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A Meta-Analysis of the Literature on Climate Change and Migration

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A Meta-Analysis of the Literature on Climate Change and Migration.*

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Abstract

Recent surveys of the literature devoted to climate change and migration emphasize the important diversity of outcomes and approaches of the empirical studies. In this paper, we carry out a meta-analysis in order to investigate the role of the various methodological choices of these empirical studies in finding some particular results concerning the role of climatic factors as drivers of human mobility. To that aim, we code 45 papers representative of the existing literature in terms of methodological approaches. This results in the coding of more than 80 variables capturing the methodology of the main dimensions of the methods. These dimensions include among others authors' reputation, type of mobility, measures of mobility, type of data, context of the study, econometric methods and last but not least measures of the climatic factors. We look at the influence of these characteristics on the probability of finding any effect of climate change, of finding a displacement effect, of finding an increase in immobility and of finding evidence in favour of a direct versus an indirect effect. Our results highlight the role of some main methodological choices, such as the frequency of the data on mobility, the level of development of the covered area, the particular measures of human mobility and of the climatic factors as well as the econometric methodology.

JEL Classification: C83, F22,J61, Q54 .

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1 Introduction

There is some increasing scientific evidence that our climate is changing and that more adverse climatic conditions will affect human activity over the world in the future. In front of this, social scientists have paid attention to the way individuals can cope with these adverse developments. The Stern report in 2007 looked at the global consequences of climate change, suggesting that many countries could suffer from the adverse developments related to changing climatic conditions. The first United Nations intergovernmental report on climate change emphasized that human migration might be the most important consequence of climate change, especially in developing countries.

A noticeable prediction of climate change on human mobility was the one of Myers (2002) who predicted that by 2050, climate change would displace more than 200 million individuals. While such a prediction did not rely mainly on scientific calculations, it reflected that human mobility was already seen as one of the most obvious adjustment mechanisms to cope with the adverse consequences of this evolution of climatic conditions.[1] Early views on the topic started from the idea that a large number of people would be forced to move. In order to refine these dire predictions and give credit to these early views, social scientists have over the subsequent years attempted to look at the possible relationships between climate change and human mobility. These scientific attempts have been facilitated by the growing availability of data needed to investigate the complex nexus between these two phenomena. On the one hand, data on climatic factors have become more available. As reported by Berlemann and Steinhardt (2017), this holds both for data concerning slow onset climatic factors such as warming and rain precipitations and for measures of the fast onset climatic shocks, i.e. the natural disasters. On the other hand, the scientific literature have also taken advantage of the growing availability of data on human migration, both at the macro and the micro levels.

The key question raised in this literature is quite simple: to what extent do climatic conditions lead to the displacement of people from their initial location? While the basic question is quite simple, the answers provided by the set of empirical studies in this area are much more complex. It is not straightforward to summarize the main finding of that extensive literature given the significant degree of heterogeneity, both in terms of results and in terms of approaches. Recent surveys (see Millock (2015), Berlemann and Steinhardt (2017),Cattaneo et al. (2018) and Piguet et al. (2011) among others) have tried to summarize the whole literature. They all emphasize the diversity in terms of findings and methods used in this literature. While a substantial proportion of papers find some evidence that climatic shocks tend to displace people, a significant number of findings reach different conclusions. A number of papers find that the connection between climate shocks at origin and movement of people initially located in this area is very weak. Also, the recent literature has also emphasized that in a number of cases, the occurrence of adverse climatic developments

[1] In a similar perspective, in a more recent study, Missirian and Schlenker (2017) predict a strong increase in the number of applications from climatic refugees as a result of increasing temperatures in developing countries. The forecasted increase would imply a number of annual applications to the European Union ranging from 400000 to 1 million at the 2100 horizon.

reduces rather than enhances the mobility of the affected population. These findings are in line with the concept of trapped population put forward by a number of contributions (see among others Black et al. (2012)).[2] This conclusion in turn drew the attention of important institutions devoted to development issues such as the United Nations and the European Commission and has been advanced as one of major current and future issues related to climate change.

A further complication of this empirical literature is the diversity of outcomes that are considered in the various analyses. While a lot of papers simply look at the mere displacement effect, other studies make a clear distinction between direct and indirect influences of climatic shocks (see Cattaneo et al. (2018) for example for a discussion). An additional distinction concerns the difference between partial and total effects of climatic factors on mobility.[3] The surveys of the literature report the significant diversity in terms of outcomes. This diversity is not totally surprising since one can reasonably expect that the effect of climatic shocks on the propensity to move from individuals might be context dependent. The way these shocks operate might depend on the level of development of the area, the type of economic activity, the various possible adaptation mechanisms and last but not least the availability of external options.

A complementary explanation of the observed heterogeneity is that findings might also depend on the methodology adopted in the empirical strategy of each paper. Recent surveys of the literature also emphasize this important source of heterogeneity. A specific paper in this literature is at the crossroad of a myriad of methodological choices underlying the empirical analysis. These methodological options concern many dimensions, including the type of country covered, the type of the key data that are used, the period of investigation, the measurement of human mobility and of the climatic shocks or the adopted econometric methodology. While most recent surveys of the literature emphasize the heterogeneity of its results, they do not look, at least explicitly, at the relationship between the results and the methodology adopted. This paper tries to fill this important gap.

In order to highlight the links between the various dimensions of the adopted methodologies and the findings of climate shocks on mobility, we conduct a meta-analysis of the literature. We understand the term methodology in a broad sense since we include not only in that concept the choice of data or statistical methods but also the context in which the studies were conducted. This for instance includes whether the area is located in a developing country or not, whether the type of mobility is within a country or across different countries or the type of climatic conditions under investigation. We also give details about the exact structure of each regression used to generate the findings. Therefore, our paper

[2]Noy (2017) documents this phenomenon of immobile populations in the specific case of Tuvalu. Koubi et al. (2018) find negative econometric effects of slow (droughts and salinity) and fast onset (floods and storms) factors for a subset of individuals in five developing countries.

[3]Beine and Parsons (2017) emphasize this distinction, arguing that failure to find some significant displacement effects might be due to the fact that some papers look at the partial effects of climatic shocks on top of those on other determinants of mobility. In the same spirit, Berlemann and Steinhardt (2017) emphasize the risks faced by some part of the literature of over-controlling for determinants of mobility that could be affected by climatic conditions.

aims at providing guidelines for the authors in that literature but also answers to more general questions. One of these important questions is whether there is more evidence of a displacement effect of climatic shocks within a country than across countries. Another one is whether the evidence of displacement effects is specific to developing countries.

In terms of details, we include in the meta-analysis 45 empirical papers that are representative of the existing literature on climate change and migration. We include published and unpublished papers, but restrict our attention to papers using econometric methods looking at the potential displacements effects exerted by climate shocks. These 45 papers give rise to about 1300 regression results that we code along a large number of dimensions. These dimensions include the context of the study, the adopted methods, the type of data and measures of the key variables as well as the exact type of outcomes that the study tries to capture. The coding of these dimensions results in more than 85 different variables that are used subsequently as potential variables in our regressions. We look in particular at the impact of these dimensions on the probability that a regression concludes in favour or not of a particular effect of climate change on human mobility. To that aim, we adopt a range of econometric models suited to limited dependent variable such as the pooled logit model, the panel logit model with random individual effects and the (pooled) order logit model.

Our results show that in general, results of the literature depend on a large variety of dimensions in terms of methodology and context of the study. The results depend on variables belonging to each broad category in terms of methodology. To illustrate, we find that results tend to depend on the context since there is more evidence of an effect of climatic factors in an area located in a developing country. In contrast, we do not find that studies looking at internal displacement effects find systematically more effects than those looking at international mobility. Results depend on the way mobility is measured in the sense that papers using direct measures of migration find on average more evidence of an effect. Measures of climatic factors tend also to influence the results, albeit in a complex way. For instance, while we find few evidence that a specific type of natural disaster is more associated to a displacement effect, we find that the way slow onset and fast onset factors are actually measured has an influence on the results. A final illustration concerns the choice of the econometric method, as we find that papers using panel data and accounting for measurement errors through instrumental variables tend to find more evidence of an effect on mobility. Another important finding is that papers allowing for conditional effects of climate shocks, i.e. effects depending on a specific condition, find aslo more evidence of an impact.

The paper is organized as follows. Section 2 gives a detailed description of how we code the literature and provides descriptive statistics gauging the representativeness of our sample. Section 3 explains how we carry out the meta-analysis and gives the results of our regressions with respect to the various outcomes of the literature. Section 4 summarizes the implications of our results and provides some concluding remarks.

2 Coding the literature

Our dataset consists of 1307 regression results extracted from 45 papers. These regression results represent our unit of analysis in the subsequent evaluation of the impact of the methodology on the findings. We provide here a short description of all the variables used in the meta-analysis. The codebook of all coded variables, including those which are not used in this paper is provided in the Appendix B.

2.1 Coding the evidence of an effect of climate on migration

An important information that we extract from each regression is whether there is evidence of an effect of climate change on migration. The existence of an effect is coded when a coefficient relative to a specific climatic factor is significant at least at the 10% level in the regression involving mobility and these climatic factors. This outcome can be then further decomposed into various categories depending on whether the effect is direct or not and whether the effect is positive or negative.

Direct effect is a binary variable equal to one if we find a significant direct effect of climate on migration in the regression. A direct effect is found if there is a direct causal link between a climate variable and migration in the regression, for example a wave of extreme temperature leading to emigration. Nevertheless, there might be also evidence of an indirect effect of climate on migration, which is captured by the binary variable *Indirect effect*. We identified two scenarios of indirect effect in the literature. The first one is when the authors do additional regressions to highlight one specific channel through which climate impacts migration. For example rainfall variability might impact mobility through its effect on GDP per capita (Coniglio and Pesce (2015)). The second one is when the authors use climate variables as instruments in a two-stage regression. An example is provided by Feng et al. (2010) who use climate variables to instrument the effect of crop yields on migration.

Direct and indirect effects can be further decomposed either as a *positive effect* (evidence of a displacement effect) or as a *negative effect* (evidence of increased immobility) using binary variables. To code if an indirect effect is either positive or negative we rely on the other results of the paper, such as the results from auxiliary regressions. For instance, if at the same time the authors find in an auxiliary regression that a climate shock decreases crop yields and in their main regression that a decrease in crop yields increases migration, we code the indirect effect as a positive effect.

Since many regressions include several different climate measures at the same time, some choices have to be made in terms of coding. We code a direct/indirect effect if at least one of the climate variables is significant. In the specific case of opposite results of several climate variables, we duplicate the regressions results. Some regressions have indeed negative and positive displacement effects at the same time. This is also the case in the multinomial regressions analyzing the effect of climate on several levels of migration (local, internal and international). If different results were found in one regression, it was duplicated and coded once as a positive effect and once as a negative effect. The binary variable *Split* keeps track of the fact that the regression results come from a splitting procedure.

2.2 Coding climate related measures

While each paper displays some specificity regarding the way the climate variables are included in the regressions, these variables can all be classified into several broad categories. To start with, they can be classified into long-run (slow onset) and short-run (fast onset) climatic factors. To control for the fact that some papers include both long and short-run variables in the same regression, we define the binary variable *Joint Inclusion*.

2.2.1 Capturing the slow onset climatic factors

The variable *Long Run* captures that the regression includes long-run climate measures. Regarding the long-run effects, we identified four measures of temperature and four measures of rainfall that span the whole spectrum of measures used in the empirical literature:

- Temperature or precipitation *levels* (see for example Cattaneo and Peri (2016));
- Temperature or precipitation *deviations* (see for example Beine and Parsons (2015));
- Temperature or precipitation *anomalies* (see for example Beine and Parsons (2015));
- Temperature or precipitation *variability* (see for example Coniglio and Pesce (2015)).

