gray and Mueller [2012b]	141	0	1
Gray and Wise [2016]	125	0	1
Gröger and Zylberberg [2016]	12	0	1

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Table 4: Summary statistics: list of original studies (cont.).

	Number of estimates	Author female	Published
Gröschl and Steinwachs [2017]	53	1	1
Gutmann et al. [2005]	28	0	1
Henderson et al. [2017]	10	0	1
Henry et al. [2004]	109	1	1
Henry et al. [2003]	2	1	1
Hirvonen [2016]	74	0	1
Hornbeck and Naidu [2014]	39	0	1
Hunter et al. [2013]	47	1	1
Iqbal and Roy [2015]	50	0	1
Jennings and Gray [2015]	128	1	1
Jessoe et al. [2016]	21	1	1
Joseph et al. [2014]	34	0	0
Khamis and Li [2018]	12	1	0
Kleemans [2015]	20	1	0
Kleemans and Magruder [2018]	16	1	1
Koubi et al. [2012]	18	1	0
Koubi et al. [2016a]	14	1	1
Koubi et al. [2016c]	18	1	1
Koubi et al. [2016b]	28	1	1
Koubi et al. [2018]	18	1	0
Kubik [2016]	62	1	0
Kubik and Maurel [2016]	21	1	1
Kumar and Viswanathan [2013]	24	0	1
Lewin et al. [2012]	5	0	1
Loebach [2016]	2	0	1
Mahajan and Yang [2018]	11	0	0
Marchiori et al. [2012]	12	0	1
Mastrorillo et al. [2016]	81	1	1
Matera [2014]	12	1	0
Maurel and Tuccio [2016]	20	1	1
Maystadt et al. [2016]	2	0	1
Missirian and Schlenker [2017]	102	1	1
Mueller et al. [2014]	248	1	1
Munshi [2003]	4	0	1
Naudé [2010]	3	0	1
Nawrotzki and Bakhtsiyarava [2016]	10	0	1
Nawrotzki and DeWaard [2016]	28	0	1
Nawrotzki and DeWaard [2018]	54	0	1
Nawrotzki et al. [2013]	6	0	1
[Nawrotzki et al., 2015a]	18	0	1
Nawrotzki et al. [2015b]	34	0	1
Nawrotzki et al. [2015c]	8	0	1
Nawrotzki and DeWaard [2016]	20	0	1
Nawrotzki and DeWaard [2016]	10	0	1
Nawrotzki et al. [2017]	4	0	1
Ouattara and Strobl [2014]	9	0	1
Pei and Zhang [2014]	2	0	1
Pei et al. [2016]	2	0	1
Pei et al. [2018]	4	0	1
Poston et al. [2009]	4	0	1
Reuveny and Moore [2009]	3	0	1

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Table 4: Summary statistics: list of original studies (cont.).

	Number of estimates	Author female	Published
Riosmena et al. [2018]	6	0	1
Robalino et al. [2015]	38	0	1
Ruiz [2017]	43	0	0
Ruyssen and Rayp [2014]	5	1	1
Saldaña-Zorrilla and Sandberg [2009]	7	0	1
Šedová and Kalkuhl [2018]	78	1	0
Shiva and Molana [2018]	8	0	0
Simon [2018]	24	0	0
Smith [2012]	4	0	0
Spencer and Urquhart [2018]	16	1	1
Strobl and Valfort [2015]	3	0	1
Tan et al. [2015]	4	1	1
Thiede and Gray [2017]	26	0	1
Thiede et al. [2016]	42	0	1
Tse [2012]	36	0	0
Viswanathan and Kumar [2015]	12	1	1
Wodon et al. [2014]	16	0	0
N	3625		

C Descriptive statistics: all variables

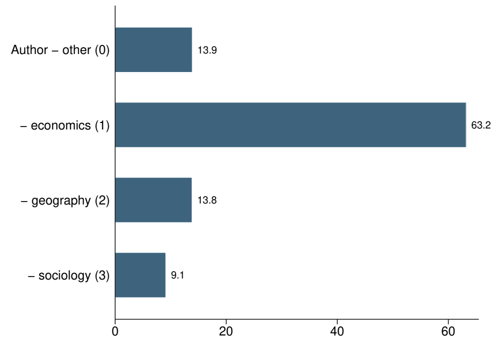
Table 5: Summary statistics: coded variables

