UNIVERSITÀ DEGLI STUDI DI FERRARA
DIPARTIMENTO DI ECONOMIA ISTITUZIONI TERRITORIO
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Does climate change foster emigration from less developed countries? Evidence from bilateral data

Giulia Bettin – Francesco Nicolli

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Giulia Bettin[*] Francesco Nicolli[**]

Abstract

The evolution of worldwide climatic conditions doubtless represents one of the major and uncertain challenges in the near future. The adaptation strategies might differ a lot according to local institutional, political and financial constraints but migration is certainly one of the main possibilities individuals have to escape from the most affected regions. Regional – maybe temporary - small-scale movements might be the first, immediate response but international mobility as well is likely to take place in response to climatic variations.

Empirical literature dealing with the effects of climate change on international migration is still rather scarce. In particular, it focuses on international migration to developed countries as a consequence of weather-related natural disasters while alternative measures for climate change based on deviations in temperature and rainfall from the long term means have been used only in a few studies.

Building on this little empirical evidence, we collect ten-year bilateral data on international migration from 1960 to 2000 and look simultaneously at both anomalies in precipitations and temperature and weather-related natural disaster as determinants of international movements. The use of bilateral data let us consider not only long-distance migration (typically from low income to developed countries) but also short-distance regional movements. International migration is found to be significantly affected by different climate change proxies in the overall sample of countries, but results are confirmed also when focusing on specific geographical areas like Africa or Asia.

Keywords: international migration, climate change, natural disasters
JEL codes: F22, Q54

[*] Dipartimento di Economia e Scienze Sociali – Università Politecnica delle Marche – P.le Martelli 8 – 60121 Ancona (Italy) – Email: g.bettin@univpm.it.
[**] Dipartimento di Economia Istituzioni Territorio – Università degli studi di Ferrara – Via Voltapaletto 11 – 44121 Ferrara.

"For my generation, coming of age at the height of the Cold War, fear of nuclear winter seemed the leading existential threat on the horizon. But the danger posed by war to all humanity — and to our planet—is at least matched by climate change." Ban Ki-moon

1. Introduction and related literature

Climate change has been widely recognised as one of the major challenges men will have to face in the near future although the exact evolution of such a complex phenomenon is still shrouded with uncertainty. This makes the analysis of the socio-economic consequences of climate change extremely important but also limited in its forecasting ability to discern how individuals, communities and nations might be affected and react to changing climatic conditions and increasing numbers of extreme weather events.

The adaptation strategies put in places will certainly differ a lot according to local institutional, political and financial constraints (IPCC, 2007) but migration is one of the main possibilities individuals have to escape from the most affected regions (Mcleman and Smith, 2006). Regional small-scale movements might be a first – maybe temporary – response but international long-distance mobility as well is a strategy likely to be pursued especially where the consequences of climate change are registered not only in small regions but even at national or supranational level.

Barrios et al. (2006) for example look at how climate change shaped rural-urban migration flows and hence urbanisation processes in Sub-Saharan Africa. Even though exploiting aggregate data in a cross-country comparison, the implicit assumption they do is that since the consequences of climate change involve mainly agricultural activities and rural areas, the adaptation channel to be analysed is that of internal migration.

Reuveny and Moore (2009) instead focus on long-distance international migration to developed countries as a consequence of environmental degradation expressed in terms of weather-related natural disasters. By means of bilateral data that include a limited set of OECD countries as destinations, they show that a rise in the number of people affected by weather-related disasters significantly acts as a push factor in increasing out-migration flows towards rich countries. The analysis is further broadened in Alexeev et al. (2011), where a bilateral framework including almost 180 sending and destination countries is used to show that disasters due to global warming positively affect emigration. Climate change in terms of natural disasters is also considered in Drabo and Mbaye (2011). Net migration rates are found to increase significantly due to weather-related disasters (expressed both in terms of frequency and of intensity). In addition, the effects seem to vary according to the educational level of emigrants: while emigration rates of low skilled people remain unchanged, high skilled individuals are those who move most in such conditions possibly exacerbating/sharpening the brain drain phenomenon in developing countries.

As an alternative to climatic proxies based on the frequency and the intensity of natural disasters, a few papers have assessed the effects of climate change on international migration employing as a measure the deviation in temperature and rainfall from the long term means. Marchiori et al. (2010) build a very complex model where climate change indirectly affects the decision to migrate through its direct effects on wages and urbanization[1]. Worsening climatic conditions induce lower wage rates (both rural and urban), which are not compensated for by the benefits of urban agglomeration, and this is how international migration occurs. Following Dell et al. (2008), who shows that economic growth is put particularly into question by annual variations in temperatures, they look at anomalies in both precipitations and temperature and find that climate change effects on local wages and urbanization significantly induce out-migration from Sub-Saharan Africa.

Building on this little empirical evidence, we exploit ten-year bilateral data on international migration from 1960 to 2000 and look simultaneously at both anomalies in precipitations and temperature and weather-related natural disaster as determinants of international movements. Our initial set of countries is a 231x231 matrix which allows us to consider not only long-distance migration (typically from low income to developed – mainly OECD - countries) but also short-distance regional movements (between countries in the same world region).

The paper is organized as follows. Section 2 deals with the issue of measuring climatic conditions and variations, illustrates the data collected for such purpose and shows preliminary descriptive evidence. Section 3 presents the empirical model to be estimated. Results are discussed in Section 4 while Section 5 concludes.

2. Climate Change: how to measure it?

In the last decade increasing attention has been posed on climate change and its effect on international migration both at the academic and the institutional level. Several conference special sessions have been dedicated to the topic[2], one of which has also become a special issue on Ecological Economics (Muradian et al., 2006). Contextually, at the institutional level several

[1] See also Marchiori and Schumacher (2011).

[2] The session "Migration, Globalization and the Environment Migration, Globalization and the Environment" has been held at the ISEE Conference 2004, while a special session entitled "Environmentally Induced Migration" was in the programme of the EAERE conference in 2011.

reports have been produced about the overall economic consequences of climate change (World Bank, 2009) and more specifically on the links between climate change and migration (IOM, 2009).

As mentioned in the previous paragraph, empirical contributes on the topic often seek to test the effect of an heterogeneous set of climate change proxies on international migration mainly by using panel estimations (Drabo and Mbaye, 2011; Marchiori et al., 2010). While the triggering effect of climate change on international migration is largely recognized, there is still a lack of consensus about the most appropriate indicators of climate change to be included in a migration choice model. 23 different aggregate environmental indexes used by several organisation like the WWF, the World Bank and Eurostat, among the others, were reviewed by the OECD in 2002. However, most of these indexes, although appropriate to account for some specific environmental problems, were not considered suitable to describe the trend of climate change at a global level. In fact, they presented several problems, both in terms of country coverage and in terms of scarce capacity to discern local effects of climate change.