More recently authors have relied on a soil moisture measure which we code separately as *Soil Moisture*. This measure is usually based on the Standard Precipitation Evapotranspiration Index (SPEI). It aims at combining rainfall and temperature in a single variable (see for example Mastrorillo et al. (2016)). We also create a dummy variable labeled *joint_ temp_ rain* capturing whether the regression includes jointly factors in terms if rainfall and temperature.

2.2.2 Capturing the fast onset climatic factors

The fast onset climatic factors considered in the literature usually belong to the category of natural disasters. We create a *Natural disasters* binary variable taking unity if the regression includes short-run climate factors. Most papers looking at the effect of natural disasters focus on one particular type of climatic event. Six specific climate related disasters tend to emerge in the literature. Among these 'popular' disatsers, earthquakes are definitely worth being investigated but it is unclear and subject to controversy if earthquakes are related to climate change. We therefore disregard earthquakes as specific disasters under investigation. We therefore consider the following specific types of disasters:

- Extreme temperatures (see for example Hirvonen (2016)).
- Extreme precipitations (see for example Thiede et al. (2016)).
- Floods (see for example Ruiz (2017)).
- Hurricanes and storms (see for example Koubi et al. (2016a) or Mahajan and Yang (2017)).

- Droughts (see for example Ruiz (2017) or Dallmann and Millock (2017)).

Additionally, we coded three variables to capture the way each considered disaster were measured and coded in the original paper. The variable *Count* takes 1 if the authors use the aggregate number of events over a period of time (see for example Beine and Parsons (2015)). *Intensity* takes 1 if the authors use an intensity measure of the disaster such as the number of affected people or the amount of damages (see for example Bohra-Mishra et al. (2014)), and *Duration* takes 1 if the authors use a measure of duration such as the number of consecutive months (see for example Dallmann and Millock (2017)or Ruiz (2017)).

2.3 Coding the dependent variable

We created four categories for the dependent variable that is used in the regressions of the literature. *Direct measure* is a binary variable capturing if migration is directly observed and measured. Examples for direct measures of migration can be found in survey data in which individuals are directly asked about their migration history (see for instance Gray and Bilsborrow (2013)). It can also be measured directly for instance when the administrative data reports the origin and the timing of the movements of people. In contrast, when mobility is inferred, the variable *Direct measure* takes teh zero value. This for instance the case when migration flows are builts from differences in migration stocks captured from Census data. Researchers also use different dependent variables to infer the impact of climate change on mobility. The dependent variable might capture a flow (*Migration Flow* (see Coniglio and Pesce (2015)), or a rate (*Migration Rate* (see Beine and Parsons (2015)) or another measure proxying mobility *Other*. *Other* can either be a alternative measure of migration or a dependent variable different from migration such as the rate of urbanization which proxies internal migration in absence of such a measure (see Barrios et al. (2006)). It can also be variables used in auxiliary regressions to capture specific channels of influence.

2.4 Coding the channel

As discussed previously, some authors analyze through which channels the climate variables affect migration. A specific channel is highlighted in different cases. The first one is when the dependent variable is not migration (for example Crop yields, or GDP per capita). The second case occurs when there is an interaction term between climate variables and another variable that refers to a specific channel. We code four main channels considered in the literature: the economic channel (Beine and Parsons (2015)), the agriculture channel (Cattaneo and Peri (2016)), other channels (such as the urbanization channel, see Marchiori et al. (2012)) and in case no channel is specifically highlighted, an aggregation of channels.

2.5 Coding Mobility

We identified three types of mobility in the literature and coded them using three binary variables. Internal migration and international migration make up for the majority of the sample but some authors also analyze local displacement (e.g. migrants moving from one village to another one).

2.6 Coding the data

We code various features of the characteristics of the data used in the regressions. The variable *Developing only* is a binary variable capturing if the regression is based on a sample of observations involving only developing areas as origins of the potential emigrants. We capture the frequency of the data as well. This variable is expressed in years. In the case of a cross-section, the frequency is set to 0. If the length between each wave of data differs, we take the average frequency (see for example Gray and Mueller (2012b)). The variable *Cross Country* identifies if the regression uses cross-country data. The starting time of the sample as well as the time span of the sample are coded as well. [4] The time span variable is expressed as the number of years of the period under study. If the data is dyadic, i.e. they capture bilateral movements from a given origin to a given destination, it is captured by the binary variable *Dyadic*.

2.7 Coding the context of the regression

A number of characteristics of each regression are also coded. The variable *Theory based* is a binary equal to one if the empirical analysis is derived from a theoretical model such as the Random Utility model which is often the underlying framework for the gravity regression models. We coded the binary variable *Main* as being equal to one if the regression belongs to the core of the econometric analysis, as opposed to being involved in a robustness analysis. We code the regression to be an *Auxiliary Regression* if the dependent variable is not directly related to migration. Many authors run auxiliary regressions to highlight the underlying channel rationalizing their findings. The binary variable *Elasticity* is equal to 1 if the estimated coefficient is an elasticity or a semi-elasticity. If the regression is restricted to a sub-sample, for example some regressions being run for male migrants only or in a subset of countries, the binary *Conditional Sample* equals one. If the climate variable is interacted with another variable to highlight a certain channel (for example rainfall level interacted with Sub-Saharan countries as in Barrios et al. (2006)), the variable *Conditional Regression* takes unity. Finally we include a binary variable to identify if the regressions control for additional variables not related to climate.

2.8 Coding the context of the study

Several characteristics of the context of the study were coded for each paper. Some of them are self-explanatory, such as the number of authors, the year of publication and whether the paper is published in a peer-reviewed journal or not. If the paper is published, we capture

[4] The starting time can be interesting to trace the period over which the study is conducted (it is claimed that migration is an increasing phenomenon), which allows to see if more recnt studies tend to find more evidence of displacement.

the impact factor of the journal as reported on the journal's webpage. We also capture the number of citations and the average and maximum h-index of the authors reported by Google Scholar. This information was coded around the same time for all papers.

2.9 Coding the estimation technique

The most popular estimation techniques in the literature are coded as binary variables. *Panel* takes 1 if the paper uses panel data along with panel specific techniques. *IV*, *OLS* , *Poisson* and *Multinomial logit* capture regression techniques using instrumental variables, ordinary least squares, Poisson and Multinomial Logit models respectively.

2.10 Representativeness

The aim of our analysis is to uncover the complex links between the methodological approaches and the results. The choice of the papers included in our analysis results from a specific strategy aimed at yielding a sample of empirical studies as representative of the literature as possible. This choice is also significantly constrained by the amount of work needed to code each regression. While the inclusion of 45 papers might seem too restrictive at first glance, it is worth emphasizing that the coding of these papers took about 2 months of work in total, which means more than one day of coding per paper.

First, we include only empirical papers making use of econometric techniques to identify any possible link between climatic factors and mobility. In that respect, we exclude papers studying the possible effects based on quantitative models of migration (see for instance Burzynski et al. (2018)) even though they estimate a subset of the parameters used to simulate expected impacts of projected climatic conditions. Second, among the econometric papers, we take only those quoted in the recent surveys of the literature mentionned before. This allows to set an implicit minimal level of perceived quality of the included papers and avoid to include more "esoteric" studies. Finally, in order to be able to pin down the methodologies that could explain the variation in the obtained findings, we make sure that we have a more or less balanced sample of regression results in terms of the main methodological approaches. Tables 1 and 2 provide evidence that our sample of regressions is more or less balanced in terms of these main methodological approaches.

Tables 1, 2 and 3 provide a set of descriptive statistics computed from our unit of analysis (regressions) on the main methodological dimensions. Table 1 reports the proportion of regressions with a specific characteristics captured through a dummy variable. Tables 2 and 3 provide the mean of the continuous covariates of our regressions (such as the specific measures of the climatic conditions). Table 19 reports in the appendix the list of the 45 empirical papers from which these regression results are extracted.

For the main dimensions, our sample of regressions generate enough variability in order to identify the impact of these methodological choices on the outcomes. By main dimensions, we mean the fact that (1) the paper is published or not, the fact that (2) the regressions use conditional regression models or not, (3) use conditional samples or not, the fact that they look at (4) international mobility or not, (5) internal mobility or not, (6) the fact they are based on some theory, (7) they cover developing countries only, (8) they use cross-country data or (9) different types of individual data (households, individual agents, ...). Another important dimension is (10) whether mobility is directly measured or not and (11) the way the dependent variable capturing mobility is expressed.

Tables 1 and 2 report the proportion of categorical variables taking 1. For some of these, we should not expect to have an equal allocation across the possible values. For instance, the fact that about a quarter of the regressions in our sample finds a negative effect of climatic factors on mobility suggests that this result is far from being anecdotical, even though a majority of regressions do not conclude in favour of such a result. Likewise, the fact that 46% are based on a theoretical framework shows that the literature pays some decent attention to the underlying theories, even though the majority of regressions are mostly data driven.

All in all, while we do not claim that this sample is fully representative of the exhaustive literature (the population of these regressions is rather unknown to most of the researchers), the fact that for most of the main methodological options there is no significant imbalance in favour of one particular option allows to produce the variability needed to estimate their influence.

3 Results

3.1 Econometric approach

In order to investigate the impact of methodology on the results in the academic literature, we carry out a meta-analysis relating these results to a set of key characteristics of these approaches. It is important to understand that the unit of the analysis is at the level of regression. We have basically 45 coded papers, leading to 1307 regression results. In order to get robust results, we conduct two different econometric procedures. We focus on the common results generated by both econometric approaches. The first one relies on a logit specification, pooling all regressions together:

$$Prob(y_{ij=1}) = \Phi(x'_{ij}\beta) + \epsilon_{ij} \tag{1}$$

where $Prob(y_{ij=1})$ is the probability that regression j in paper i gets a specific outcome y, x_{ij} is a vector of characteristics of regression j in paper i,β is a vector of parameters to be estimated.$\Phi()$ is the logistic function and ϵ_{ij} is an *iid* error term. In order to account for the underlying correlation between regressions of the same paper, we cluster the standard errors of the β coefficients at the paper level. A panel approach with paper fixed effect is obviously unfeasible, given the low variability between regressions of the same paper. Nevertheless, we can account for unobserved heterogeneity using a panel regression model with (paper) random effects (RE). The RE logit model takes the following form:

$$Prob(y_{ij=1}) = \Phi(x'_{ij}\beta + c_i) + \epsilon_{ij} \tag{2}$$

with c_i is the set of random effects at the paper level, with no particular assumption about how these are related to the x_{ij} (see Wooldridge (2010), chap. 15 for a discussion).

3.2 Explaining outcomes of studies

In this section, we look at the impact of the methodological choices in terms of the results. We consider a large variety of outcomes : evidence of any effect, direct vs indirect effect, positive, negative or no effect on mobility. We consider the main features of the analyses, such as the type of data, the econometric methods or the way they capture and measure mobility. Given the large set of potential factors, we do not consider here the issues of the specific modelling choices of climatic factors, which is also an important issue. This will be investigated in more details in the subsequent section.

3.2.1 Probability of any effect

Tables 4 through 7 report the estimation results concerning the impact of methodology on any type of effect of climatic factors. By any type, we mean that the effect can be positive (displacement effect) or negative (increase in immobility), direct or indirect. Table 4 and 5 report the results using all regression results while Tables 6-7 are based only on a sample that excludes auxiliary regressions. Auxiliary regressions in that literature are usually conducted to provide a refined assessment of a previous piece of analysis, such as uncovering indirect effects in the case of little evidence of a direct one (see for instance Beine and Parsons (2017), Cattaneo and Peri (2016) or Feng et al. (2010)). Tables 4 and 6 use pooled logit estimates while results in tables 5 and 7 rely on the random effect panel estimation.