Variable	Mean	Std. Dev.	Min.	Max.	Description
Dependent variable					
Migration (binary)	0.3992	0.4898	0	1	binary
Migration (categorical)	2.0792	0.6269	1	3	categorical
Climatic variables					
Slow	0.7418	0.4377	0	1	binary
Temperature increase	0.3194	0.5419	0	2	categorical
Precipitation decrease	0.363	0.5099	0	2	categorical
Drought	0.0709	0.2567	0	1	binary
Sea-level rise	0.0262	0.1598	0	1	binary
Flood	0.1062	0.3081	0	1	binary
Hurricane/cyclone/typhoon	0.083	0.276	0	1	binary
Self-reported	0.1164	0.3208	0	1	binary
Direct effect	0.4844	0.4998	0	1	binary
Study-level variables					
Author - female	0.5561	0.4969	0	1	binary
Author - discipline	1.1815	0.78	0	3	categorical
Year of publication/ latest draft	2014.9354	2.9738	2003	2018	continuous
Peer-reviewed	0.7302	0.4439	0	1	binary
Sample characteristics					
Micro	0.5663	0.4956	0	1	binary
Multiple countries	0.2047	0.4035	0	1	binary
Low-income included	0.3942	0.4887	0	1	binary
Lower-middle income included	0.5972	0.4905	0	1	binary
Upper-middle income included	0.5484	0.4977	0	1	binary
1960s	0.0604	0.2383	0	1	binary
1970s	0.1404	0.3475	0	1	binary
1980s	0.2866	0.4522	0	1	binary
1990s	0.6681	0.4709	0	1	binary
2000s	0.4154	0.4929	0	1	binary
2010s	0.3763	0.4845	0	1	binary
Migration-related variables					
Origin	1.1526	0.9797	0	2	categorical
Destination 1	0.7167	0.7572	0	2	categorical
Destination 2	1.8086	0.5313	0	2	categorical
Temporary	0.0298	0.17	0	1	binary
Measurement	0.2756	0.4469	0	1	binary
Migrants	2.2789	1.1515	0	4	categorical
Econometric modeling variables					
Approach	1.8651	1.099	0	3	
Clustered std. errors	0.6152	0.4866	0	1	binary
Nr. of climatic variables	3.7807	2.7441	0	15	count
Controls	14.4246	10.0084	0	45	count
Income-related controls	0.6513	0.4766	0	1	binary
Polit. stability-related controls	0.2251	0.4177	0	1	binary
Main model	0.2814	0.4497	0	1	binary
N		3625			

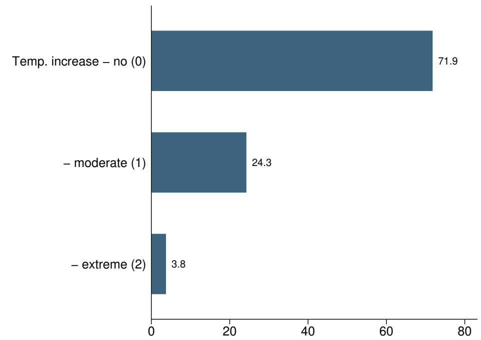
Table 6: Weighted summary statistics: coded variables

Variable	Mean	Std. Dev.	Min.	Max.
Dependent variable				
Migration (binary)	0.4007	0.4901	0	1
Migration (categorical)	2.0779	0.6283	1	3
Climatic variables				
Slow	0.7595	0.4274	0	1
Temperature increase	0.3296	0.5605	0	2
Precipitation decrease	0.3779	0.5244	0	2
Drought	0.0664	0.2491	0	1
Sea-level rise	0.0391	0.1939	0	1
Flood	0.109	0.3116	0	1
Hurricane/cyclone/typhoon	0.0656	0.2477	0	1
Self-reported	0.1085	0.311	0	1
Direct effect	0.4736	0.4994	0	1
Study-level variables				
Author - female	0.5496	0.4976	0	1
Author - discipline	1.2162	0.8308	0	3
Year of publication/ latest draft	2014.897	3.0527	2003	2018
Peer-reviewed	0.7419	0.4377	0	1
Sample characteristics				
Micro	0.6321	0.4823	0	1
Multiple countries	0.2097	0.4072	0	1
Low-income included	0.3955	0.4890	0	1
Lower-middle income included	0.6009	0.4898	0	1
Upper-middle income included	0.547	0.4979	0	1
1960s	0.0621	0.2414	0	1
1970s	0.148	0.3551	0	1
1980s	0.3154	0.4647	0	1
1990s	0.6547	0.4755	0	1
2000s	0.4188	0.4934	0	1
2010s	0.3603	0.4801	0	1
Migration-related variables				
Origin	1.1359	0.9828	0	2
Destination 1	0.7198	0.7592	0	2
Destination 2	1.8083	0.5341	0	2
Temporary	0.0314	0.1743	0	1
Measurement	0.2505	0.4334	0	1
Migrants	2.3011	1.1297	0	4
Econometric modeling variables				
Approach	1.9624	1.0987	0	3
Clustered std. errors	0.5978	0.4904	0	1
Nr. of climatic variables	3.8717	2.845	0	15
Controls	15.396	10.4082	0	45
Income-related controls	0.6515	0.4766	0	1
Polit. stability-related	0.195	0.3963	0	1
Main model	0.3005	0.4585	0	1
N		3625		

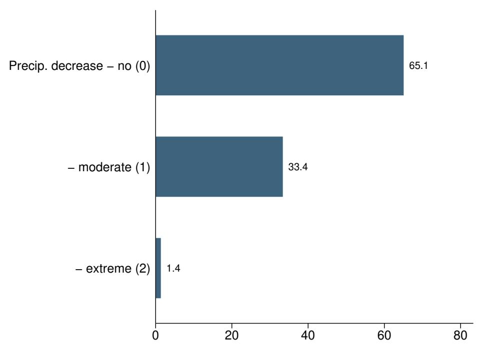
Figure 11: Categorical variables: distribution of specific categories (percent)