Empirical studies therefore moved towards meteorological data, which may better reflect the real effects of climate change and are generally (widely) available in long time series for most of the countries worldwide. Anomalies in rainfall, for example, were shown to determine the urbanisation patterns in Sub-Saharan Africa (Barrios et al., 2006) and more in general - through their effects on agriculture - to play a significant role in determining the economic performances of Sub-Saharan countries. Similarly, Marchiori et al. (2010) employed both rainfall and temperature anomalies and estimated that climate change is responsible for displacing 2.55 million people in net terms over the period 1960-2000 in Sub-Saharan Africa. All these studies are based on the Inter-Governmental Panel on Climate Change (IPCC) meteorological data set, which provides long time series data on annual precipitations and temperature for most countries in the world between 1901 and 1998 (Mitchell et al., 2002). Such a long time span together with its wide geographical coverage allows building reliable climate change proxies. In particular, following the climatology literature all the above mentioned works calculated the proxies for climate change as anomalies in the values of precipitations and temperatures. These anomalies are constructed for every country *i* at time *t* as a variable z-score:

$$Temperature\ Anomaly_{i,t} = \frac{Temperature_{i,t} - Long\ run\ country\ average\ value_i}{Long\ run\ country\ standard\ Deviation_i} \quad (1)$$

Thanks to the time coverage, it is in fact possible to represent yearly anomalies with respect to long run tendencies. According to Barrios et al. (2010), the main advantage of using anomalies over year by year variation is that they eliminate possible scale effects and take into account the possibility of higher variance in the data for the more arid countries (see Nicholson, 1986, and Munoz-Diaz and Rodrigo, 2004). The recent contribution of Dell et al. (2008) instead used the annual variation of precipitation and temperature as a proxy for climate change to study its impact on economic growth thus reflecting a major interest in cross country differences over the long run climatic changes.

Alternative measures for dramatic changes in climatic conditions are given by the number and the intensity of natural disasters in a country. These information are contained in the Emergency Events Database (EM-DAT) developed in 1988 and constantly updated by the Centre for Research on the Epidemiology of Disasters (CRED)[3]. Data are available since 1900 and can be used as a valuable proxy for climate change.

As shown in the extensive narrative analyses conducted by Rauveny (2007), there are many examples of environmental migrations induced by big disasters. Case studies like Bangladesh migrations and the 2005 Hurricane Katrina in the U.S. fully support the prediction that weather-related disasters are important push factors for migration decisions. In addition, Alexeev et al. (2011) and Drabo et al. (2011) used data on disasters as main climate change proxies in empirical analyses on the determinants of international migration.

Even though all the above mentioned proxies for climate change are based on a solid meteorological and conceptual ground, there is still a lack on consensus on the best way to express climate change effects in empirical models. Moreover, as highlighted in IPCC (2007) climate change shows itself through temperature change, precipitation change, sea level rise and extreme events and consequently the above mentioned proxies are not mutually exclusive. For these reasons in the present analysis we prefer to include both temperature and rainfall anomalies and the number of people affected by climate change related disasters as proxies for climate change. A brief description of the data used and some descriptive statistics are presented in the following paragraph.

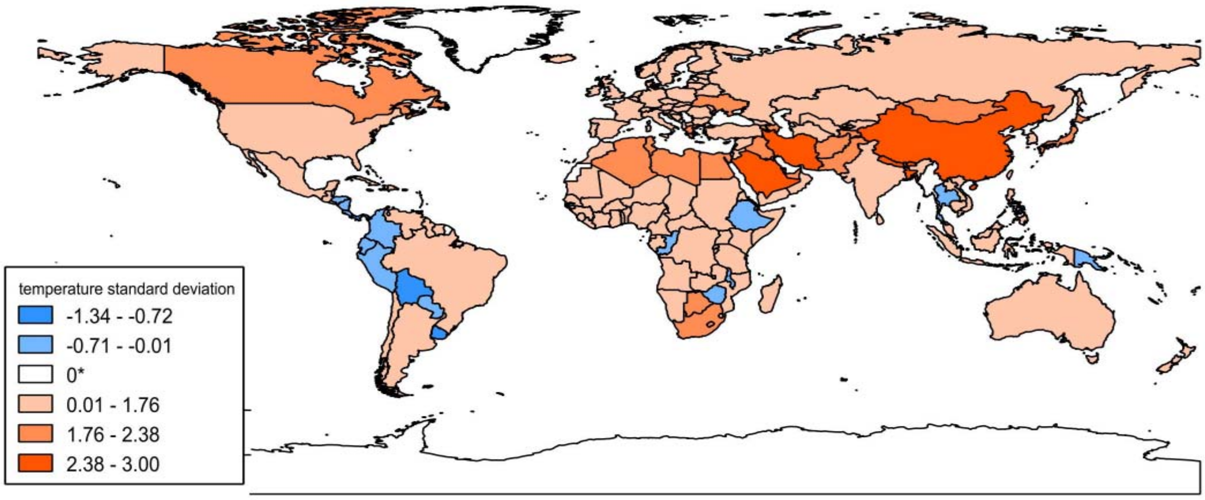
2.1 Variable definition and descriptive statistics

Our climatic variables are calculated using data from the TYN CY 1.11[4] database elaborated by Mitchell et al. (2004, 2005), which includes 9 main variables: daily mean, minimum and maximum temperature (degrees Celsius); daily temperature range (degrees Celsius); frost day frequency (days); precipitation (millimetres); wet day frequency (days); vapour pressure

[3] The dataset is publicly accesible at http://www.cred.be/emdat/.
[4] The database is available at http://www.cru.uea.ac.uk/~timm/cty/obs/TYN_CY_1_1.html.

(hectaPascals); cloud cover (percentage). Meteorological observations were modelled on a 0.5° latitude by 0.5° longitude grid that covers the world land surface (New et al., 1999, 2000). For transforming the gridded data into country-level mean values, each grid box has been allocated to a single territory and the weighted mean has been calculated. Weights were chosen according to climatological reasons. If the data were insufficient to obtain a value, it has been relaxed towards the 1961-1990 mean (Mitchell et al., 2002), that represents the long rung climatological mean to refer to (IPCC, 2007). The result is a dataset with country level climatological information from 1901 to 2000, that is perfectly suitable for econometric analyses in which to combine climatological data with demographic, cultural and socio-economic information. As in Barrios et al. (2010), we compute country-level anomalies in rainfall and temperature, calculated as the deviations from the country's long-term mean divided by its long-run standard deviation (see equation 1 above). The anomalies in temperatures and precipitations are shown in Figures 1 and 2. These figures confirm an increase in temperatures for most of the countries; except for some Central and South-American countries, the temperature rise in year 2000 has been a worldwide phenomenon. Anomalies in precipitations do not show an evident positive or negative trend however their irregularity compared to the long term mean can be appreciated. Moreover, Figures A1-A4 in the appendix depict the mean long-term trends in the temperature anomalies for nine world regions, calculated as five-years moving averages of yearly anomalies expressed as in Equation 1. Interestingly, in most of the region the average anomalies were fairly stable until the 1970s, and then experienced a general increase at the beginning of the 1980s to reach a fairly high level in 2000 which is, on average, one standard deviation above the long term mean. An interesting exception is given by Oceania and South Asia which show a much less stable, although increasing, path and experienced a large variability between the 1980s and the 1990s. Long-run trends in rainfall anomalies (again expressed as five-years moving averages) are represented in Figures A5-A8. Ideally, world regions can be divided into three different groups: *i)* the first, composed by Latin American, European and Asian countries has a fairly regular trend for precipitation with cyclical fluctuations around the mean; *ii)* Sub-Saharan Africa, whose average rainfall anomalies experienced a first considerable drop in the 1970s and a further, more serious one in the 1980s, thus staying under the average level until the year 2000; *iii)* North American countries, which were constantly above the average level during the 1970s and 1980s, and than decreased in the late 1990s to reach a level close to the long term mean.