Our results bring support in favour of some influence of the various methodological categories. First, the way mobility is measured matters. In particular, we find that the use of migration flow rather than other measures (such as migration rates or proxies of mobility) increases the probability of finding an effect. The type of data used in the econometric analysis is definitely an important factor. Frequency plays a clear role: data sampled at higher frequencies tend to support more the case of an effect on mobility. Such a result is consistent with the fact that migration measures spread over several years might be less able to capture short-term movement of individuals in response to climatic conditions. We find also a role for a negative impact of the amount of time spanned in the study, albeit the interpretation is less obvious. Results form Table 6 suggest that a direct measure of mobility (rather than proxies or indirect measures such as differences in migration stocks) is also more likely to deliver significant results.

Second, the way regressions are conducted is also an important factor. The use of conditional regressions allowing the impact on mobility to be dependent on a specific condition (such as the importance of the agricultural sector) tends to generate more evidence of an effect. This finding tends to be quite robust across a lot of investigations that we carry out throughout this meta-analysis. The use of panel data along with the appropriate techniques tends to increase the probability of having some evidence of an effect. Relying on instrumental variable estimation (although its use remains quite limited in the literature) tends to generate more evidence of an effect. This might reflect that attenuation bias associated to measurement errors of the climatic factors is an important issue in this literature.

Third, the context of the study seems to play some role. The results clearly support a role for more recent analyses (see the negative effect of the starting period of the sample). This might reflect that migration plays a more important role over time as an adjustment mechanism but also that climatic shocks have tended to become more adverse over time. The context in terms of geographical coverage also matters. Analyses (excluding auxiliary regressions) involving mainly developing countries tend to find a more important role of mobility, which is in line with the perception that developing countries face a double risk in terms of climate change (Cattaneo et al. (2018)). Finally, while we do not really find a role for authors' reputation (through the use of some measures involving the h index), we find some evidence in favour of a small publication bias. We find some influence of a variable capturing the fact that the paper is published in a journal with a high impact factor in Tables 6 and 7. Nevertheless, the publication bias in this literature tends to be rather modest, as assessed by the insignificant effect of a simple variable capturing whether the paper has been published or not. Finally, excluding auxiliary regressions (results provided by Tables 6-7) generates the same type of results. The results tend to provide stronger evidence of an impact when considering developing countries only and emphasize further the importance of using a direct measure of mobility.

3.2.2 Probability of a direct effect

We carry out a similar analysis, but restricting our attention to evidence in favour of a direct effect of climatic factors. We therefore look at the probability of a direct effect as opposed to either no effect or an indirect effect. Tables 8 and 9 reports the results. In each table, columns (1) and (2) include the results using all regressions, while results in Columns (3) and (4) are obtained excluding auxiliary regressions as before.

The results are quite similar with those of Tables 4 through 7, which is not totally surprising given the fact that most regressions focus on direct effects. The identification of indirect effects has been considered in a few papers (6 out of 45 in our sample) and is often provided as a complementary piece of analysis to the core of the paper.[5] The results of Tables 8 and 9 emphasize the role of the starting period of time, of using conditional effects, of the frequency of the data, of the geographical coverage involving developing countries and of measuring directly mobility. On top of that, the results show that the use of dyadic data that are for instance involved in gravity models produces more evidence in favour of a direct effect.

[5]For this reason, we do not conduct any specific analysis of the indirect effect. Also, given that indirect effects are often analyzed through auxiliary regressions, the number of relevant observations on which such an analysis is based is more restricted (we have 144 auxiliary regressions in our sample). The results are nevertheless available upon request.

3.2.3 Probability of a displacement effect

We turn now to the investigation on the probability to find some displacement effect of climatic shocks, i.e. the fact that these shocks lead to an increase in human mobility. This is probably the effect that has received the most important attention from researchers in that literature. Tables 10 and 11 report the results. In each table, columns (1) and (2) report estimates aiming at looking at the probability of a positive effect. The alternative to a positive effect is therefore either no effect or a decrease in mobility triggered by climate shocks. In columns (3) and (4), the analysis looks at the impact on the probability of finding a direct displacement effect.

Most determinants that explained the probability of having an effect of any type or a direct effect tend also to explain the evidence in favour of a displacement effect. From the estimates in columns (1) and (2) of tables 10 and 11, variables relative to the starting time of the analysis, the publication in a good journal, the data frequency, the coverage of developing countries, the use of dyadic data and the adoption of IV estimation tend to provide more evidence of a displacement effect. In contrast, using conditional regressions does not seem to have some explanatory power, which suggests that this approach is relevant for both positive and negative effects of climate shocks in terms of mobility. The same holds for the direct measurement of mobility, the use of flows as the dependent variable in the regressions and the use of panel data estimation techniques. These methodological choices turn out therefore to be as important for uncovering displacement effects and the trapped population phenomenon recently emphasized in the literature.

When talking about the impact of climate change on migration, the most immediate effect people have in mind is probably the combination of a positive and a direct effect of climatic shocks. Still, such an effect results from the combination of two separate effects, which in turn might be influenced by different methodological choices. Columns (3) and (4) of Tables 10 and 11 show that a subset of the variables explaining the previous considered effect tend to explain the occurrence of this type of result. This is the case of the period of the analysis, the publication in a good journal, the data frequency, the coverage of developing countries and the use of direct measures of mobility. On top of that, additional methodological choices tend to lead to more evidence of a direct displacement effect. This is basically the case for regressions using cross-country data. Measuring mobility through other variables than migration flows (including proxies such as urbanisation rates) tends to lower the probability of such an effect. This result confirms that the measure of mobility is of tremendous important in this literature.

3.2.4 Probability of a negative effect

The issue of adverse climatic events such as natural disasters as shocks trapping the affected population has been increasingly emphasized by some authors, such as Black et al. (2012). Empirically, the case for finding negative effects of climate shocks on mobility, i.e. cases in which individuals tend to stay more on average in the affected area is not an isolated econometric fact. An increasing number of papers have documented such cases in a variety of contexts. Our sample of regressions reflect this trend. About 20% of our regressions report such an effect associated at least to one of the included climatic shock. In fact, a large majority of the papers (10 out of 45) included in our analysis tend to display at least one effect of this type, albeit some time in a isolated or subtle way.

In general, as reported by Table 12, we do not find many obvious patterns for generating negative effects of climate shocks. The only convincing feature is the use of conditional regressions. The possibility of conditioning the mobility effect on specific conditions (such as the level of income) increases the possibility of capturing the immobility effect of climate shocks.[6] This result is in line with the findings of some papers in favour of a liquidity conditioning effect of natural disasters for instance. Direct measures of mobility also seem, to a certain extent, to favour the results of some increased immobility, but this finding is not supported by the panel regressions. The results suggest that studies documenting the so-called trapped population effect come from quite heterogenous backgrounds in terms of the adopted methodology.

3.2.5 Ordered Logit estimates

In this section, we combine in a single regression the three possible outcomes on mobility in order to overcome the limitations of using binary alternatives. We carry out an ordered logit estimation with outcomes ordered with respect to an increase in mobility. The three modalities are therefore (i) evidence of a negative effect, (ii) no effect and (iii) evidence of a positive effect of climatic shocks on the propensity of people to move. This means that we look at the features in the analysis favouring either a displacement effect or a reduction in immobility of people. Of course, the combination of both effects in the same regression rests on a potentially strong assumption that implicitly considers the reduction of immobility and the increase of mobility as comparable effects. Nevertheless, such an analysis has the advantage of including all regressions in the same estimation on the one hand, and to overcome the limitation of binary alternatives (with alternatives capturing heterogenous situations) on the other hand.

The results allow to identify the methodological choices that favour a displacement effect of climate shocks. These include the fact that the paper is published in a journal with a high impact factor, the use of a conditional sample, the use of high frequency data, the use of dyadic data and the adoption of IV estimation. We should nevertheless emphasize that the fit of the ordered logit model remains quite low. This might reflect that mixing up the three possible outcomes in a single analysis relies on some strong assumptions that are not supported by the data.

3.3 Modelling choices of climatic factors

In this section, we focus on the influence of specific choices in terms of modelling and/or measuring climatic factors. This dimension is important and in the literature, there are

[6] This is the case for example in papers of Cattaneo and Peri (2016), Coniglio and Pesce (2015), Marchiori et al. (2012) and Gray and Mueller (2012a).

extensive discussions about the consequences of adopting particular measures of the climatic conditions.[7]

3.3.1 Joint inclusion of slow and fast onset factors

In this section, we raise a simple question: to what extent is it important to include jointly the slow onset factors such as gradual warming or decrease in rainfall and the fast onset climatic shocks such as natural disasters? There is to a certain extent a dichotomy in the literature. A first portion of the literature focuses specifically on the impact of gradual changes in the climatic conditions such as the increase in temperature, the decrease in average rainfall or the changes in the cyclical patterns of annual rainfalls. Other papers investigate the role of fast onset adverse climatic events. These papers look at the impact of various types of natural disasters. More recently, some papers have tried to integrate both types of factors in order to isolate their respective influence in a more convincing way. Nevertheless, it is unknown whether the joint inclusion of both factors exerts an actual influence on the findings.[8]

Table 14 reports the results. The key variable is the joint inclusion of the long-run and short-run factors ('joint inclusion LR-SR' variable in Table 14). In our sample, 10 papers and about a quarter of the regressions (23.3 %) jointly include both types of factors. Columns (1) and (2) look at the impact on finding any type of effect while columns (3) and (4) look at direct effects. As before, we use pooled and panel logit estimation. In order to keep the model parsimonious, we include only controls for which we found significant effects in the previous estimations of subsection 3.2.

The results dismiss the idea that failure to include both measures might significantly affects the results. In some sense it is some good news as it suggests that the findings emerging from the majority of papers that focus only on one factor are not subject to some bias due to the omission of the other factors. It is also a positive result to the extend that collecting appropriate measures of one type of factor is already an important and often tedious task.

3.3.2 Influence of modelling slow onset climatic factors

In Tables 15 and 16, we look at the role of modelling choices of slow onset factors. The literature does not display any strong consensus about the way researchers should model long-run climatic factors. As reported by Berlemann and Steinhardt (2017), most papers consider temperature and/or rainfall, but diverge on their specific measures. We therefore code basically these two main dimensions and capture the diversity of measures which are used in the literature. In that respect, authors use either levels of these factors, deviations from some long-run average (with or without scaling with variability measures) or measures

[7] See for instance Berlemann and Steinhardt (2017) and in particular their section 3.2 devoted to the way climate and disasters are measured in the recent empirical literature.

[8] A similar argument has been made by Auffhammer et al. (2013) who argue that failure to include jointly temperature and rainfall might generate an omitted variable bias in the assessment of the impact of climate change on economic outcomes. Here we focus on the distinction between fast and slow onset factors. The influence of jointly introducing rainfall and temperature is treated here below.

pertaining to variability of these factors. Another issue is whether the papers include jointly temperature and rainfall in their analysis. Auffhammer et al. (2013) claim that failure to include both factors can lead to an issue of omitted variables in the estimation of the economic impact of climate change. We also test whether this might have an impact on the mobility outcome. Related to that, in recent papers, researchers use measures of soil moisture which combines both type of long-run factors.

The results of tables 15 and 16 suggest that the way these long-run factors are modeled definitely plays a role. Studies relying on measures that capture the variability of precipitation seems more inclined to find an effect on mobility[9]. The opposite holds for regressions using soil moisture as a measure of long-run climate change. The use of deviations in temperatures tends to be associated with less evidence of a direct impact, either of any type or positive. In contrast, the use of rainfall deviations tends to deliver more evidence in favour of a direct and positive impact of these factors on mobility. We do not find that failure to account jointly for both long-run factors tend to influence the outcomes on mobility: the joint_temp_rain variable capturing the joint presence of rainfall and temperature measures is never significant in any regression.