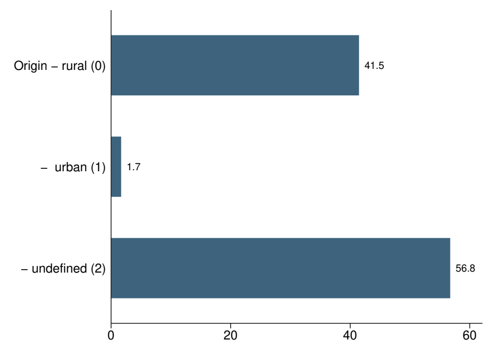
(a) Authors' discipline



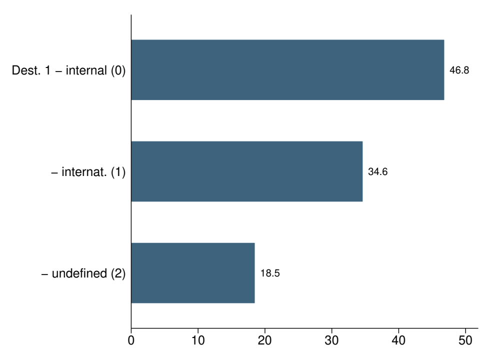
(b) Temperature increase



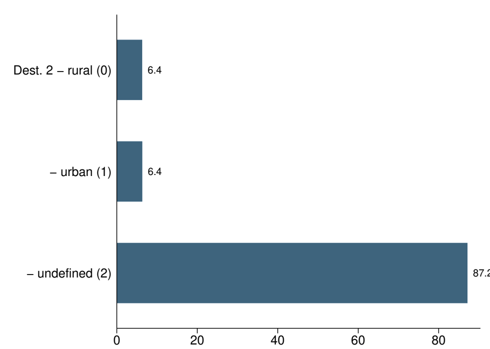
(c) Precipitation decrease



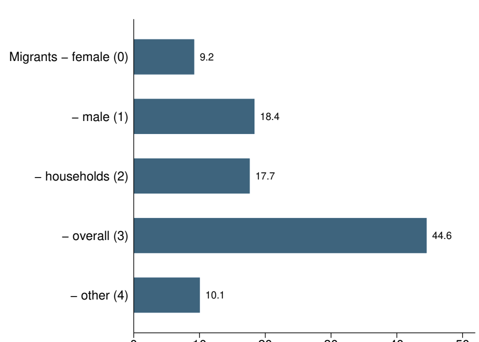
(d) Origin



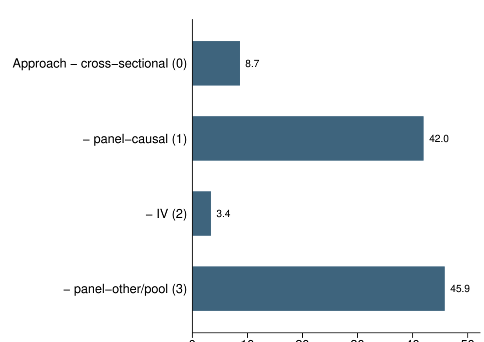
(e) Destination 1



(f) Destination 2



(g) Migrants



(h) Approach

D Aggregate MRA: main outcomes

Table 7: Meta-analytic probit (1) and multinomial probit (2) models

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.015	-0.050	-0.009	0.059
	(0.17)	(-1.16)	(-0.10)	(0.69)
- extreme (2)	0.037	-0.134***	-0.064	0.198
	(0.31)	(-3.88)	(-0.51)	(1.60)
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.109	-0.092**	0.111	-0.019
	(-1.37)	(-1.98)	(1.41)	(-0.27)
- extreme (2)	-0.048	-0.131***	0.044	0.087
	(-0.38)	(-2.88)	(0.33)	(0.68)
Drought (1)	-0.023	-0.140***	-0.023	0.163
	(-0.25)	(-5.45)	(-0.24)	(1.64)
Sea level rise (1)	-0.282***	-0.149***	0.249***	-0.100
	(-4.67)	(-7.90)	(3.42)	(-1.46)
Flood (1)	-0.192***	-0.075**	0.208***	-0.133**
	(-2.95)	(-2.21)	(3.29)	(-2.55)
Hurricane/cyclone/typhoon (1)	-0.133	-0.092**	0.127	-0.034
	(-1.52)	(-2.57)	(1.39)	(-0.40)
Self-reported event (1)	-0.056	-0.001	0.041	-0.040
	(-0.98)	(-0.01)	(0.69)	(-0.83)
Direct effect (1)	-0.036	-0.074***	0.034	0.040
	(-1.03)	(-3.25)	(0.99)	(1.15)
Study-level variables				
Author: female (1)	0.026	-0.037	-0.022	0.060
	(0.60)	(-1.53)	(-0.52)	(1.50)
Author - economics (1)/ref.: other (0)	0.085	-0.076	-0.071	0.147***
	(1.34)	(-1.55)	(-1.09)	(3.10)
- geography (2)	-0.042	-0.171***	0.027	0.144**
	(-0.54)	(-3.22)	(0.34)	(2.18)
- sociology (3)	-0.098	-0.083	0.095	-0.012
	(-1.12)	(-1.25)	(1.09)	(-0.23)
Year of publication/ latest draft	-0.021**	-0.013***	0.021***	-0.008
	(-2.51)	(-2.85)	(2.58)	(-1.25)
Peer-reviewed: yes (1)	-0.002	0.045*	0.009	-0.054
	(-0.06)	(1.65)	(0.25)	(-1.58)
Sample characteristics				
Micro-level analysis (1)	-0.040	0.012	0.045	-0.057
	(-0.69)	(0.35)	(0.74)	(-0.97)
Multiple countries (1)	-0.022	-0.037	0.032	0.005
	(-0.38)	(-1.02)	(0.56)	(0.09)
Low income included (1)	-0.000	-0.014	0.001	0.013
	(-0.01)	(-0.79)	(0.07)	(0.61)
Lower-middle income included (1)	-0.052*	-0.052**	0.049	0.003
	(-1.65)	(-2.53)	(1.55)	(0.09)
Higher-middle income included (1)	0.066**	0.006	-0.065**	0.058**
	(2.02)	(0.32)	(-1.97)	(1.98)
1960s (1)	-0.013	0.080	-0.002	-0.078
	(-0.19)	(1.61)	(-0.03)	(-1.39)
1970s (1)	-0.176***	-0.097***	0.183***	-0.085*
	(-3.17)	(-3.89)	(3.32)	(-1.69)