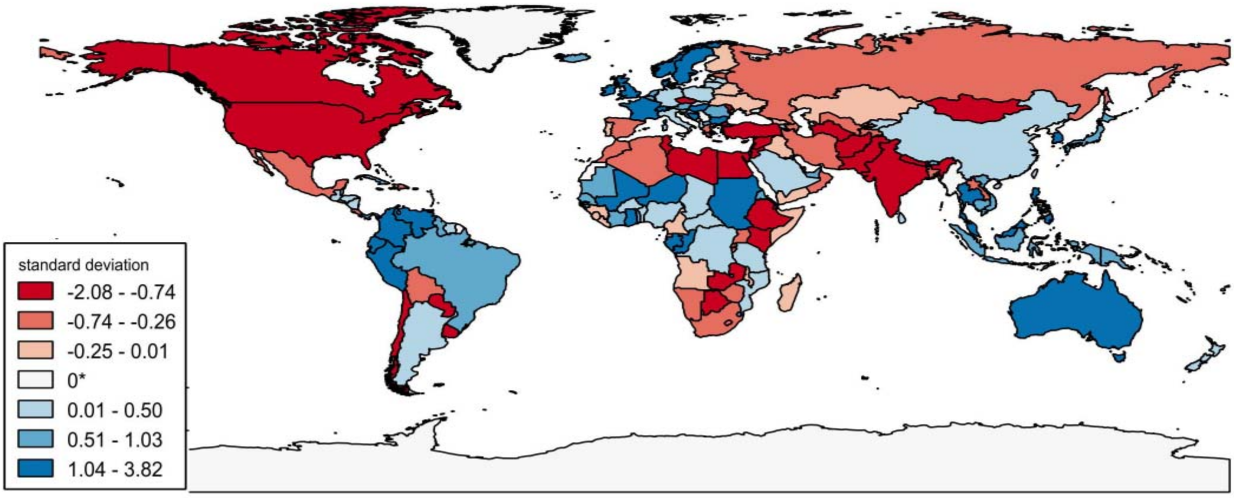
Figure 1. Anomalies in temperature, world, 2000.



* 0= no data.

Source: Elaboration on TYN CY 1.1 data.

Figure 2. Anomalies in precipitations, world, 2000.



* 0= no data.

Source: Elaboration on TYN CY 1.1 data.

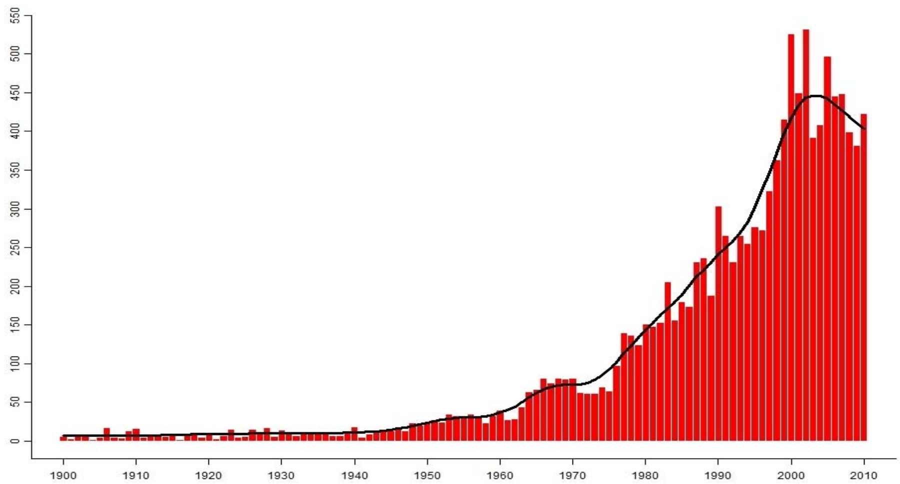
As an additional proxy for climate change, we refer to the intensity of different type of weather-related natural disasters in terms of total number of people affected by extreme events. By considering the total affected, i.e. the sum of injured, homeless and affected people, we have a better representation of the overall effect of the event compared to what the number of people killed by the disaster would give us. Obviously, in this way a storm or a flood in a desert region is *de facto* not considered in the analysis; this is in our opinion a reasonable choice, since we might expect climate change to act as a push factor in triggering migration from inhabited areas only. In the empirical analysis, we consider the climate change related type of disasters[5] reported in Table 1:

Table 1: Disaster Groups included in the analysis

Disaster Subgroup	**Definition**	**Disaster Main Type**
Meteorological	Events caused by short-lived/small to mesoscale atmospheric processes (in the spectrum from minutes to days)	Storm
Hydrological	Events caused by deviations in the normal water cycle and/or overflow of bodies of water caused by wind set-up	Flood, Mass Movement (wet)
Climatological	Events caused by longlived/meso to macroscale processes (in the spectrum from intraseasonal to multidecadal climate variability)	Extreme Temperature, Drought, Wildfire

Only these specific type of disasters, and not the whole spectrum of natural disasters made available in the CRED dataset, are considered in our analysis because we clearly want to focus on the events which are directly related to climate change (Drabo and Mbaye, 2012). The CRED Dataset is available from 1900. Figure 3 unambiguously shows how the frequency of the events dramatically increased since the 1960s. Apart from Oceania, all the continents have experienced a significant increase in the frequency of extreme events, but Asia is by far the most affected region, as shown in Figure 4.