3.3.3 Influence of modelling natural disasters

We look at the role of the way fast onset factors, namely natural disasters, are captured in empirical studies on the impact of climate change. In this section, we look at the way these natural disasters are measured and disregard the type of natural disaster. The benchmark reference level is the simple occurrence of at least one natural disaster in each period of time. To overcome the simplicity of the simple occurrence measure, papers use different alternative measures : the number of these events over the period of investigation (aggregate count), a measure of intensity such as the number of casualties of affected individuals (intensity) or a measure of duration (such as the proportion of the period subject to such a natural disaster).[10]

Table 17 reports the estimation results regarding these features. We look at the three possible outcomes (any effect, direct effect and direct displacement effect), using as usual pooled and panel logit regressions. Among the alternative measures of natural disasters, taking into account the duration of the disaster seems important to capture a possible effect of these events on the mobility of individuals. Studies using a duration measure of natural disasters tend to find more evidence in favour of an effect on mobility, and to a less extend more evidence of a direct displacement effect.

3.3.4 Influence of type of natural disasters

Finally, we look at whether some specific natural disasters tend to be more associated to evidence of a mobility effect of these events. While there are numerous types of various

[9]See for instance Coniglio and Pesce (2015).

[10]Interestingly Ruiz (2017) provides a sensitivity analysis for all different measures of natural disasters in the context of the impact of droughts and floods in Mexico.

disasters, we restrict our attention to the most used ones in the literature. Table 18 reports the results of this investigation. The structure of this table mimics the one of Table 17, with the exception that the last two columns (5) and (6) which report the impact for a displacement effect instead of a direct displacement effect. To sum up the main findings, we do not find some robust evidence that a particular type of disaster is more (or less) associated to an effect of these events in terms of mobility, with the exception of disasters classified as extreme temperatures. Studies focusing on extreme temperatures find less evidence that such a shock has an impact on the mobility of people. Nevertheless, the whole picture still remains, in that no particular disaster seems to be more prone to induce some effect on mobility of populations.

4 Conclusion

This paper provides a meta-analysis of the empirical literature devoted to the identification of the complex link between climatic factors and mobility of people. This literature has reached very different results in terms of the effect of climatic shock on the propensity of people to relocate elsewhere. This diversity of results is reflected by the fact that a significant subset of papers conclude in favour of the three possible outcomes with respect to this basic relationship. While some papers find evidence of a displacement effect, others find either no evidence of an effect of climate shocks or an opposite effect, i.e. adverse climatic developments increasing the immobility of the affected individuals. As such, this diversity is not surprising given the large range of different contexts that are covered in the literature. Our meta-analysis allows to investigate the specific role of the adopted methodology in explaining specific results obtained in the empirical studies, on top of the context dependent findings.

In our analysis, the term methodology encompasses many dimensions. We start from the fact that each regression in each paper is at the crossroad of a large set of various methodological choices that can potentially affect the findings. We indeed code a large set of characteristics in terms of methodological approaches adopted in each paper and each regression used to assess the impact of climate change. We look at the type of mobility that is considered in each regression. We code the type of data and measures used to capture mobility of individuals. The same applies to the way climatic variables are modelled in the various papers of the literature. Our analysis takes into account the context of the study (e.g. whether it concerns a developing country or not). We also code the context of each regression (e.g. use of a conditional sample). We also pay attention to the econometric methods. Finally, we look at the characteristics of the authors such as their previous citations and the reputation of the journals when the paper is published. One of the goals of our analysis is to identify the most important features of the empirical studies in this literature that can lead to more (or less) evidence of a displacement effect of climate change.

Our results emphasize the importance of the various broad categories of methodological choices. First, the adoption of particular measures matters a lot in this literature. Using high frequency data such as annual data allows to capture the short-run mobility of people, which obviously increases the probability of finding an effect. The use of direct measures of mobility is also important. Measures of mobility computed or derived from proxies tend to generate less evidence in favour of an effect. The use of migration flow as the dependent variable in the regressions also increases the probability of finding an impact. The way climatic factors are modeled and measured turns out to play some role, too. The way slow-onset factors such as temperature and rainfall variations are measured is also important. Using variability and deviations in rainfall tend to deliver more evidence of an effect. The opposite holds for the use of deviations in temperatures as well as for the recent use of soil moisture which aims at combining warming and precipitation in a single indicator. Regarding fast onset climatic factors, while we do not find any strong pattern for a stronger role of a specific type of natural disasters, we do find that the way they are measured matters. In general, relying on indicators simply capturing the occurrence of a disaster over a certain period of time tends to lower the probability of finding an effect. Indicators capturing the intensity of the disaster such as the number of affected people, or reflecting the duration of a climatic event deliver more evidence in favour of a displacement effect of this disaster.

Second, the context of the paper and the specificity of each regression play a role. Investigating the occurrence of mobility in the developing world increases the probability of finding some effect. This confirms that the issue of climate change and migration concerns primarily developing countries. This might be explained by the fact that these countries face a double issue related to climate change, namely a higher exposition to adverse climatic developments and a lower capacity to cope with these developments. Another interesting finding is that papers covering more recent investigation periods tend to find more often some effect. At the level of the regressions, analyses allowing a conditional effect of climate shocks tend to find more evidence of an effect - positive or negative- of climatic variables on the propensity to move. This confirms the importance of identifying the channels or the mechanisms through which climate shocks affect the movement of people. Related to that, a significant proportion (16% in our sample) has attempted to document indirect effects of climate change, i.e. evidence that climatic events can affect determinants of migration of people. We think that this is a valuable development of the literature as it obviously helps explaining the diversity of situations and contexts in which climate plays a role.

Third, the statistical approach of the analyses plays a role, too. Using dyadic data or panel data tends to favour the evidence of an effect. Related to that, the use of the relevant estimation techniques for these data structures, i.e. panel estimation techniques accounting for unobserved heterogeneity and Poisson regressions also tend to provide more evidence of an effect. Instrumental variable estimation, albeit not so widespread in the literature, also increases the probability of an effect. This might be due to the fact that IV estimations mitigate the attenuation bias related to the error of measures on climatic factors.[11] Finally, we find only some modest publication bias. Papers published in relatively good journals tend to find more effects, including displacement ones exerted by climatic variables. In contrast, we do not find any bias related to the simple fact that the paper is published or not, or any bias related to the reputation of the authors. In general, the literature seems to have been quite honest in terms of the reported findings.

[11] Measurement errors of climatic factors have been increasingly documented in the literature. This is the case for instance for natural disasters. Kron et al. (2012) cover the issue of data reliability of these disasters in the major databases and stress that the data are often subject to errors due to reporting bias and classical reporting errors.

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A List of coded papers

Table 19: Coded Papers

Paper	Authors	Year	Published	Nb. Of Regressions
Modelling inter-provincal migration in Burkina Faso, West Africa: The role of socio-demographic and environmental factors	Henry et al. (2003)	2003	1	5
The Impact of Rainfall on the First out-Migration: A multi-level Event-History Analysis in Burkina Faso	Henry et al. (2004)	2004	1	12
Climatic change and rural?urban migration	Barrios et al. (2006)	2006	1	6
The Impact of Environmental Degradation on Migration across Countries	Afifi and Warner (2008)	2008	0	5
Environment, Land, and Rural Out-migrqtion in the Southern Ecuadorian Andes	Gray (2009)	2009	1	1
Does Environmental Degradation Influence Migration? Emigration to Developed Countries in the late 1980s and 1990s	Reuveny and Moore (2009)	2009	1	3
Linkages among climate change, crop yields and Mexico-US cross-border migration	Feng et al. (2010)	2010	1	34
Does climate change foster emigration from less developed countries? Evidence from bilateral data	Bettin and Nicolli (2012)	2012	0	18
Climate Change, Crop Yields, And Internal Migration in the United States	Feng et al. (2012)	2012	0	48
Natural disasters and population mobility in Bangladesh	Gray and Mueller (2012b)	2012	1	10
Drought and population mobility in rural ethiopia	Gray and Mueller (2012a)	2012	1	24
Climate Change and the Relocation of Population	Gröschl (2012)	2012	0	45
The impact of weather anomalies on migration in sub-saharan africa	Marchiori et al. (2012)	2012	1	9
Environmental Influences on Human Migration in Rural Ecuador	Gray and Bilsborrow (2013)	2013	1	6
Is internal Migration in Yemen Driven by Climate or Socio-economic Factors?	Joseph and Wodon (2013)	2013	1	4
Do Rainfall Deficits Predict U.S.-bound Migration from Rural Mexico? Evidence from the Mexican Census	Nawrotzki et al. (2013)	2013	1	6
Nonlinear permanent migration response to climatic variations but minimal response to disasters	Bohra-Mishra et al. (2014)	2014	1	10
Rainfall patterns and U.S Migratoin from Rural Mexico	Hunter et al. (2013)	2014	1	6
Climate variability and migration: Evidence from Tanzania	Maurel et al. (2014)	2014	0	11
Heat Stress Increases Long Term Human Migration in Rural Pakistan	Mueller et al. (2014)	2014	1	22
Do climate variations explain bilateral migration? A gravity model analysis	Backhaus et al. (2015)	2015	1	9
Climatic factors as determinants of international migration	Beine and Parsons (2015)	2015	1	45
Climate Variability and International Migration: an empirical analysis	Coniglio and Pesce (2015)	2015	1	44
Natural Disasters, Migration and Education:	Drabo and Mbaye (2015)	2015	1	46
Climate Change, Agriculture and Migration: Evidence from Bangladesh	Iqbal and Roy (2015)	2015	1	14
Climate variability and human migration in the Netherlands, 1865-1937	Jennings and Gray (2015)	2015	1	21
Weather, agriculture and rural migration: evidence from state and district level migration in India	Viswanathan and Kumar (2015)	2015	1	13
Climatic Factors as Determinants of International Migration: Redux	Beine and Parsons (2017)	2016	0	12
Climate variability and international migration: The importance of the agricultural linkage	Cai et al. (2016)	2016	1	88
The Migration response to increasing temperatures	Cattaneo and Peri (2016)	2016	1	47
Climate variability and Inter-state Migration in India	Dallmann and Millock (2017)	2016	0	106
Country-Specific effects of climate variable on human migration	Gray and Wise (2016)	2016	1	60
Do Natural Hazards Cause International Migration?	Gröschl and Steinwachs (2017)	2016	0	20
Temperature changes, household consumption, and international migration: Evidence from Tanzania	Hirvonen (2016)	2016	1	20
Environment matters: new evidence from mexican migration	Khamis and Xiyue (2016)	2016	0	18
The role of environmental perceptions in migration decision-making: evidence from both migrants and non-migrants in five developing countries	Koubi et al. (2016b)	2016	1	9
Environmental Stressors and Migration: Evidence from Vietnam	Koubi et al. (2016a)	2016	1	7
The influence of climate variability on internal migration flows in South Africa	Mastrorillo et al. (2016)	2016	1	58
Climate Instability, Urbanisation and International Migration	Maurel and Tuccio (2016)	2016	1	30
International Climate Migration: Evidence for the Climate Inhibitor Mechanism and Agricultural Pathway	Nawrotzki and Bakhtsiyarava (2017)	2016	1	10
Heterogeneous climate effects on human migration in Indonesia	Thiede and Gray (2017)	2016	1	12
Climate Variability and inter-provincial migration in South America, 1970-2011	Thiede et al. (2016)	2016	1	35
Has climate change driven urbanization in Africa	Henderson et al. (2017)	2017	1	30
Taken By Storm: Hurricanes, Migrant Networks, and U.S. Immigration	Mahajan and Yang (2017)	2017	0	41
Do Climatic events Influence Internal Migration ? Evidence from Mexico.	Ruiz (2017)	2017	0	56

B Complete Codebook

Regression characteristics	
Regression number	Unique identifier of the regression for a particular paper
Table	Table number in the paper
Main	(1/0). Equal to 1 if main regression, 0 otherwise (e.g. robustness check)
Preferred specification	(1/0). Equal to one if preferred specification, 0 otherwise (e.g. non parsimonious specification, sub samples with omitted significant variables, ...)
Aux regression	(1/0). Equal to one if dependent variable is not related to migration. (e.g. wish to highlight a certain channel)
Direct effect	(1/0). Equal to 1 if evidence of direct effect of climate on migration.
Significance direct	If there is a direct effect, its significance level (0.01, 0.05 or 0.1).
Indirect effect	(1/0). Equal to 1 if evidence of an indirect effect of climate on migration.
Significance indirect	If there is an indirect effect, its significance level (0.01, 0.05 or 0.1).
Negative effect	(1/0). Equal to 1 the result is evidence for immobility.
Split	(1/0). Equal to 1 the regression was duplicated into two distinct regressions. (See section 2.)
Elasticity	(1/0). Equal to 1 if the estimated coefficient is an elasticity.
Other Variables	(1/0). Equal to 1 if the regression controls for other factors.
Conditional sample	(1/0). Equal to 1 if the regression is done on a subsample. (e.g. men and women, poor countries,...)
Conditional regression	(1/0). Equal to 1 if a climate variable is interacted with another variable. (e.g. Temperature level x agriculture variable). variables in the regression.
Climatic Variables	
Joint Inclusion LR-SR	(1/0) Equal to one if the regression includes both long-run and short-run climatic measures.
Long-run measures	
Joint inclusion temperature rainfall	(1/0) Equals one if regression includes both temperature and rainfall.
Long-Run Changes	(1/0) Equal to one if the regression includes long-run or gradual changes.
Temperature Levels	(1/0) Equal to one if the regression includes levels of temperature.
Temperature Deviations	(1/0) Equal to one if the regression includes temperature deviations.