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Table 7: Meta-analytic probit (1) and multinomial probit (2) models (cont.).

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
1980s (1)	0.028	0.006	-0.031	0.026
	(0.60)	(0.18)	(-0.65)	(0.57)
1990s (1)	0.029	-0.019	-0.019	0.038
	(0.65)	(-0.63)	(-0.43)	(0.92)
2000s (1)	0.057	0.168***	-0.055	-0.113***
	(1.44)	(5.72)	(-1.41)	(-2.75)
2010s (1)	0.039	0.026	-0.043	0.017
	(0.80)	(0.78)	(-0.88)	(0.37)
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.199**	-0.119***	0.198**	-0.080
	(-2.14)	(-3.54)	(2.19)	(-1.16)
- undefined (2)	0.021	-0.000	-0.010	0.011
	(0.61)	(-0.02)	(-0.30)	(0.29)
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.010	-0.021	-0.003	0.023
	(-0.14)	(-0.56)	(-0.03)	(0.30)
- undefined (2)	-0.001	-0.000	0.002	-0.002
	(-0.03)	(-0.01)	(0.05)	(-0.04)
Dest. 2 - urban (1)/ ref.: rural (0)	-0.069	-0.091	0.081	0.010
	(-0.77)	(-0.92)	(0.89)	(0.19)
- undefined (2)	-0.014	-0.074	0.019	0.055
	(-0.20)	(-0.85)	(0.27)	(1.03)
Temporary (1)	0.097	0.010	-0.088	0.077
	(1.08)	(0.26)	(-0.91)	(0.94)
Measurement - bilateral (1)	-0.107**	-0.001	0.106**	-0.105***
	(-2.43)	(-0.02)	(2.38)	(-2.69)
Migrants - male (1)/ ref.: female (0)	0.057	0.044	-0.056	0.012
	(1.37)	(0.99)	(-1.41)	(0.48)
- households (2)	0.216***	0.146***	-0.205***	0.059
	(3.33)	(3.09)	(-3.31)	(1.17)
- overall (3)	0.198***	0.073*	-0.198***	0.125***
	(3.32)	(1.69)	(-3.41)	(2.85)
- other (4)	0.269***	0.081*	-0.267***	0.186***
	(4.48)	(1.69)	(-4.57)	(4.48)
Econometric modelling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.076	0.020	0.066	-0.087*
	(-1.09)	(0.33)	(1.01)	(-1.77)
- IV (2)	0.071	0.106	-0.097	-0.009
	(0.63)	(1.23)	(-0.86)	(-0.12)
- panel-other/pool (3)	0.034	0.034	-0.038	0.004
	(0.53)	(0.65)	(-0.59)	(0.07)
Clustered std. errors (1)	0.033	0.002	-0.019	0.017
	(0.91)	(0.09)	(-0.53)	(0.52)
Nr. of climatic variables	-0.016**	-0.004	0.015**	-0.011*
	(-2.51)	(-1.02)	(2.32)	(-1.82)
Nr. of controls	-0.002	-0.003**	0.002	0.001
	(-1.13)	(-2.12)	(1.11)	(0.26)
Income-related controls (1)	-0.038	0.041*	0.037	-0.078**
	(-0.93)	(1.68)	(0.92)	(-2.19)
Polit. stability-related controls (1)	-0.009	0.072*	0.004	-0.076*
	(-0.19)	(1.68)	(0.09)	(-1.92)
Main model (1)	0.015	0.005	-0.011	0.006

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Table 7: Meta-analytic probit (1) and multinomial probit (2) models (cont.).