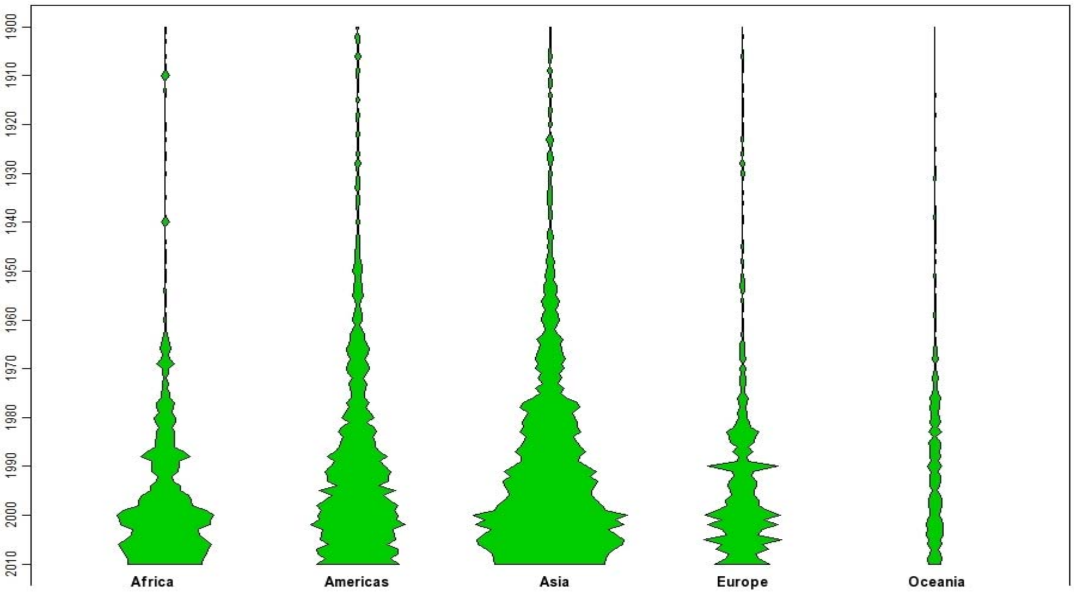
Figure 3. Reported natural disasters, 1900-2010.



[5] The unit of analysis employed in the raw data is the single disaster event. An event is classified by CRED as a natural disaster if it fulfills at leas one out of four selection criteria: ten or more people were killed; 100 or more people were affected, injured or became homeless afterwards; a declaration of a state of emergency was made; the government called for international assistance (see http://www.emdat.be/criteria-and-definition).

Source: EM-DAT: the OFDA/CRED international disasters database.

Figure 4. Reported number of disasters by continent, 1900-2010.



Source: EM-DAT: the OFDA/CRED international disasters database.

3. The empirical model

Our empirical setup broadly builds on the classic gravity equation that has long been recognised as the most powerful tool to explain bilateral trade flows (Anderson, 1979). Gravity models have more recently been employed also to explain migration flows between country pairs either in their most simple formulation (Lewer and Van den Berg, 2009) or by adding specific determinants whose impact needed to be analysed and identified (Karemera et al., 2000; Mayda, 2010). The basic empirical specification looks as follows:

$$Mig_{ijt} = \alpha_0 + \alpha_1 c\lim_{it} + \alpha_2 pop_{it} + \alpha_3 pop_{jt} + \alpha_4 \frac{gdp_{it}}{gdp_{jt}} + \alpha_5 dist_{ij} + \alpha_6 lang\_off_{ij} + \\ + \alpha_7 lang\_ethn_{ij} + \alpha_8 col_{ij} + \alpha_9 agr_{it} + \alpha_{10} agr_{it} * c\lim_{it} + \alpha_{11} I_t + \varepsilon_{ijt} \qquad (2)$$

The dependent variable Mig_{ijt} is calculated as the variation in the stock of migrants in country j from country i between t-10 and t given that we employ ten-year data[6]. In this way we approximate better the flow of migrants between country pairs instead of relying simply on the stock measure. Data on migrant stocks come from the World Bank Global Bilateral Migration

[6] For example, if we refer to the year 2000, Mig_{ij2000} represents the variation in the stock of migrant from country i in country j between 1990 and 2000.

Database that provides bilateral data for 1960, 1970, 1980, 1990 and 2000 for a 231x231 matrix of countries.

Climate change in the country of origin ($clim_{it}$) is proxied through different variables. As already illustrated in Section 2, we build measures for extreme values of anomalies in precipitations and temperature which are either jointly or separately considered in the estimated specifications. In particular, for both temperatures and rainfall we define a dummy variable that takes value 1 if the cumulated values of anomalies (expressed in absolute terms[7]) in the previous five years is above the 90th percentile of the overall sample distribution of anomalies. To verify the robustness of our results, we first relax this definition of extreme anomalies in temperatures and precipitations by alternatively considering values above the 80th percentile of the distribution. Then, we also adopt a continuous variable calculated as the average anomalies in rainfall/temperature registered in the country in the last five years, where the yearly anomalies are calculated as in Equation 1.

To take into account the empirical evidence of a positive and significant effect of weather-related natural disasters on out-migration, we include in our specifications a dummy which takes the value 1 if the population of country *i* has been affected by meteorological, hydrogeological or climatological disasters[8] in the previous 5 years. Given the nature of the dataset, and according to the main literature on climate change and migrations, we used five-year averages of all the variables included in the regression analysis[9].

We mainly follow Mayda (2010) and Lewer and Van den Berg (2009) to select the control variables commonly employed in migration models. Economic distance between countries certainly represents one of the main determinants of migration. In particular, the literature has typically referred to the income differential[10], which in our case is expressed by the ratio of the countries' GDP per equivalent adult at 2005 PPP constant prices (gdp_{it}/gdp_{jt}). In addition, population living in both origin and destination countries (pop_{it} and pop_{jt}, respectively) is included in the model in

[7] The use of anomalies expressed in absolute terms makes it possible to consider at this stage both positive and negative deviations from long term means. A future analysis might be useful to disentangle effects on migration deriving from extreme negative or extreme positive anomalies in both temperature and precipitation.

[8] As indicated in Table 1, meteorological disasters are defined as events caused by short-lived/small to meso scale atmospheric processes and the main type of disasters are storms. Hydrological events are caused by deviations in the normal water cycle and/or overflow of bodies of water caused by wind set-up and are mainly flood or wet mass movements. Climatological events are caused by long-lived/meso to macro scale processes (in the spectrum from intra-seasonal to multi-decadal climate variability) and are typically droughts, wildfires and extreme temperatures.

[9] Barrios (2006) in particular stress the importance of using five-year inteval observation, which avoid issues related to temporal dependence.

[10] The classical reference in this context is the model by Harris and Todaro (1970) where the difference in expected wages – actual wages weighted by unemployment rates - is the main trigger for rural-urban migration. Unfortunately, unemployment data on developing countries are not widely available so we prefer to follow empirical analyses like Lewer and Van den Berg (2009) and simply include income differentials in the estimated model.

natural logarithm[11]. A further traditional control in gravity models is geographic distance, which is supposed to negatively affects both goods and people flows between countries. Distance ($dist_{ij}$) here is expressed as bilateral distances between the biggest cities of the two countries weighted by the share of each city in the overall country's population. Such a measure is made available by CEPII[12] together with two common languages dummies based on the fact that two countries share a common official language ($lang\_off_{ij}$) or a language spoken by at least 9% of the population in both countries ($lang\_ethn_{ij}$) and a dummy referring to past colonial relationships in the country pair (col_{ij}). The relevance of agriculture in the national economy is expressed as the percentage of the overall GDP produced by the agricultural sector (agr_{it})[13]. We also interact the agricultural variable with the measure of anomalies in precipitations and temperature (agr_{it}* $clim_{it}$). By adding the interaction term, we are able to check if the role of climate change as a push factor in determining migration outflows is stronger/weaker in those countries which are more/less dependent on their own agricultural sector. Temperature and rainfall anomalies may in fact negatively affect the length of the growing season and more generally the overall agricultural productivity (Dell et al., 2008).