Temperature Anomalies	(1/0) Equal to one if the regression includes temperature anomalies.
Temperature Variability	(1/0) Equal to one if the regression includes measures of temperature variability.
Signed (excess)	(1/0) Equal to one if the measure is about a specific deviation or anomaly in terms of excess temperature.
Rainfall Levels	(1/0) Equal to one if the regression includes levels of rainfall.
Rainfall Deviations	(1/0) Equal to one if the regression includes rainfall deviations.
Rainfall Anomalies	(1/0) Equal to one if the regression includes rainfall anomalies.
Rainfall Variability	(1/0) Equal to one if the regression includes measures of rainfall variability.
Signed (shortage)	(1/0) Equal to one if the measure is about a specific deviation or anomaly in terms of rain shortage.
Soil Moisture	(1/0) Equal to one if the regression includes a measure of soil moisture.
	Short-run measures
Natural Disasters	(1/0) Equal to one if the regression includes a measure of sudden change.
Aggregate Count	(1/0) Equal to one if the measure captures the aggregate number of disasters within a period of time.
Intensity	(1/0) Equal to one if the measure captures the intensity of the disaster, such as the number of casualties.
Duration	(1/0) Equal to one if the measure captures the duration of the disaster. (e.g. number of days the drought lasted)
Extreme Temperature	(1/0) Equal to one if the regression includes a measure of extreme temperature. (e.g. number of days above 33 degrees.)
Extreme Precipitation	(1/0) Equal to one if the regression includes a measure of extreme precipitation.
Floods	(1/0) Equal to one if the regression includes floods as a specific variable.
Hurricane / Storm	(1/0) Equal to one if the regression includes hurricanes or storms as a specific variable.
Drought	(1/0) Equal to one if the regression includes drought as a specific variable.
	Dependent Variable
Direct Measure	(1/0) Equal to one if mobility is directly observed.

Flows	(1/0) Equal to one if the dependent variable is migration flow.
Rate	(1/0) Equal to one if the dependent variable is migration rate.
Other	(1/0) Equal to one if the dependent variable is another measure. (e.g. crop yields or urbanization)
Estimation strategy	
Panel	(1/0) Equal to one if the model uses panel techniques.
Poisson	(1/0) Equal to one if the estimation is done with Poisson or Negative Binomial technique.
OLS or SOLS	(1/0) Equal to one if the estimation is done with OLS or SOLS.
IV	(1/0) Equal to one if the regression uses instrumental variable techniques. (One case of Heckman Selection model)
Multinomial model	(1/0) Equal to one if the regression uses a multinomial model.
Channels	
Theory Based	(1/0). Equal to one it the specification is derived from a theoretical model. (e.g. The gravity model)
Economic Channel	(1/0). Equal to one if the regression tries to capture the economic channel of climate change.
Agriculture Channel	(1/0). Equal to one if the regression tries to capture the agriculture channel of climate change.
Other Channel	(1/0). Equal to one if the regression tries to capture any other specific channel of climate change.
Type of Mobility	
International	(1/0). Equal to one for internal migration
Internal	(1/0). Equal to one for internal migration
Local	(1/0). Equal to one for local migration
Data and Sample	
Developing Countries	(1/0) Equal to one if the countries of origin are mainly developing countries.
Frequency	Frequency of observations in years.
Cross Country	(1/0). Equal to one for cross country regression
Household	(1/0). Equal to one for micro data with households as units of observation
Individual	(1/0). Equal to one for micro data with individuals as units of observation
Survey	(1/0). Equal to one for survey data.
Starting Time	First year included in the sample.
Time Span	Number of years in the sample.

Corridor	(1/0). Equal to one if mobility in a specific movement corridor.
Dyadic	(1/0). Equal to one if the data is dyadic.
	Paper characteristics
Paper number	Unique identifier of the paper
Title	The title of the paper
Author 1	Name of first author
Author 2	Name of second author
Author 3	Name of third author
Published	(1/0). Equal to one if the paper is published.
Name of journal	If published, the name of the journal
Imapact factor	If published, the impact factor of the journal
Citations	Number of citations. Source : Google Scholar
Average h-index	Average h-index of authors who have a h-index. Source : Google Scholar.
Max h-index	Maximum h-index of all authors. Source : Google Scholar.
Year	Year of publication

Table 1: Summary Statistics of Categorical Variables - Part 1

Variable	**Number of regressions**	**Mean**
Paper characteristics		
Published	897	0.69
Regression characteristics		
Main Regression	764	0.58
Preferred Regression	1200	0.92
Auxiliary Regression	147	0.11
Evidence of effect	1015	0.78
Direct effect	804	0.62
Indirect effect	211	0.16
Positive effect	747	0.74
Negative effect	268	0.26
Splitted	332	0.25
Elasticity	976	0.75
Conditional Sample	525	0.40
Conditional Regression	378	0.29
Outcome/Channel		
Theory based	598	0.46
Economic Channel	214	0.16
Agricultural Channel	253	0.19
Aggregate Channel	773	0.59
Other Channel	181	0.14
Type of Mobility		
International	738	0.56
Internal	748	0.57
Local	16	0.01
Data/Sample		
Developing countries	880	0.67
Cross country	604	0.46
Households	164	0.13
Individuals	233	0.18
Survey data	290	0.22
Dependent Variable		
Direct Measure	489	0.47
Migration Flow	271	0.21
Migration Rate	437	0.33
Other	599	0.46

Table 2: Summary Statistics of Categorical Variables - Part 2

Variable	**Number of regressions**	**Mean**
Climatic Factors		
Joint long term and Short term	305	0.23
Long run effects	900	0.69
Joint rainfall and temperature	632	0.48
Temperature levels	387	0.30
Temperature deviations	63	0.05
Temperature anomalies	201	0.15
Temperature variability	36	0.03
Signed excess	108	0.08
Rainfall levels	507	0.39
Rainfall deviations	118	0.09
Rainfall anomalies	198	0.15
Rainfall variability	73	0.06
Signed shortage	110	0.08
Soil moisture	40	0.03
Short run effects	673	0.51
Count	319	0.24
Intensity	165	0.13
Duration	47	0.04
Extreme Temperature	126	0.10
Extreme Precipitation	62	0.05
Floods	190	0.15
Hurricanes/Storms	209	0.16
Droughts	255	0.20
Methodology		
Panel	1221	0.93
Other factors included	997	0.76
Dyadic	657	0.50
Binomial / Poisson	404	0.31
OLS	499	0.38
IV	139	0.11
Multinomial Model	153	0.12
Corridor	26	0.02

Table 3: Summary Statistics of Continuous Variables

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Paper characteristics					
Authors	1307	2.45	1.10	1	6
Citations	1307	38.41	64.14	0	338
Impact factor	875	3.43	3.39	0.56	17.18
Number pages	1307	29.72	17.78	6	67
Year publication	1307	2014.81	2.30	2003	2017
Average h-index	1307	18.01	16.87	0	82
Max h-index	1307	24.59	23.73	0	96
Regression characteristics					
Significance direct	1307	0.02	0.03	0	0.10
Significance indirect	1307	0.00	0.01	0	0.10
Data/Sample					
Frequency	1250	6.05	4.55	0	28
Starting time	1284	1978.98	24.23	1865	2013

Table 4: Probability of any effect: pooled logit estimates

Variables	(1)	(2)	(3)	(4)	(5)
starting_time	-0.050**	-0.046**	-0.046**	-0.056**	-0.042**
	(0.023)	(0.023)	(0.023)	(0.027)	(0.018)
elasticity	0.476	0.560	0.555	0.567	
	(0.437)	(0.448)	(0.448)	(0.438)	
theory_based	-0.132	-0.026	-0.031	0.012	
	(0.513)	(0.515)	(0.516)	(0.497)	
conditional_sample	-0.447	-0.442	-0.439	-0.478	
	(0.291)	(0.294)	(0.296)	(0.287)	
conditional_regression	1.500***	1.553***	1.556***	1.631***	1.376***
	(0.529)	(0.526)	(0.529)	(0.517)	(0.396)
international	0.098	0.100	0.089	-0.092	
	(0.512)	(0.503)	(0.502)	(0.481)	
cross_country	-0.551	-0.664	-0.647	-0.505	
	(0.726)	(0.746)	(0.733)	(0.688)	
aggregate	-0.104	-0.062	-0.072	-0.012	
	(0.345)	(0.343)	(0.343)	(0.335)	
frequency	-0.064**	-0.066**	-0.066**	-0.059**	-0.068***
	(0.027)	(0.026)	(0.027)	(0.028)	(0.025)
time_span	-0.050	-0.045	-0.044	-0.059	-0.055**
	(0.032)	(0.032)	(0.032)	(0.036)	(0.027)
developing_only	1.254**	1.130**	1.134**	0.911	1.011**
	(0.503)	(0.481)	(0.484)	(0.508)	(0.463)
direct_measure	0.673	0.761	0.742	0.788	
	(0.698)	(0.706)	(0.714)	(0.708)	
migration_flow	1.086**	1.102**	1.099**	1.026**	1.084**
	(0.464)	(0.481)	(0.478)	(0.491)	(0.425)
other_dependent	1.670***	1.658***	1.668***	1.514***	1.665***
	(0.509)	(0.516)	(0.521)	(0.522)	(0.365)
other_covariates	-0.322	-0.478	-0.467	-0.547	
	(0.507)	(0.490)	(0.494)	(0.505)	
main	-0.104	-0.115	-0.117	-0.168	
	(0.330)	(0.329)	(0.328)	(0.319)	
panel	1.792***	1.650***	1.650**	1.419**	1.637**
	(0.673)	(0.644)	(0.642)	(0.666)	(0.664)
dyadic	1.355*	1.415**	1.402**	1.392**	0.974*
	(0.707)	(0.684)	(0.698)	(0.658)	(0.556)
poisson	-0.130	-0.079	-0.075	-0.025	
	(0.497)	(0.504)	(0.510)	(0.433)	
iv	1.194**	1.276**	1.261**	1.286**	1.329***
	(0.562)	(0.548)	(0.550)	(0.517)	(0.452)
published	-0.427				
	(0.370)				
avhpub		-0.001			
		(0.009)			
maxhpub			-0.002		
			(0.005)		
imppub				0.084	
				(0.057)	
Constant	98.954**	90.416**	89.915**	111.242**	81.667**
	(46.956)	(45.601)	(45.434)	(53.475)	(35.294)
Pseudo R^2	0.158	0.155	0.155	0.160	0.130
Pct Correct cases	81.22	82.23	82.23	81.99	82.23
N Obs	1294	1294	1294	1294	1294

Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Probability of any effect: panel logit estimates