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
	(0.63)	(0.28)	(-0.48)	(0.28)
Observations	3625	3625	3625	3625

E Aggregate MRA: sensitivity tests

Here, we present a series of sensitivity tests. First, in Table 8, we analyze whether there is generally a difference in implications of slow- and sudden-onset climatic events (summarized by a binary variable *Slow*). Models 1 and 2 display average marginal effects from probit models and model 3 from a multinomial probit. Model 1 applies study-specific fixed effects to account for observable and possible unobservable effects at the study-level.[13] Models 2 and 3 are fully specified, accounting for all moderator variables, but the fixed effects. Coefficients of the moderator variables provide further evidence for the results from the main analysis, but are not reported in the interest of space.[14] The outcomes suggest that slow events are by approximately 9-12 percentage points (p.p.) more likely to significantly affect and by 8 p.p. to increase migration compared to sudden-onset events. This further underlines conclusions derived in the main analysis that migration strategy is more likely to serve as an adaptation to slow-onset events.

Second, in Tables 9, 10 and 11 we employ alternative weighting strategies (recall that in the main analysis we apply log-transformation of the sample size square root as weights). When using a log-transformation of the sample size (Table 9) or no weights (Table 11), the estimated results largely provide further evidence for the main findings. In Table 10, we use a square root of the sample size and obtain coefficients with generally larger magnitudes, likely due to the wide range of weight values. For most coefficients, the direction and significance levels remain unchanged, with some notable exceptions. Most prominently, we find a clear positive association between extremely high temperatures and extremely dry conditions (extreme precipitation decrease or droughts) and migration. This importantly complements the outcomes from the main analysis, where we only find a weak indication of this positive relationship. We also find that if applying an instrumental variable approach, researchers are less likely to find an insignificant effect. Generally, if coefficients have become insignificant at the conventional levels as compared to the main analysis, the

[13] Since we have several studies with only one estimate, and a lot of explanatory variables are at the study-level, we lose numerous observations and explanatory power when using the fixed effects approach. Therefore, this MRA model is only applied for a robustness check.

[14] The full set of coefficients from models 2 and 3 in Appendix E, Table 8 is available upon request.

effect direction remains unchanged. An exception is the variable *Low-income included*, which now explicitly indicates that if low income countries are included in the sample, it is less likely to find evidence of climate migration.

Third, in Table 12 we meta-analyze a sub-sample of effects derived from panel analyses. These studies produce coefficients that can be interpreted causally and thus are established as a quality standard in the literature. Largely, we find additional evidence for the main outcomes. If coefficients loose their significance at conventional levels, they nevertheless largely maintain the same effect direction as in the main analysis. There are two new noteworthy findings, compared to the main analysis. First, we find explicit evidence that international migration is less likely to increase in response to adverse climatic events compared to internal. Second, the destination of climate migration are likely to be urban areas. Overall, this evidence implies that including studies, which are not quasi-experiments does not bias evidence from this meta-analysis. [15]

Fourth, in Table 13 we meta-analyze a sub-sample of effects with focus on international migration to understand whether there are different climatic drivers of internal and international moves. We only report climatic effects as these are of main interest.[16] We find evidence that only a moderate temperature increase likely reduces international migration; the remaining coefficients of climatic events are insignificant. This suggests that climate migration mostly takes place internally, likely due to the costly nature of migration and stricter budgetary constraints imposed by adverse climatic events.[17]

[15]Due to problems with multicollinearity, in models presented in Appendix, Table 12, several variables are dropped including *Sea-level rise*, *Author*, *Temporary*, *Origin* or *Approach*. We generated a few binary variables to capture some of the feature in this more restricted environment, including *Author: economics*, *Precipitation decrease* or *Origin - rural*.

[16]The full set of results from Table 13 is available upon request.

[17]Due to problems with multicollinearity, in models presented in Appendix, Table 13, several variables are dropped including *Sea-level rise*, and sudden-onset events.

Table 8: Meta-analytic probit (1 and 2) and multinomial probit (3) models

	(1)	(2)	(3)		
	Significant effect	Significant effect	Decrease	No effect	Increase
Slow (1)	0.115*	0.091**	0.015	-0.091**	0.077*
	(0.064)	(0.042)	(0.027)	(0.041)	(0.042)
N	3500	3625	3625	3625	3625
Study FE	Yes	No	No	No	No
Full model	No	Yes	Yes	Yes	Yes

Coefficients in models 1 and 2 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 3 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level. Both models also control for decade-specific dummies. In the interest of space the coefs. of the moderator variables are not reported. * p<0.10, ** p<0.05, *** p<0.01. The full set of results is available upon request. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: Meta-analytic probit (1) and multinomial probit (2) models - alternative weights (log. sample size)