The standard practice when estimating gravity models is to log-linearize the gravity relation and estimate the resulting equation with OLS. However, this approach is limited in the sense that it forces to either exclude zeros in the dependent variable from the estimates or to transform them by taking the log of (*1+dependent variable*). Since migration is very unlikely to occurr among all world's country pairs, the incidence of zero values is rather high in our sample. In addition, the migration variable essentially represents discrete data whose nature is better accounted for in the so-called count data models such as the Poisson and the negative binomial model (Cameron and Trivedi, 1998). A zero-inflated negative binomial model is hence employed for the estimation of Equation 2. This is a specific class of count models used for treating count variables with a relevant number of zero observations generated by a process that may be separated from the one that generated the positive values. An additional probit equation is included in the model to determine the probability of observing zero in the migration variable as a function of the set of control variables included in the main equation: population living in the origin and in the destination country (in natural logs), income differential, distance and the dummies $lang\_ethn_{ij}$, $lang\_off_{ij}$ and col_{ij}. The idea behind the zero-inflation equation in our model is that the determinants of "structural" positive migration flows between two countries are the factors more commonly considered in migration models such as income differentials and cultural and language proximity,

[11] Data on both GDP and population come from the Penn World Table (Heston et al., 2011).
[12] See Mayer and Zignago (2011) for a detailed technical description of the CEPII's *GeoDist* database.
[13] Data are drawn from the World Development Indicators.

while the effects of climate change can be mainly detected on the size of the outflows. In other words, migrants from India are according to our expectations on the zero-inflation equation more likely to choose to migrate to the United Kingdom compared to Germany, for example. The 2004 tsunami is expected to increase the number of environmentally displaced people who actually moved to the UK after the disaster.

The preference for a negative binomial with respect to a Poisson model is justified on the basis of the test statistics reported and discussed in the next Section even though estimation results did not appear significantly different. Since an extension to take the panel dimension into account in a zero inflated count model would not be easy to implement, we choose to address the issue of excessive zeros first, and simply control for common time effects by means of the time dummies I_t included in the model.

4. Empirical results

Table 2 presents the results from estimation of equation 2 above. All eight columns are estimated by means of a zero-inflated negative binomial regression, using a first stage probit model to take into account the excess zeros in the data. A likelihood-ratio test comparing the zero-inflated negative binomial model with the zero-inflated Poisson model has been run for all the specifications below; the over dispersion coefficient is always significantly different from zero[14] and since our data is overdispersed, a zero-inflated negative binomial model is more appropriate than a zero-inflated Poisson model and the test statistic always favours the negative binomial estimates. Moreover, the Vuong test (1989) [15] suggests that the zero-inflated model is a significant improvement over a standard negative binomial model.

The first two specifications refer to the full sample available, while in the following ones we restrict the set of origin countries included in the analysis (leaving the destination countries unchanged). As Kahn (2005) clearly points out, countries' income level and geographic location are key determinants of death toll from natural disasters. Columns I-IV show result for migration from low-income countries[16], columns V-VI for migration from African countries and columns VII-VIII for migration from Asian countries.

[14] The p-value reported below estimation results always leads to the rejection of the null hypothesis alpha=0 where alpha is the over-dispersion coefficient.
[15] The Vuong's test is used to compare non nested-models in terms of the difference in their respective Kullback-Leibler distance from the unknown "true" model.
[16] Low income countries are chosen according to the World Bank country classification and include low income, lower middle and upper middle income countries.

The main results tend to be coherent with the theoretical prediction of international migration models and with our expectations about the effect of the climate change variables. The variables included in the zero-inflation equation are statistically significant across all subsamples with the expected signs.

Our gravity specification confirms the results previously obtained in the literature both in terms of expected signs and in terms of statistical significance. In particular, economic and geographical distance plays a fundamental role in determining migration flows, as confirmed by the significant negative coefficients (Lewer and Van den Berg, 2008; Mayda, 2010). Cultural and language similarities instead increase the probability and the intensity of migration between country pairs (Letouzé et al., 2009); positive coefficients are also associated to the population of both origin and destination countries (Letouzé et al., 2009). The time dummies added in order to control for unobserved time varying factors are always statistically significant across the different subsamples and confirm the overall increasing trend in worldwide migration in the second half of the 20th century.

The share of GDP produced by the agricultural sector in the country of origin shows an unexpected negative correlation with migration flows. In fact, countries that rely more on the agricultural sector can be generally considered more inclined towards international migration, while across all subsamples it turns out that the share of the agricultural sector is negatively correlated with migration outflows.

Moving to our main variables of interest, the three proxies for climate change exert a positive effect on migration flows in the full sample in column I. However, only the dummy associated with extreme temperature anomalies is statistically significant, thus indicating that climate change seems to affect international migration mainly through the intensity of temperature anomalies.

Such a result, however, is likely to be biased by the geographical distribution of precipitations anomalies and natural disasters. In fact many industrialised countries like U.S., Canada and Europe, which are also top destination countries for immigrants from all over the world, experienced strong precipitation anomalies and also many disasters (see Figure 1-2, 6; see also Kahn, 2005). By including them amongst the origin countries the overall effect of climate change on migration might appear more feeble than what actually is. As a consequence, we proceed by restricting the sample of the origin countries respectively to low-income, African and Asian countries. Interestingly, these restrictions do not alter the previous result; on the contrary, column IV shows that once we include the interaction with the variable for agriculture, also the positive coefficient associated to the rainfall anomalies becomes statistically significant at 95% level. This last result is strongly confirmed once we further reduce the sample by considering only African countries of origin. Both precipitation and temperature anomalies are statistically significant in columns VI-VII, in line with the preliminary evidence from Figure A6 which shows how precipitation anomalies strongly affected Sub-Saharian countries since the end of the 1970s.

Finally, a significant role for disasters in determining migration flows emerges when the sample is limited to the Asian countries of origin in the last two columns of Table 2. The high frequency of climate change related disasters in this region (see Figure 6) arguably increases the outward migratory pressure. Kahn (2005) finds that, all other things being equal, Asian countries are 28.5 percentage points more likely to experience a natural disaster in a given year compared to African countries.

In general, the interaction between our proxies for rainfall and temperature anomalies and the share of agriculture in GDP is negative: surprisingly, other things being equal, the triggering effect of climate change on migration flows is stronger in countries that rely less on agriculture. This may partially be explained by the fact that we do not distinguish between negative and positive climatic anomalies that indeed might have contrasting effects on migration outflows. However, also Marchiori et al. (2010) get similar results when interacting rainfall and temperature anomalies with a dummy variable that is equal to 1 if the country has an agricultural value added above the median in 1995 sample. In our case, when looking at estimates in column II, the overall effect of temperature anomalies is positive on migration outflows for countries in which the share of GDP produced in the agricultural sector is below 39%.