Variables	(1)	(2)	(3)	(4)	(5)
starting_time	-0.064**	-0.058**	-0.052*	-0.051	-0.059**
	(0.029)	(0.029)	(0.028)	(0.028)	(0.029)
elasticity	0.648	0.771	0.769	0.754	
	(0.541)	(0.545)	(0.548)	(0.542)	
theory_based	-1.550	-1.526	-1.534	-1.491	
	(1.036)	(1.064)	(1.079)	(1.118)	
conditional_sample	-0.751**	-0.728**	-0.732**	-0.742**	-0.701**
	(0.331)	(0.334)	(0.333)	(0.326)	(0.322)
conditional_regression	2.002***	2.026***	2.024***	2.026***	1.882***
	(0.600)	(0.598)	(0.600)	(0.596)	(0.527)
international	0.035	-0.017	-0.025	-0.063	
	(0.610)	(0.619)	(0.618)	(0.601)	
cross_country	0.236	0.247	0.258	0.119	
	(0.982)	(1.012)	(1.023)	(1.021)	
aggregate	0.082	0.074	0.065	0.089	
	(0.479)	(0.476)	(0.475)	(0.492)	
frequency	-0.088**	-0.098**	-0.103**	-0.099**	-0.086**
	(0.042)	(0.046)	(0.047)	(0.048)	(0.041)
time_span	-0.073*	-0.067	-0.058	-0.050	-0.087**
	(0.042)	(0.042)	(0.040)	(0.042)	(0.043)
developing_only	1.546*	1.403	1.394	1.242	0.957
	(0.814)	(0.851)	(0.848)	(0.871)	(0.642)
direct_measure	0.754	0.537	0.576	0.701	
	(0.751)	(0.736)	(0.754)	(0.773)	
migration_flow	1.258**	1.268**	1.263**	1.161*	1.050*
	(0.558)	(0.609)	(0.607)	(0.641)	(0.550)
other_dependent	1.865**	1.884**	1.896**	1.785**	1.750***
	(0.826)	(0.871)	(0.871)	(0.864)	(0.497)
other_covariates	0.101	0.013	0.022	0.001	
	(0.564)	(0.595)	(0.590)	(0.598)	
main	-0.042	-0.063	-0.059	-0.060	
	(0.380)	(0.379)	(0.380)	(0.375)	
panel	2.651***	2.314**	2.273**	2.072**	2.841***
	(1.007)	(0.932)	(0.940)	(0.994)	(0.964)
dyadic	1.450	1.390	1.413	1.639*	
	(0.946)	(0.921)	(0.930)	(0.930)	
poisson	0.315	0.500	0.506	0.412	
	(0.724)	(0.741)	(0.739)	(0.750)	
iv	1.633	1.702*	1.695*	1.725*	
	(1.020)	(1.028)	(1.027)	(1.014)	
published	-1.180*				-1.283
	(0.629)				(0.719)
avhpub		-0.019			
		(0.012)			
maxhpub			-0.013		
			(0.009)		
imppub				0.066	
				(0.095)	
Constant	125.348**	113.273	101.878*	98.715*	117.469**
	(58.392)	(58.799)	(56.483)	(56.878)	(58.870)
log-likelihood	-511.867	-512.640	-512.745	-513.173	-523.681
chi-square	98.433	106.850	101.766	88.954	50.895
N	1294.000	1294.000	1294.000	1294.000	1294.000

Standard errors clustered at the paper level.
Panel Logit estimation with paper random effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Probability of any effect excluding auxiliary regressions: pooled logit estimates

Variables	(1)	(2)	(3)	(4)	(5)
starting_time	-0.039*	-0.037*	-0.039*	-0.053**	-0.052***
	(0.021)	(0.021)	(0.021)	(0.024)	(0.020)
elasticity	0.425	0.421	0.424	0.328	
	(0.433)	(0.416)	(0.416)	(0.391)	
theory_based	0.096	0.130	0.134	0.215	
	(0.587)	(0.568)	(0.567)	(0.556)	
conditional_sample	-0.405	-0.404	-0.403	-0.430	
	(0.310)	(0.303)	(0.303)	(0.302)	
conditional_regression	1.756***	1.781***	1.774***	1.978***	1.404***
	(0.623)	(0.626)	(0.616)	(0.626)	(0.430)
international	0.077	0.083	0.105	-0.270	
	(0.494)	(0.478)	(0.473)	(0.436)	
cross_country	-0.039	-0.048	-0.046	0.350	
	(0.765)	(0.739)	(0.737)	(0.688)	
aggregate	0.220	0.330	0.329	0.426	
	(0.429)	(0.475)	(0.462)	(0.408)	
frequency	-0.064**	-0.066**	-0.063**	-0.052*	-0.040
	(0.028)	(0.027)	(0.026)	(0.029)	(0.032)
time_span	-0.033	-0.028	-0.031	-0.055	-0.069**
	(0.033)	(0.033)	(0.034)	(0.036)	(0.030)
developing_only	1.492***	1.501***	1.510***	1.186**	0.695*
	(0.577)	(0.529)	(0.530)	(0.576)	(0.386)
direct_measure	1.765**	1.969***	1.976***	1.945***	
	(0.776)	(0.762)	(0.758)	(0.720)	
migration_flow	1.285**	1.280**	1.289**	1.094**	1.004***
	(0.530)	(0.553)	(0.548)	(0.539)	(0.375)
other_dependent	0.720	0.594	0.585	0.174	
	(0.523)	(0.497)	(0.496)	(0.474)	
other_covariates	-0.208	-0.202	-0.224	-0.146	
	(0.518)	(0.490)	(0.488)	(0.506)	
main	-0.218	-0.184	-0.196	-0.318	
	(0.352)	(0.354)	(0.353)	(0.348)	
panel	1.374*	1.299*	1.320*	0.923	
	(0.740)	(0.748)	(0.740)	(0.751)	
dyadic	1.146	1.226	1.206	0.975	
	(0.747)	(0.682)	(0.690)	(0.691)	
poisson	0.014	0.037	0.023	0.126	
	(0.552)	(0.542)	(0.535)	(0.465)	
iv	2.018***	2.160***	2.161***	2.107***	0.944**
	(0.685)	(0.675)	(0.666)	(0.642)	(0.465)
published	0.019				
	(0.395)				
avhpub		0.009			
		(0.010)			
maxhpub			0.006		
			(0.006)		
imppub				0.146***	0.144**
				(0.049)	(0.064)
Constant	74.902*	71.229*	74.447*	104.422**	104.109***
	(42.051)	(42.721)	(43.058)	(48.221)	(39.448)
Pseudo R^2	0.166	0.167	0.167	0.180	0.111
Pct Correct cases	81.08	81.34	80.99	81.17	80.99
N Obs	1147	1147	1147	1147	1147

Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Probability of any effect excluding auxiliary regressions: Panel logit estimated

Variables	(1)	(2)	(3)	(4)	(5)
published	-0.270				
	(0.772)				
starting_time	-0.061**	-0.056	-0.056*	-0.063**	-0.052
	(0.030)	(0.029)	(0.029)	(0.029)	(0.032)
elasticity	0.368	0.386	0.384	0.318	
	(0.508)	(0.501)	(0.498)	(0.486)	
theory_based	-0.577	-0.512	-0.500	-0.284	
	(1.011)	(1.066)	(1.065)	(1.044)	
conditional_sample	-0.849**	-0.849**	-0.849**	-0.840**	-0.691**
	(0.352)	(0.355)	(0.354)	(0.346)	(0.343)
conditional_regression	2.355***	2.355***	2.357***	2.388***	1.979***
	(0.751)	(0.749)	(0.6751)	(0.750)	(0.553)
international	-0.361	-0.358	-0.356	-0.492	
	(0.583)	(0.580)	(0.677)	(0.517)	
cross_country	1.663	1.603	1.584	1.579	
	(1.077)	(1.098)	(1.085)	(1.032)	
aggregate	0.474	0.468	0.474	0.497	
	(0.624)	(0.630)	(0.636)	(0.621)	
frequency	-0.104**	-0.108**	-0.107**	-0.096*	-0.069
	(0.051)	(0.051)	(0.051)	(0.053)	(0.050)
time_span	-0.066	-0.057	-0.057	-0.064	-0.074*
	(0.045)	(0.042)	(0.042)	(0.044)	(0.043)
developing_only	1.830*	1.775*	1.769*	1.582	0.819
	(1.007)	(0.980)	(0.979)	(0.978)	(0.861)
direct_measure	3.768**	3.837**	3.863**	3.707***	
	(1.524)	(1.620)	(1.685)	(1.367)	
migration_flow	0.781	0.763	0.752	0.611	0.919*
	(0.732)	(0.750)	(0.752)	(0.704)	(0.516)
other_dependent	-0.563	-0.589	-0.603	-0.797	
	(0.957)	(0.977)	(0.981)	(0.891)	
other_covariates	0.438	0.414	0.412	0.388	
	(0.620)	(0.619)	(0.617)	(0.625)	
main	-0.056	-0.051	-0.050	-0.075	
	(0.409)	(0.409)	(0.409)	(0.402)	
panel	2.371**	2.282**	2.284**	1.846*	1.832*
	(1.136)	(1.077)	(1.080)	(1.087)	(0.981)
dyadic	1.119	1.185	1.209	1.366	
	(1.077)	(1.069)	(1.0600)	(1.054)	
poisson	1.013	1.037	1.026	0.861	
	(1.033)	(1.016)	(1.019)	(0.974)	
iv	2.963***	3.012***	3.024***	3.012***	
	(1.051)	(1.068)	(1.068)	(1.008)	
avhpub		0.002			
		(0.017)			
maxhpub			0.003		
			(0.012)		
imppub				0.184***	0.164**
				(0.069)	(0.067)
Constant	117.093*	107.444*	108.878	121.126**	103.054
	(60.854)	(58.515)	(58.860)	(59.191)	(63.328)
log-likelihood	-463.529	-463.578	-463.554	-461.645	-480.392
Chi-square	98.814	96.626	96.703	114.814	35.342
N Obs	1147	1147	1147	1147	1147

Standard errors clustered at the paper level.
Panel Logit estimation with paper random effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Probability of a direct effect: pooled logit estimates

Variables	(1) all	(2) all	(3) excl aux	(4) excl aux
starting_time	-0.026***	-0.037***	-0.027**	-0.034***
	(0.010)	(0.011)	(0.012)	(0.012)
imppub	0.118**	0.103**	0.035	
	(0.049)	(0.048)	(0.054)	
year_of_publication	-0.068		0.009	
	(0.075)		(0.072)	
elasticity	-0.680*	-0.440	-0.088	-0.078
	(0.401)	(0.430)	(0.529)	(0.353)
theory_based	0.335		0.495	
	(0.622)		(0.665)	
conditional_sample	-0.028		-0.315	
	(0.352)		(0.294)	
conditional_regression	1.207***	1.562***	1.552***	1.535***
	(0.359)	(0.316)	(0.502)	(0.458)
international	-0.747		-0.108	
	(0.473)		(0.465)	
cross_country	1.481**		0.409	
	(0.641)		(0.785)	
frequency	-0.101***	-0.080***	-0.092***	-0.093***
	(0.026)	(0.024)	(0.027)	(0.028)
developing_only	1.317***	1.529***	1.743***	1.702***
	(0.460)	(0.421)	(0.516)	(0.478)
direct_measure	3.411***	2.789***	2.164***	1.907***
	(0.937)	(0.555)	(0.808)	(0.526)
migration_flow	0.676	0.798	0.765	0.733
	(0.636)	(0.534)	(0.611)	(0.530)
other_dependent	-1.389	-1.209**	0.499	
	(0.721)	(0.578)	(0.739)	
main	0.043		-0.103	
	(0.236)		(0.324)	
panel	0.172		0.634	
	(0.737)		(0.682)	
dyadic	1.150*	1.467***	1.752***	1.498**
	(0.628)	(0.519)	(0.607)	(0.594)
poisson	0.149		-0.013	
	(0.391)		(0.477)	
iv	-1.258		-1.196**	-1.164*
	(0.908)		(0.580)	(0.651)
multinomial_logit	0.770	0.699	0.940	0.872
	(0.684)	(0.671)	(0.818)	(0.666)
Constant	186.863	71.614***	32.629	65.522***
	(154.902)	(20.904)	(142.583)	(23.329)
Pseudo R^2	0.300	0.273	0.266	0.250
Pct Correct cases	80.64	80.33	81.55	82.41
N Obs	1307	1307	1160	1160

Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Probability of a direct effect: panel logit estimates

Variables	(1) all	(2) all	(3) excl aux	(4) excl aux
starting_time	-0.023		-0.034*	-0.053***
	(0.022)		(0.020)	(0.019)
imppub	0.098		0.063	
	(0.180)		(0.123)	
year_of_publication	-0.210		-0.111	
	(0.152)		(0.108)	
elasticity	-0.875		0.530	
	(1.091)		(0.700)	
theory_based	-0.314		-0.116	
	(1.080)		(1.439)	
conditional_sample	-0.557		-0.739**	-0.684**
	(0.419)		(0.375)	(0.343)
conditional_regression	1.786***	1.749***	1.798***	1.808***
	(0.521)	(0.488)	(0.634)	(0.621)
international	-3.367***	-3.122***	-0.608	
	(0.955)	(0.878)	(0.483)	
cross_country	5.516**	5.347***	2.149	
	(2.476)	(1.607)	(1.434)	
frequency	-0.212**	-0.141*	-0.179***	-0.139**
	(0.104)	(0.083)	(0.066)	(0.055)
developing_only	1.391*	1.251	1.887**	1.714**
	(0.797)	(0.828)	(0.937)	(0.849)
direct_measure	7.304***	7.569***	5.209**	4.082***
	(2.419)	(1.984)	(2.053)	(1.113)
migration_flow	-1.359		-0.683	
	(1.294)		(0.841)	
other_dependent	-4.014***	-2.783***	-0.391	
	(1.320)	(1.041)	(1.145)	
main	-0.163		-0.064	
	(0.367)		(0.417)	
panel	0.588		1.139	
	(1.755)		(1.303)	
dyadic	-0.457		3.351***	3.486***
	(2.316)		(1.224)	(1.090)
poisson	0.349		0.837	
	(0.977)		(0.864)	
iv	-0.010		-0.528	
	(1.276)		(0.888)	
multinomial_logit	0.974		1.086	
	(0.782)		(0.832)	
Constant	467.941	-1.489	287.001	101.805***
	(303.992)	(1.295)	(220.827)	(37.861)
Log. Lik	-538.839	-549.616	-463.406	-470.864
Chi2	71.058	22.035	84.235	26.182
N Obs	1307	1307	1160	1160

Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Probability of displacement effect: pooled logit estimates

variables	(1) displ	(2) displ	(3) pos direct	(4) pos direct
starting_time	-0.009**	-0.007**	-0.014***	-0.017***
	(0.004)	(0.003)	(0.005)	(0.004)
imppub	0.102***	0.119***	0.131***	0.120***
	(0.028)	(0.022)	(0.034)	(0.036)
year_of_publication	-0.035		-0.051	
	(0.050)		(0.061)	
elasticity	0.340		-0.380	-0.301
	(0.290)		(0.309)	(0.301)
theory_based	-0.042		0.176	
	(0.313)		(0.396)	
conditional_sample	-0.436**	-0.503***	-0.341	
	(0.194)	(0.178)	(0.248)	
conditional_regression	0.391*	0.252	0.471**	0.654***
	(0.207)	(0.183)	(0.208)	(0.236)
international	-0.175		-0.451	-0.429
	(0.301)		(0.309)	(0.332)
cross_country	-0.424		0.811	0.897**
	(0.399)		(0.502)	(0.424)
frequency	-0.052**	-0.043**	-0.048**	-0.050**
	(0.021)	(0.020)	(0.021)	(0.021)
developing_only	0.761***	0.646**	0.993***	1.076***
	(0.277)	(0.288)	(0.377)	(0.397)
direct_measure	-0.092		1.674***	1.861***
	(0.443)		(0.433)	(0.395)
migration_flow	0.559*	0.417	0.567	0.588
	(0.297)	(0.308)	(0.353)	(0.358)
other_dependent	0.302		-1.286**	-0.976**
	(0.375)		(0.603)	(0.447)
main	-0.371*	-0.457**	-0.112	
	(0.207)	(0.204)	(0.212)	
panel	0.345		-0.101	
	(0.380)		(0.467)	
dyadic	1.203***	0.954***	1.213**	1.305***
	(0.390)	(0.348)	(0.573)	(0.471)
poisson	-0.442		-0.420	
	(0.269)		(0.267)	
iv	1.122**	1.330***	-1.143	
	(0.537)	(0.420)	(0.827)	
multinomial_logit	-0.048		0.280	
	(0.415)		(0.408)	
Constant	87.386	13.209**	129.627	31.467***
	(103.193)	(5.976)	(124.415)	(8.054)
Pseudo R^2	0.092	0.077	0.167	0.149
Pct Correct cases	66.18	63.27	69.24	66.87
N obs	1307	1307	1307	1307

Standard errors clustered at the paper level.

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

Table 11: Probability of displacement effect: panel logit estimates

variables	(1) displ	(2) displ	(3) pos direct	(4) pos direct
starting_time	-0.010**	-0.008**	-0.017***	-0.017***
	(0.005)	(0.004)	(0.006)	(0.004)
imppub	0.099***	0.115***	0.146**	0.145**
	(0.035)	(0.028)	(0.058)	(0.066)
year_of_publication	-0.014		-0.067	
	(0.048)		(0.058)	
elasticity	0.451		-0.293	
	(0.330)		(0.476)	
theory_based	-0.484		0.097	
	(0.440)		(0.614)	
conditional_sample	-0.487**	-0.603***	-0.534**	
	(0.226)	(0.210)	(0.249)	
conditional_regression	0.269		0.341	0.359
	(0.224)		(0.226)	(0.227)
international	-0.169*		-1.055	-1.160***
	(0.360)		(0.577)	(0.522)
cross_country	-0.070		1.706**	1.794***
	(0.517)		(0.835)	(0.746)
frequency	-0.038*	-0.031	-0.046	-0.050*
	(0.023)	(0.018)	(0.025)	(0.026)
developing_only	0.808**	0.483	1.025***	0.924***
	(0.316)	(0.282)	(0.335)	(0.345)
direct_measure	0.042		2.383***	2.366***
	(0.569)		(0.598)	(0.587)
migration_flow	0.818	0.228	0.269	
	(0.451)	(0.463)	(0.771)	
other_dependent	0.489		-1.428**	-1.237**
	(0.442)		(0.610)	(0.526)
main	-0.269		-0.169	
	(0.224)		(0.237)	
panel	0.363		0.018	
	(0.449)		(0.636)	
dyadic	1.242**	0.847	1.222	1.147
	(0.500)	(0.437)	(0.787)	(0.861)
poisson	-0.346		-0.240	
	(0.343)		(0.417)	
iv	1.429**	1.453**	-0.959	
	(0.658)	(0.623)	(1.029)	
multinomial_logit	-0.131		0.052	
	(0.384)		(0.330)	
Constant	47.760	15.437**	166.772	30.776***
	(98.651)	(6.863)	(116.341)	(10.941)
Log-Lik	-791.057	-803.052	-728.216	-737.334
Chi2	67.067	49.344	145.138	44.441
N Obs	1307	1307	1307	1307

Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Probability of a negative effect

variables	Pooled (1)	(2)	Panel (3)	(4)
starting_time	-0.001		0.009	
	(0.005)		(0.008)	
imppub	-0.081	-0.041	-0.106*	-0.004
	(0.046)	(0.051)	(0.061)	(0.050)
year_of_publication	0.033		0.046	
	(0.061)		(0.077)	
elasticity	0.092		-0.203	
	(0.432)		(0.540)	
theory_based	-0.013		0.108	
	(0.374)		(0.428)	
conditional_sample	0.334		0.223	
	(0.279)		(0.372)	
conditional_regression	0.637**	0.345	0.922***	0.833***
	(0.280)	(0.319)	(0.273)	(0.296)
international	0.113		0.191	
	(0.351)		(0.377)	
cross_country	0.738		0.371	
	(0.547)		(0.619)	
frequency	-0.016		-0.038	
	(0.034)		(0.039)	
developing_only	0.322	0.423	0.093	0.654
	(0.327)	(0.468)	(0.479)	(0.544)
direct_measure	1.083**		0.700	
	(0.532)		(0.538)	
migration_flow	0.231		-0.579	
	(0.379)		(0.589)	
other_dependent	1.096		0.686	
	(0.560)		(0.570)	
main	0.110		0.084	
	(0.320)		(0.349)	
panel	0.376	0.324	0.984	
	(0.659)	(0.621)	(0.742)	
dyadic	-0.416	-0.772**	-0.565	
	(0.487)	(0.385)	(0.580)	
poisson	0.569		0.310	
	(0.441)		(0.477)	
iv	-1.264		-2.023**	-2.312**
	(0.986)		(0.864)	(1.009)
multinomial_logit	0.235		0.719	
	(0.310)		(0.445)	
Constant	-68.110	-1.625**	-114.928	-2.109***
	(123.502)	(0.789)	(158.433)	(0.502)
Pseudo R^2	0.106	0.035		
Prop Corr Cases	78.80	79.49		
Log-Lik	-592.865	-639.566	-568.143	-580.266
Chi2	112.657	8.692	81.666	16.427
N Obs	1307	1307	1307	1307

Standard errors clustered at the paper level.

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

Table 13: Probability of an increase in mobility: ordered logit estimates

Variables	(1)	(2)
starting_time	0.007	
	(0.007)	
imppub	0.093***	0.086***
	(0.032)	(0.031)
year_of_publication	-0.046	
	(0.045)	
elasticity	0.320	
	(0.300)	
theory_based	0.067	
	(0.252)	
conditional_sample	-0.360*	-0.397**
	(0.189)	(0.186)
conditional_regression	-0.051	
	(0.185)	
international	-0.050	
	(0.250)	
cross_country	-0.456	
	(0.355)	
frequency	-0.058**	-0.039**
	(0.024)	(0.020)
time_span	0.025*	0.007
	(0.015)	(0.006)
developing_only	0.610***	0.479
	(0.229)	(0.302)
direct_measure	-0.130	
	(0.417)	
migration_flow	0.301	
	(0.237)	
other_dependent	0.125	
	(0.354)	
main	-0.295	
	(0.209)	
panel	-0.212	
	(0.291)	
dyadic	1.085***	1.248***
	(0.371)	(0.315)
poisson	-0.404*	-0.416
	(0.239)	(0.256)
iv	0.899*	1.376***
	(0.516)	(0.379)
multinomial_logit	-0.224	
	(0.334)	
Pseudo R^2	0.060	0.051
N Obs	1294	1294

The 3 modalities in order are negative effect, no effect and positive effect.
Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Impact of joint inclusion of LR and SR factors

variables	(1)	(2)	(3)	(4)
	Any effect		Direct effect	
	Pooled	Panel	Pooled	Panel
joint inclusion LR-SR	-0.610	-0.856	0.151	-0.578
	(0.494)	(0.655)	(0.546)	(0.878)
conditional_regression	0.953**	1.843***	1.809***	1.844***
	(0.416)	(0.547)	(0.382)	(0.444)
frequency	-0.104***	-0.139***	-0.054**	-0.105**
	(0.034)	(0.048)	(0.024)	(0.054)
developing_only	0.858**	1.013*	1.032**	1.250
	(0.388)	(0.590)	(0.479)	(0.915)
migration_flow	1.290***	1.236**	1.396**	-0.323
	(0.461)	(0.630)	(0.580)	(1.551)
other_dependent	1.377***	1.969***	-0.999*	-1.906***
	(0.463)	(0.498)	(0.528)	(0.687)
panel	1.421**	1.700**	1.096*	1.333
	(0.588)	(0.788)	(0.652)	(1.214)
long_run	1.088**	2.111***	0.892	1.132
	(0.493)	(0.806)	(0.624)	(1.138)
nat_disasters	1.247**	2.016***	1.003	1.691**
	(0.487)	(0.748)	(0.616)	(0.747)
direct_measure			2.487***	3.796***
			(0.631)	(0.705)
Constant	-2.063***	-3.252***	-3.047***	-2.768
	(0.790)	(1.181)	(1.150)	(2.212)
Pseudo R^2	0.119		0.245	
Pct Corr Cases	80.10		77.05	
Log-Lik	-567.315	-516.528	-642.685	-567.122
Chi2	46.217	52.684	33.536	55.589
N obs	1307	1307	1307	1307

Standard errors clustered at the paper level.