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.015	-0.050	-0.009	0.059
- extreme (2)	0.037	-0.134***	-0.064	0.198
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.109	-0.092**	0.111	-0.019
- extreme (2)	-0.048	-0.131***	0.044	0.087
Drought (1)	-0.023	-0.140***	-0.023	0.163
Sea level rise (1)	-0.282***	-0.149***	0.249***	-0.100
Flood (1)	-0.192***	-0.075**	0.208***	-0.133**
Hurricane/cyclone/typhoon (1)	-0.133	-0.092**	0.127	-0.034
Self-reported event (1)	-0.056	-0.001	0.041	-0.040
Direct effect (1)	-0.036	-0.074***	0.034	0.040
Study-level variables				
Author: female (1)	0.026	-0.037	-0.022	0.060
Author - economics (1)/ref.: other (0)	0.085	-0.076	-0.071	0.147***
- geography (2)	-0.042	-0.171***	0.027	0.144**
- sociology (3)	-0.098	-0.083	0.095	-0.012
Year of publication/ latest draft	-0.021**	-0.013***	0.021***	-0.008
Peer-reviewed: yes (1)	-0.002	0.045*	0.009	-0.054
Sample characteristics				
Micro-level analysis (1)	-0.040	0.012	0.045	-0.057
Multiple countries (1)	-0.022	-0.037	0.032	0.005
Low income included (1)	-0.000	-0.014	0.001	0.013
Lower-middle income included (1)	-0.052*	-0.052**	0.049	0.003
Higher-middle income included (1)	0.066**	0.006	-0.065**	0.058**
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.199**	-0.119***	0.198**	-0.080
- undefined (2)	0.021	-0.000	-0.010	0.011
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.010	-0.021	-0.003	0.023
- undefined (2)	-0.001	-0.000	0.002	-0.002
Dest. 2 - urban (1)/ ref.: rural (0)	-0.069	-0.091	0.081	0.010
- undefined (2)	-0.014	-0.074	0.019	0.055
Temporary (1)	0.097	0.010	-0.088	0.077
Measurement - bilateral (1)	-0.107**	-0.001	0.106**	-0.105***
Migrants - male (1)/ ref.: female (0)	0.057	0.044	-0.056	0.012
- households (2)	0.216***	0.146***	-0.205***	0.059
- overall (3)	0.198***	0.073*	-0.198***	0.125***
- other (4)	0.269***	0.081*	-0.267***	0.186***
Econometric modelling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.076	0.020	0.066	-0.087*
- IV (2)	0.071	0.106	-0.097	-0.009
- panel-other/pool (3)	0.034	0.034	-0.038	0.004
Clustered std. errors (1)	0.033	0.002	-0.019	0.017
Nr. of climatic variables	-0.016**	-0.004	0.015**	-0.011*
Nr. of controls	-0.002	-0.003**	0.002	0.001
Income-related controls (1)	-0.038	0.041*	0.037	-0.078**
Polit. stability-related controls (1)	-0.009	0.072*	0.004	-0.076*
Main model (1)	0.015	0.005	-0.011	0.006
Observations	3625	3625	3625	3625

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: Meta-analytic probit (1) and multinomial probit (2) models - alternative weights (square root of sample size)

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.142	0.014	-0.157	0.144
- extreme (2)	0.402***	-0.018	-0.409***	0.427***
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.021	-0.094*	-0.008	0.102
- extreme (2)	0.114	-0.124**	-0.103	0.227**
Drought (1)	0.086	-0.126***	-0.169	0.294***
Sea level rise (1)	-0.286***	-0.123***	0.217**	-0.094
Flood (1)	-0.052	-0.039	0.100	-0.061
Hurricane/cyclone/typhoon (1)	0.036	-0.079**	-0.102	0.181
Self-reported event (1)	-0.028	-0.010	-0.034	0.044
Direct effect (1)	0.007	-0.056	-0.015	0.071
Study-level variables				
Author: female (1)	0.070	-0.014	-0.075	0.089*
Author - economics (1)/ref.: other (0)	0.229***	-0.015	-0.237***	0.252***
- geography (2)	0.069	-0.081	-0.099	0.180*
- sociology (3)	-0.046	-0.006	0.022	-0.016
Year of publication/ latest draft	-0.026**	-0.025***	0.024**	0.001
Peer-reviewed: yes (1)	0.025	0.041	-0.020	-0.021
Sample characteristics				
Micro-level analysis (1)	-0.049	0.006	0.070	-0.076
Multiple countries (1)	-0.007	-0.042	0.008	0.034
Low income included (1)	-0.051*	-0.057***	0.050	0.007
Lower-middle income included (1)	-0.013	-0.033	0.009	0.024
Higher-middle income included (1)	0.025	-0.001	-0.036	0.037
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.108	-0.045*	0.132	-0.087
- undefined (2)	0.090	0.070*	-0.054	-0.016
Dest. 1 - internat. (1)/ ref.: internal (0)	0.129	0.047	-0.140	0.094
- undefined (2)	0.005	0.051	-0.011	-0.040
Dest. 2 - urban (1)/ ref.: rural (0)	-0.120*	-0.259*	0.182*	0.078
- undefined (2)	-0.070	-0.284**	0.143	0.141***
Temporary (1)	0.070	0.049	-0.061	0.012
Measurement - bilateral (1)	-0.113**	-0.039	0.119**	-0.080
Migrants - male (1)/ ref.: female (0)	0.034	0.049	-0.015	-0.034
- households (2)	0.104	0.113***	-0.084	-0.029
- overall (3)	0.100	0.073**	-0.090	0.017
- other (4)	0.296***	0.058	-0.287***	0.230***
Econometric modelling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.050	0.018	0.032	-0.050
- IV (2)	0.273*	0.151	-0.286**	0.136
- panel-other/pool (3)	0.056	0.000	-0.068	0.068
Clustered std. errors (1)	0.021	-0.017	-0.020	0.037
Nr. of climatic variables	-0.019***	-0.008**	0.021***	-0.012***
Nr. of controls	0.002	-0.003	-0.003	0.006***
Income-related controls (1)	-0.121**	0.025	0.126**	-0.151***
Polit. stability-related controls (1)	-0.040	0.030	0.024	-0.054
Main model (1)	-0.016	-0.011	0.024	-0.013
Observations	3625	3625	3625	3625

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * p<0.10, ** p<0.05, *** p<0.01.