Robustness checks run with different proxies of precipitation and temperature anomalies are presented in Tables 3 and 4. In particular, precipitation and temperature anomalies are proxied in Table 3 with a dummy which takes value 1 if the cumulated values of absolute anomalies in the previous five years is above the 80^{th} percentile of the overall sample distribution of anomalies. This first test has been reported for both the full sample and the low income sample, and results generally confirm the main findings, except for the precipitation anomalies which are now statistically significant also in the full sample.

Table 4 instead shows results obtained when using the 5-year average levels of both rainfall and temperature anomalies on the full sample, and for the subsets of African and Asian countries of origin. Also in this case the use of a different climatic proxy does not alter the main results. Precipitations and temperature anomalies are statistically significant and the total number of people affected by climate related disasters is significant only for the Asian sub-sample, as in Table 2.

Table 2. Determinants of bilateral migrations flows: main specification.

Variable	I	II	III	IV	V	VI	VII	VIII
rainfall$_{it}$	0.036	0.057	0.078	0.291**	0.332***	0.570**	-0.095	0.354
temperature$_{it}$	0.152***	0.310***	0.184***	0.601***	0.131*	0.703***	0.613***	1.147***
disasters$_{it}$	0.044	0.053	-0.015	-0.014	0.064	0.049	0.873***	0.891***
population$_{jt}$	0.632***	0.631***	0.654***	0.651***	0.448***	0.465***	0.522***	0.515***
population$_{jt}$	0.846***	0.847***	0.868***	0.869***	0.817***	0.823***	0.888***	0.891***
GDP$_{it}$/GDP$_{jt}$	-0.052***	-0.053***	-0.194***	-0.193***	-0.119***	-0.117***	-0.051***	-0.050***
distance$_{ij}$	-1.524***	-1.520***	-1.841***	-1.842***	-2.077***	-2.069***	-2.074***	-2.072***
col$_{ij}$	1.840***	1.842***	2.142***	2.165***	2.039***	2.037***	1.673***	1.660***
lang_off$_{ij}$	0.681***	0.672***	0.752***	0.727***	0.919***	0.910***	0.951***	0.958***
lang_ethn$_{ij}$	0.735***	0.741***	0.583***	0.597***	1.129***	1.152***	0.558***	0.530***
agr$_{it}$	-0.019***	-0.018***	-0.024***	-0.022***	-0.015***	-0.012***	-0.026***	-0.023***
rainfall $_{it}$ *agr$_{it}$		-0.002		-0.011**		-0.007		-0.034*
temperature $_{it}$ *agr$_{it}$		-0.008***		-0.016***		-0.018***		-0.018***
N	56606	56606	42623	42623	20941	20941	9367	9367
Sample	**All Countries**	**All Countries**	**Low Income**	**Low Income**	**Africa**	**Africa**	**Asia**	**Asia**
	Inflation equation							
population$_{jt}$	-0.381***	-0.381***	-0.327***	-0.327***	-0.357***	-0.355***	-0.348***	-0.347***
population$_{jt}$	-0.250***	-0.249***	-0.275***	-0.275***	-0.337***	-0.336***	-0.250***	-0.249***
GDP$_{it}$/GDP$_{jt}$	0.018***	0.018***	0.081***	0.081***	0.047***	0.048***	0.014***	0.015***
distance$_{ij}$	0.765***	0.766***	0.772***	0.772***	0.800***	0.802***	1.025***	1.025***
col$_{ij}$	-1.779*	-1.774*	-1.148*	-1.148*	-5.539	-5.59	-0.013	-0.011
lang_off$_{ij}$	-0.167**	-0.169**	-0.273***	-0.273***	-0.711***	-0.716***	-0.163	-0.151
lang_ethn$_{ij}$	-0.236***	-0.234***	-0.243***	-0.243***	0.234**	0.241**	-0.163	-0.172

Zero inflated negative binomial estimations. * p = 0.1; ** p = 0.05; *** p = 0.01.

Table 3. Robustness: climate change proxied by five years cumulated anomalies above the 80th percentile of the temperature and rainfall anomalies distribution

Variable	I	II	III	IV
$rainfall_{it}$	0.095***	0.198***	0.094**	0.643***
$temperature_{it}$	0.148***	0.211***	0.090*	0.237***
$disasters_{it}$	0.041	0.051	-0.006	0.029
$population_{jt}$	0.633***	0.630***	0.656***	0.651***
$population_{jt}$	0.847***	0.846***	0.868***	0.869***
GDP_{it}/GDP_{jt}	-0.053***	-0.053***	-0.195***	-0.197***
$distance_{ij}$	-1.522***	-1.524***	-1.836***	-1.857***
col_{ij}	1.830***	1.830***	2.124***	2.105***
$lang\_off_{ij}$	0.688***	0.670***	0.761***	0.693***
$lang\_ethn_{ij}$	0.723***	0.735***	0.577***	0.629***
agr_{it}	-0.019***	-0.017***	-0.024***	-0.020***
$rainfall_{it} * agr_{it}$		-0.006**		-0.024***
$temperature_{it} * agr_{it}$		-0.003*		-0.006***
N	56606	56606	56606	56606
Sample	**All Countries**	**All Countries**	**Low Income**	**Low Income**

Zero inflated negative binomial estimations. * p = 0.1; ** p = 0.05; *** p = 0.01.

Table 4. Robustness: climate change proxied as five-years averages in temperature and rainfall anomalies compared to countries' long term values

Variable	I	II	III	IV	V	VI
$rainfall_{it}$	0.113***	-0.011	0.355***	0.841***	-0.135	0.538*
$temperature_{it}$	0.125***	0.145***	0.449***	0.611***	0.265**	0.322**
$disasters_{it}$	0.017	0.026	-0.008	-0.001	0.766***	0.755***
$population_{jt}$	0.632***	0.631***	0.448***	0.446***	0.519***	0.512***
$population_{jt}$	0.845***	0.847***	0.814***	0.819***	0.888***	0.886***
GDP_{it}/GDP_{jt}	-0.052***	-0.052***	-0.120***	-0.119***	-0.049***	-0.049***
$distance_{ij}$	-1.521***	-1.518***	-2.102***	-2.086***	-2.051***	-2.061***
col_{ij}	1.854***	1.855***	2.068***	2.067***	1.730***	1.735***
$lang\_off_{ij}$	0.668***	0.659***	0.888***	0.902***	0.844***	0.892***
$lang\_ethn_{ij}$	0.739***	0.750***	1.127***	1.116***	0.575***	0.537***
agr_{it}	-0.019***	-0.018***	-0.015***	-0.014***	-0.022***	-0.022***
$rainfall_{it} * agr_{it}$		0.006***		-0.017***		-0.021**
$temperature_{it} * agr_{it}$		-0.001		-0.006***		-0.003
N	56606	56606	20941	20941	9367	9367
Sample	**All Countries**	**All Countries**	**Africa**	**Africa**	**Asia**	**Asia**

Zero inflated negative binomial estimations. * p = 0.1; ** p = 0.05; *** p = 0.01.