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

Table 15: Impact of modelling slow onset factors: pooled logit estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Any effect		direct		posit direct	
temp_levels	-0.197		-0.056		-0.347	
	(0.471)		(0.631)		(0.503)	
temp_deviations	-0.375		-1.781***	-1.679***	-2.150***	-1.928***
	(0.610)		(0.556)	(0.419)	(0.468)	(0.398)
temp_variability	-12.651***	-13.044***	-0.679		0.089	
	(1.001)	(0.979)	(1.745)		(1.026)	
rainfall_levels	0.870**	0.759**	-0.336		0.140	
	(0.413)	(0.355)	(0.609)		(0.422)	
rainfall_deviations	0.596		0.620		1.418***	1.159***
	(0.496)		(0.762)		(0.478)	(0.426)
rainfall_variability	13.693***	13.969***	1.763		0.724**	
	(0.948)	(0.915)	(1.110)		(0.362)	
nat_disasters	1.599**	0.785*	3.287***	1.255**	1.254***	0.384
	(0.744)	(0.410)	(0.940)	(0.508)	(0.448)	(0.290)
soil_moisture	-0.901*	-0.894**	1.167	1.389***	1.284**	
	(0.464)	(0.398)	(0.720)	(0.418)	(0.579)	
direct_measure			2.937***	3.127***	1.149**	1.090*
			(0.614)	(0.691)	(0.568)	(0.589)
imppub	0.121**	0.100**	0.150*		0.132***	0.118**
	(0.059)	(0.048)	(0.079)		(0.051)	(0.048)
conditional_regression	1.722***	1.643***	2.485***	2.096***	0.975***	0.876**
	(0.540)	(0.551)	(0.516)	(0.551)	(0.324)	(0.390)
frequency	-0.074**	-0.057***	-0.032		-0.062***	-0.056***
	(0.031)	(0.021)	(0.040)		(0.023)	(0.017)
developing_only	0.608	0.510	0.608		0.281	
	(0.399)	(0.379)	(0.576)		(0.361)	
migration_flow	2.163***	2.178***				
	(0.445)	(0.467)				
other_dependent	1.323***	1.335***	-2.097***	-1.827***	-1.726***	-1.578**
	(0.366)	(0.387)	(0.727)	(0.673)	(0.622)	(0.626)
panel	0.687					
	(0.787)					
joint_LRSR	-0.795		-2.014**		-0.853	
	(0.665)		(0.788)		(0.529)	
joint_temp_rain	-0.053		0.281		0.751	
	(0.408)		(0.510)		(0.419)	
Constant	-1.355	-0.689	-1.075	-0.419	-1.142*	-0.350
	(0.838)	(0.500)	(0.887)	(0.602)	(0.673)	(0.501)
Pseudo R^2	0.197	0.191	0.290	0.239	0.139	0.119
N	900	900	900	900	900	900

Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Impact of modelling slow onset factors: panel logit estimates

variables	(1) Any effect	(2)	(3) direct	(4)	(5) posit direct	(6)
temp_levels	0.301		0.077		-0.147	
	(0.553)		(1.036)		(0.465)	
temp_deviations	-0.940		-3.039**	-3.050**	-1.788***	-1.646**
	(0.881)		(1.383)	(1.418)	(0.681)	(0.649)
temp_variability	-17.001		2.107**	1.420*	0.470	
	(10.346)		(0.967)	(0.750)	(0.922)	
rainfall_levels	0.576		0.383		0.580	
	(0.465)		(0.884)		(0.412)	
rainfall_deviations	0.915		2.622*	2.495*	1.608**	1.321*
	(0.757)		(1.520)	(1.458)	(0.646)	(0.683)
rainfall_variability	18.236***	1.184**	-0.667		0.166	
	(0.525)	(0.518)	(0.647)		(0.198)	
nat_disasters	1.355		4.196***	2.994***	1.148*	-0.063
	(1.163)		(1.206)	(0.694)	(0.661)	(0.325)
soil_moisture	-0.161	-0.881***	2.025**		1.024*	
	(0.514)	(0.272)	(1.001)		(0.607)	
imppub	0.079		0.052		0.070	
	(0.083)		(0.194)		(0.098)	
conditional_regression	2.594***	2.566***	2.968***	2.869***	0.554*	
	(0.750)	(0.790)	(0.483)	(0.485)	(0.317)	
frequency	-0.152**	-0.117***	-0.154*	-0.135*	-0.068**	-0.059**
	(0.061)	(0.043)	(0.083)	(0.070)	(0.026)	(0.025)
developing_only	0.845		1.069		0.737*	
	(0.698)		(0.899)		(0.427)	
migration_flow	1.719***	1.393**				
	(0.549)	(0.580)				
direct_measure	0.731		4.661***	4.362***	1.047	
	(0.905)		(1.635)	(1.437)	(0.753)	
other_dependent	1.949***	2.131***	-2.126*	-2.025*	-1.285	-1.017
	(0.488)	(0.471)	(1.258)	(1.174)	(0.750)	(0.637)
panel	1.549					
	(1.233)					
joint_LRSR	-0.276		-3.211***	-2.195***	-0.911	
	(0.848)		(1.167)	(0.753)	(0.736)	
joint_temp_rain	0.727		1.710		1.263**	
	(0.588)		(1.305)		(0.496)	
Constant	-2.471*	1.096*	-2.059	0.160	-2.078**	0.280
	(1.318)	(0.578)	(1.406)	(0.764)	(0.895)	(0.511)
Log Lik	-343.224	-353.561	-373.774	-381.015	-507.079	-519.194
Chi2	.	58.821	88.483	65.564	78.392	11.976
N obs	900	900	900	900	900	900

Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Impact of modelling and measuring natural disasters

	(1)	(2)	(3)	(4)	(5)	(6)
	Any effect		Direct effect		Positive direct	
variables	pooled	panel	pooled	panel	pooled	panel
aggregate_count	0.787	-0.482	-0.368	-1.244**	0.109	0.079
	(0.689)	(1.251)	(0.720)	(0.621)	(0.284)	(0.385)
intensity	0.174	0.371	-0.715	-1.136**	-0.175	-0.013
	(0.742)	(0.564)	(0.643)	(0.451)	(0.305)	(0.482)
duration	1.738**	1.251***	-0.739	-0.722	0.356	0.955*
	(0.682)	(0.400)	(0.637)	(0.545)	(0.299)	(0.529)
joint_lrsr	1.778***	1.524***	0.187	0.780*	-0.479	-0.217
	(0.593)	(0.449)	(0.606)	(0.468)	(0.364)	(0.448)
conditional_regression	0.784	1.562**	1.025**	1.285**	0.234	0.098
	(0.596)	(0.646)	(0.404)	(0.558)	(0.272)	(0.327)
frequency	-0.327***	-0.389***	-0.149**	-0.178	-0.056	-0.089
	(0.080)	(0.121)	(0.066)	(0.116)	(0.049)	(0.057)
developing_only	0.964*	0.780	0.826	1.626	0.666	0.700
	(0.519)	(1.061)	(0.730)	(1.405)	(0.493)	(0.532)
migration_flow	2.671***	2.384**	1.287	1.309	0.694	0.929
	(0.921)	(1.098)	(0.834)	(2.081)	(0.464)	(0.665)
other_dependent	3.150***	3.603***	-0.766	-2.491	-0.974	-1.488
	(0.589)	(0.769)	(1.252)	(1.869)	(0.610)	(0.945)
panel	1.619	2.365	-0.014	0.023	-0.063	-0.075
	(1.351)	(1.860)	(0.976)	(1.663)	(0.579)	(0.708)
imppub			0.291**	0.456**	0.142*	0.165*
			(0.145)	(0.218)	(0.074)	(0.087)
Constant	-1.411	-0.546	1.043	1.750	0.127	0.311
	(1.636)	(2.460)	(1.745)	(2.903)	(1.058)	(1.264)
Pseudo R^2	0.255		0.172		0.090	
Pct corr cases	86.92		79.94		64.93	
Log-Lik	-228.211	-205.788	-325.403	-276.545	-422.921	-408.391
Chi2	80.303	280.999	58.305	38.846	88.165	85.388
N Obs	673.000	673.000	673.000	673.000	673.000	673.000

Standard errors clustered at the paper level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Impact of type of natural disasters

	(1)	(2)	(3)	(4)	(5)	(6)
	Any effect		Direct effect		Positive effect	
variables	pooled	panel	pooled	panel	pooled	panel
extreme_temp	-1.379**	-1.508***	-0.216	-1.614***	0.139	-0.844
	(0.626)	(0.508)	(0.774)	(0.508)	(0.532)	(1.028)
extreme_preci	-0.505	-1.236***	-0.258	-1.736***	0.123	0.772
	(0.623)	(0.341)	(0.990)	(0.401)	(0.475)	(0.698)
floods	0.826**	0.294	0.594**	-0.353	-0.008	-0.803
	(0.414)	(0.743)	(0.292)	(0.598)	(0.403)	(0.600)
hurricanes_storm	-0.863	0.302	-0.619	0.888	-0.227	0.207
	(0.656)	(0.581)	(0.475)	(0.798)	(0.345)	(0.546)
droughts	0.119	-1.011***	0.147	-0.319	0.357	0.696
	(0.470)	(0.247)	(0.418)	(0.487)	(0.582)	(0.784)
joint_lrsr	0.606	1.309***	0.262	1.152***	-0.281	0.379
	(0.473)	(0.389)	(0.337)	(0.297)	(0.331)	(0.397)
conditional_regression	0.839	1.577***	0.662	1.355***	0.030	0.100
	(0.550)	(0.591)	(0.494)	(0.423)	(0.317)	(0.342)
frequency	-0.230***	-0.343**	-0.102*	-0.170	-0.076	-0.098
	(0.069)	(0.135)	(0.057)	(0.182)	(0.050)	(0.087)
developing_only	1.055**	1.481	1.230	3.685***	0.460	0.267
	(0.499)	(0.770)	(0.804)	(1.123)	(0.323)	(0.483)
migration_flow	2.749***	3.045**	1.614**	1.003	0.752*	1.046
	(0.770)	(1.213)	(0.686)	(2.401)	(0.445)	(1.002)
other_dependent	3.440***	4.305***	0.125	-2.744	0.189	1.020
	(0.646)	(1.152)	(1.005)	(1.994)	(0.410)	(0.681)
panel	2.121	2.778	0.066	0.181	0.703	1.032
	(1.217)	(1.537)	(0.876)	(1.650)	(0.726)	(1.071)
Constant	-1.325	-1.470	0.095	1.340	-0.365	-1.093
	(1.394)	(1.847)	(1.634)	(2.161)	(0.933)	(1.269)
Pseudo R^2	0.297		0.158		0.046	
Pct corr cases	86.68		78.87			64.01
Log-Lik	-210.519	-194.068	-323.560	-264.362	-417.181	-405.445
Chi2	117.958	169.318	222.069	182.713	39.203	31.418
N Obs	653.000	653.000	653.000	653.000	653.000	653.000

Standard errors clustered at the paper level.

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