Table 11: Meta-analytic probit (1) and multinomial probit (2) models - no weights

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	-0.016	-0.054	0.025	0.030
- extreme (2)	-0.025	-0.140***	-0.003	0.143
Precip. decrease - moderate (1) / ref.: no precip. (0)	-0.138*	-0.087**	0.143*	-0.056
- extreme (2)	-0.083	-0.137***	0.077	0.060
Drought (1)	-0.048	-0.140***	0.011	0.129
Sea level rise (1)	-0.283***	-0.149***	0.252***	-0.103
Flood (1)	-0.234***	-0.080**	0.246***	-0.166***
Hurricane/cyclone/typhoon (1)	-0.146*	-0.094***	0.147*	-0.053
Self-reported event (1)	-0.064	0.010	0.050	-0.060
Direct effect (1)	-0.031	-0.069***	0.030	0.039
Study-level variables				
Author: female (1)	0.024	-0.037	-0.018	0.055
Author - economics (1)/ref.: other (0)	0.054	-0.077	-0.040	0.117***
- geography (2)	-0.065	-0.177***	0.051	0.126*
- sociology (3)	-0.121	-0.089	0.120	-0.031
Year of publication/ latest draft	-0.017**	-0.010**	0.017**	-0.007
Peer-reviewed: yes (1)	-0.005	0.047*	0.012	-0.059*
Sample characteristics				
Micro-level analysis (1)	-0.032	0.008	0.032	-0.040
Multiple countries (1)	-0.009	-0.041	0.022	0.019
Low income included (1)	0.002	-0.003	-0.002	0.004
Lower-middle income included (1)	-0.058*	-0.055***	0.056*	-0.001
Higher-middle income included (1)	0.069**	0.009	-0.068**	0.059**
Migration-related variables				
Origin - urban (1)/ ref.: rural (0)	-0.214**	-0.131***	0.212**	-0.081
- undefined (2)	0.006	-0.012	0.000	0.012
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.048	-0.034	0.034	-0.000
- undefined (2)	-0.004	-0.009	0.001	0.008
Dest. 2 - urban (1)/ ref.: rural (0)	-0.084	-0.086	0.096	-0.010
- undefined (2)	-0.004	-0.051	0.007	0.044
Temporary (1)	0.113	0.003	-0.102	0.100
Measurement - bilateral (1)	-0.115***	0.005	0.112***	-0.117***
Migrants - male (1)/ ref.: female (0)	0.054	0.038	-0.054	0.016
- households (2)	0.244***	0.145***	-0.232***	0.087*
- overall (3)	0.196***	0.066	-0.197***	0.131***
- other (4)	0.270***	0.086*	-0.267***	0.181***
Econometric modelling variables				
Approach - panel-causal (1)/ref.: cross-section (0)	-0.072	0.019	0.064	-0.083*
- IV (2)	0.015	0.087	-0.040	-0.047
- panel-other/pool (3)	0.025	0.036	-0.028	-0.008
Clustered std. errors (1)	0.030	0.006	-0.015	0.009
Nr. of climatic variables	-0.015**	-0.001	0.013*	-0.012*
Nr. of controls	-0.003	-0.003*	0.003	-0.001
Income-related controls (1)	-0.024	0.031	0.020	-0.051
Polit. stability-related controls (1)	-0.001	0.081**	-0.002	-0.078**
Main model (1)	0.014	0.002	-0.011	0.009
Observations	3625	3625	3625	3625

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * p<0.10, ** p<0.05, *** p<0.01.

Table 12: Meta-analytic probit (1) and multinomial probit (2) models - panel studies only