Conclusions

This paper presents comprehensive empirical evidence on the effect of climate change on international migration. This long-term analysis has been made possible by employing a ten-year bilateral data set on migration flows covering all the country pairs over the period 1960 to 2000. The value of such an analysis is manifold. First of all, this is the first study that makes an attempt to include in a regression framework all the channels through which a complex phenomenon like climate change can manifest its effect, i.e. variations in the level of temperatures, variations in the level of precipitations and weather-related natural disasters. Moreover, the use of bilateral data allows for a big improving in disentangling the influence of climate change on international migration since we do not simply focus on migration flows towards OECD countries but we can also take regional movements into account (between African or Asian countries, for example). Finally, we address the potential problem of selection by using a zero-inflated negative binomial estimation technique.

The main regression results confirm our expectations and what found in previous empirical evidence. All traditional control variables used in migration studies, like income, geographical distance and common language are significant with the expected signs. Migration flows are found to be in general positively affected by climate change indicators, especially when we focus on Africa or Asia as regions of origin. Compared to other studies on the effects of natural disasters on migration (Alexeev et al., 2011; Drabo and Mbaye, 2011), our estimates show that once we take anomalies in rainfall and temperature into account, the direct effect of disasters on outmigration flows is statistically significant only in Asian countries. The fact that we fail in most cases to identify a positive and significant relation between natural disasters and migration might partly be due to the different migration strategies adopted. While persistent anomalies in rainfalls and temperature are likely to have a strong impact on long-term living conditions in a specific region and can therefore stimulate permanent emigration, natural disasters may simply stimulate temporary migration that is not adequately depicted in our dependent variable.

Regression results are robust to a battery of sensitivity tests on the climate change proxies used.

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Appendix

Figure A1. Long run temperature anomalies: Latin America and North America. (5 years moving average)

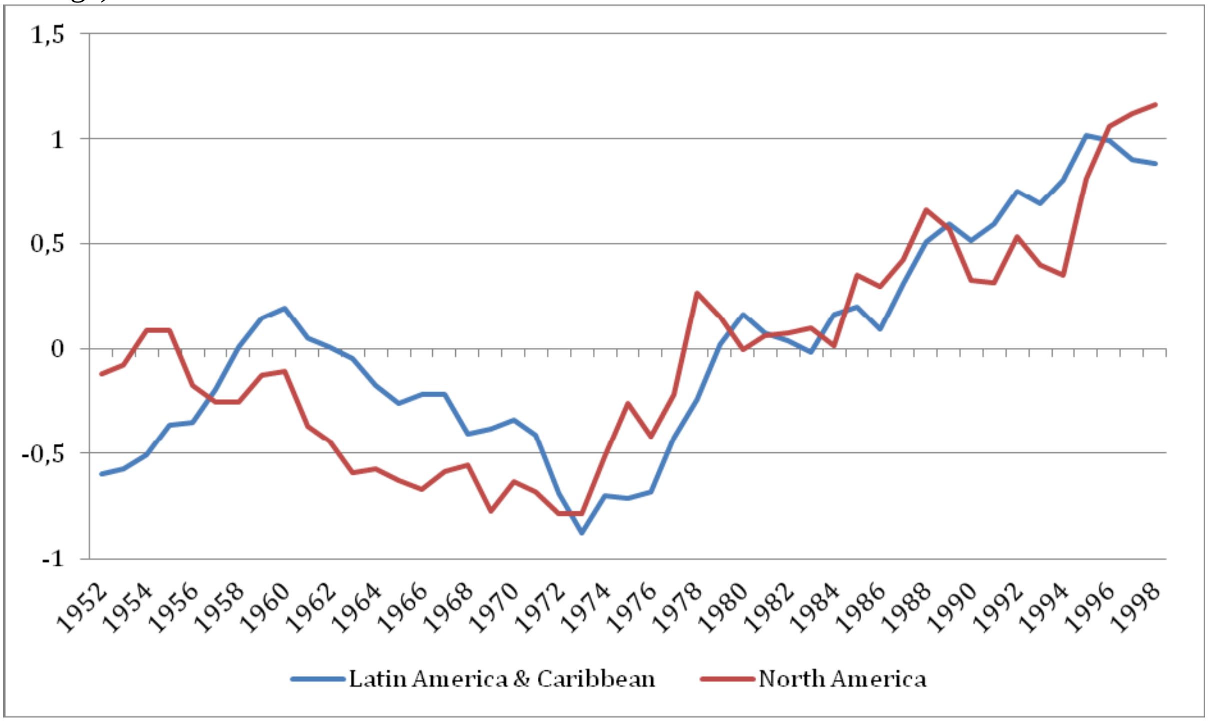

Figure A2. Long run temperature anomalies: Middle East & North Africa, Sub-Saharian Africa. (5 years moving average)

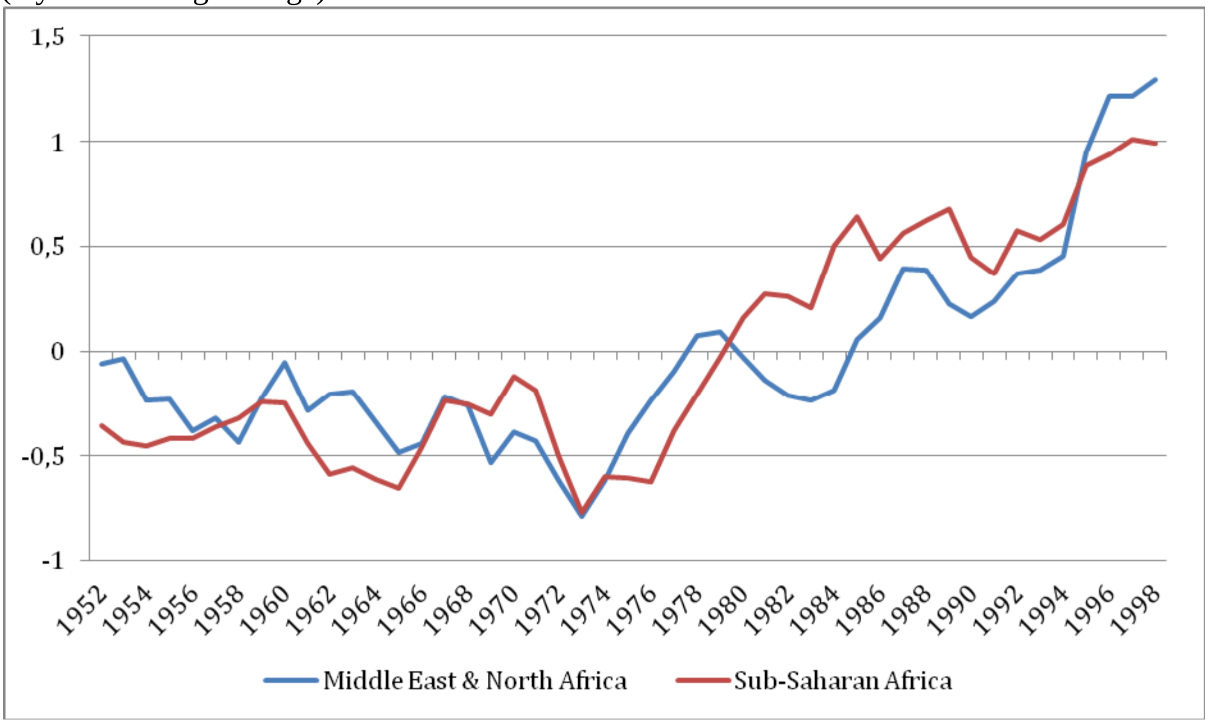

Figure A3. Long run temperature anomalies: East Asia & Pacific, Europe, Central Asia. (5 years moving average)