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	-0.025	-0.141**	0.061	0.079
- extreme (2)	-0.167*	-0.231***	0.108	0.123
Precipitation decrease (1)	-0.085	-0.135**	0.121	0.013
Drought (1)	-0.083	-0.193***	-0.009	0.201
Flood (1)	-0.208***	-0.134***	0.212***	-0.078
Hurricane/cyclone/typhoon (1)	-0.188*	-0.168***	0.200*	-0.033
Direct effect (1)	-0.029	-0.079	0.041	0.038
Study-level variables				
Author: female (1)	-0.010	-0.078*	0.023	0.055
Author: economics (1)	0.120	0.025	-0.088	0.063
Year of publication/ latest draft	-0.012	0.002	0.020	-0.022
Peer-reviewed: yes (1)	-0.085	-0.001	0.122**	-0.121*
Sample characteristics				
Micro-level analysis (1)	-0.088	-0.015	0.058	-0.043
Multiple countries (1)	0.045	-0.059	-0.062	0.121
Low income included (1)	0.020	-0.028	-0.016	0.044
Lower-middle income included (1)	0.008	0.020	-0.026	0.006
Higher-middle income included (1)	0.113*	0.026	-0.085	0.059
Migration-related variables				
Origin - rural (1)	0.052	0.003	0.010	-0.013
Dest. 1 - internat. (1)/ ref.: internal (0)	-0.138	0.047	0.163	-0.210**
- undefined (2)	0.112	0.014	-0.110	0.096
Dest. 2 - urban (1)/ ref.: rural (0)	0.160***	-0.025	-0.144*	0.169**
- undefined (2)	0.181*	0.050	-0.180*	0.129**
Measurement - bilateral (1)	-0.117***	-0.042	0.117***	-0.076
Migrants - male (1)/ ref.: female (0)	0.211***	0.112***	-0.180***	0.068
- households (2)	0.323	0.255*	-0.213	-0.042
- overall (3)	0.355***	0.158***	-0.294***	0.136
- other (4)	0.499***	0.307***	-0.471***	0.164*
Econometric modelling variables				
Nr. of climatic variables	-0.012	0.000	0.009	-0.009
Income-related controls (1)	-0.077	0.057*	0.072	-0.129***
Main model (1)	0.016	0.019	-0.031	0.011
Observations	1524	1524	1524	1524

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * p<0.10, ** p<0.05, *** p<0.01.

Table 13: Meta-analytic probit (1) and multinomial probit (2) models - international migration

	(1)	(2)		
	Significant effect	Decrease	No effect	Increase
Climatic variables				
Temp. increase - moderate (1) / ref.: no temp. (0)	0.153*	0.074*	-0.160*	0.086
- extreme (2)	0.124	-0.072	-0.120	0.192
Precip. decrease - moderate (1) / ref.: no precip. (0)	0.115	0.025	-0.114	0.089
- extreme (2)	0.093	0.063	-0.107	0.045
Drought (1)	0.077	0.016	-0.087	0.072
Observations	1256	1256	1256	1256

Coefficients in model 1 capture the rate of change in probability of finding a significant effect of adverse climatic events on migration. Coefficients in model 2 capture the rate of change in probability of finding a significantly negative (1), no (2) or significantly positive (3) effect of adverse climatic events on migration. Std. errors are clustered at the study-level (not reported). Both models also control for decade-specific dummies. In the interest of space and because we do not find strong results the coefs. are not reported. The full set of results is available upon request. * p<0.10, ** p<0.05, *** p<0.01.

F Differences in model specifications

Section 5.1, sub-sample for **temperature-related effects**: In this more restricted sample, the following variables were causing multicollinearity problems: *Origin*, *Destination 2*. Thus, they were omitted from the analysis. The meta-analytic model also includes decade-specific dummies that cover the time dimension of the sample analyzed. In the interest of space, these dummies are not reported.

Section 5.1, sub-sample for **precipitation-related effects**: In this more restricted sample, the following variables were causing multicollinearity problems: *Nr. of controls*, *Self-reported*, *Micro-level analysis*, *Temporary* and *Measurement*. Thus, we did not include these variables in the analysis. The meta-analytic model also includes decade-specific dummies, which do not show any strong results. In the interest of space, these dummies are not reported.

Section 5.1, sub-sample for **drought-related effects**: In this more restricted sample, the following variables were causing multicollinearity problems: *Year of publication/latest draft*, *Low income included*, *Upper-middle income included*, decadal dummies, *Measurement - bilateral*, *Temporary*, *Destination 2*, *Nr. of climatic variables*, *Nr. of controls*, *Main model*, *Income-related controls* and *Polit. stability controls*. Thus, we did not include these variables in the analysis. Further, since the categorical variable capturing authors' disciplines was causing multicollinearity problems, we generated a binary variable capturing whether the lead author is an economist (*Author: economist*) or not. Similarly, the categorical variable capturing migration origin, destinations, domain and approach, as used in the main analysis, were causing multicollinearity problems, so we generated binary variables capturing whether the migration origin is rural (*Origin - rural*); migration destination is internal (*Dest. - internal*), whether the migration variable captures women (*Migrants - female*) and whether an effect is derived from a model using causal inference *Panel-causal*.

Section 5.1, sub-sample for **flood-related effects**: In this more restricted sample, the following variables were causing multicollinearity problems: decadal dummies, *Lower-middle income* *included*, *Destination 2*, *Measurement - bilateral*, *Clustered std. errors*, *Nr. of controls*, *Income-related controls* and *Polit. stability controls*. Thus, we did not include these variables in the analysis. Further, the categorical variable capturing authors' disciplines was causing multicollinearity problems, so we generated a binary variable capturing whether the lead author is an economist (*Author: economist*) or not. Similarly, categorical variables capturing migration origin, destinations and domain, as well as variable *Approach* used in the main analysis, were causing multicollinearity problems, so we generated binary variables capturing whether the migration origin is rural (*Origin - rural*); whether the migration variable captures women (*Migrants - female*); and whether a coefficient is derived from a model using causal inference (*Panel - causal*).