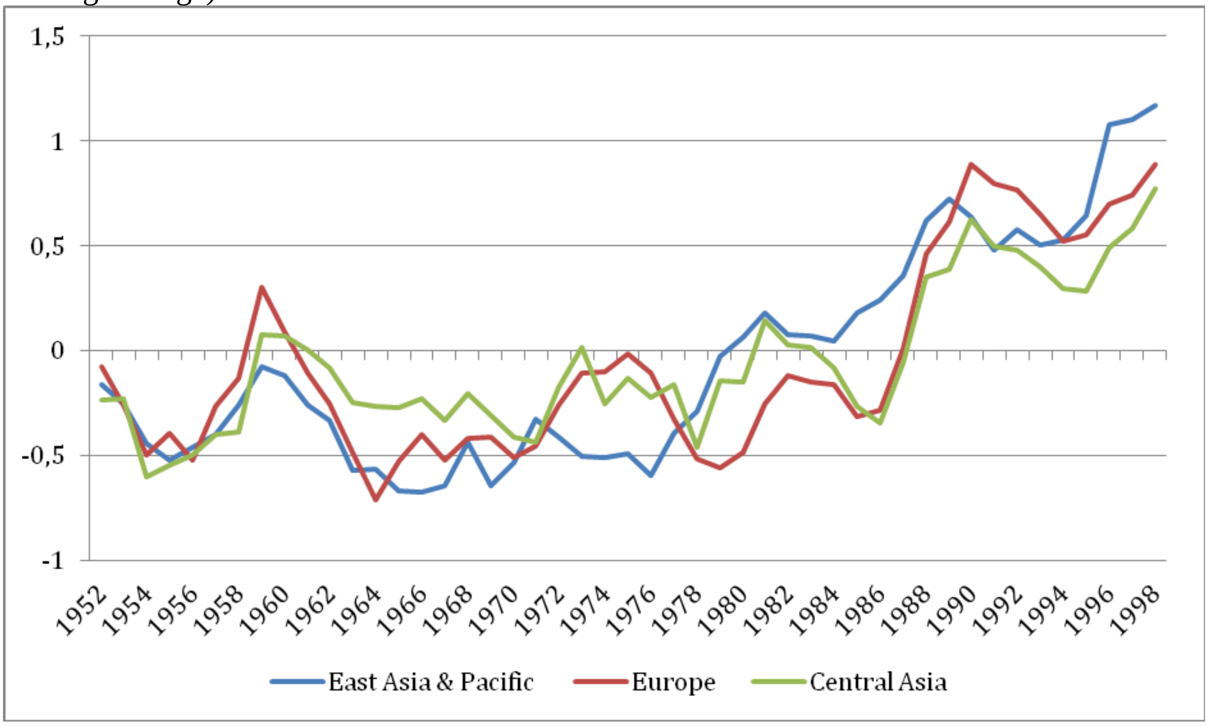

Figure A4. Long run temperature anomalies: East Asia & Pacific, Europe, Central Asia.

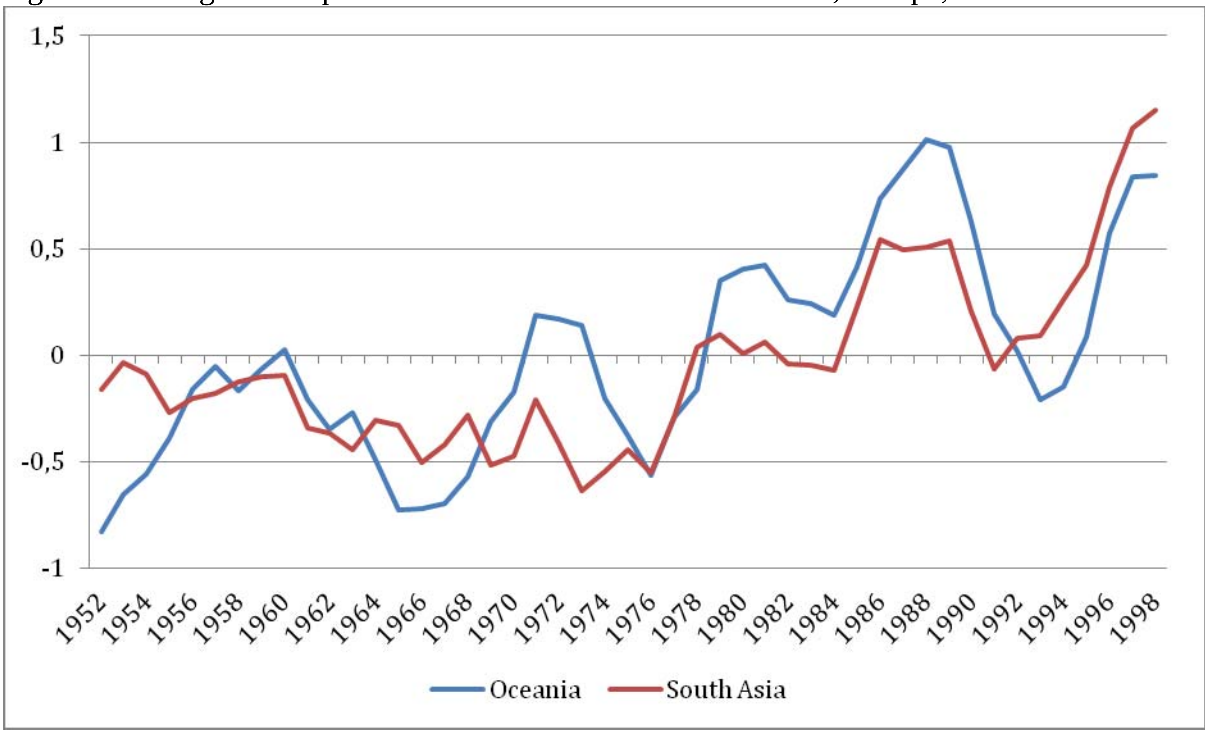

Figure A5. Long run precipitation anomalies: Latin America and North America. (5 years moving average)

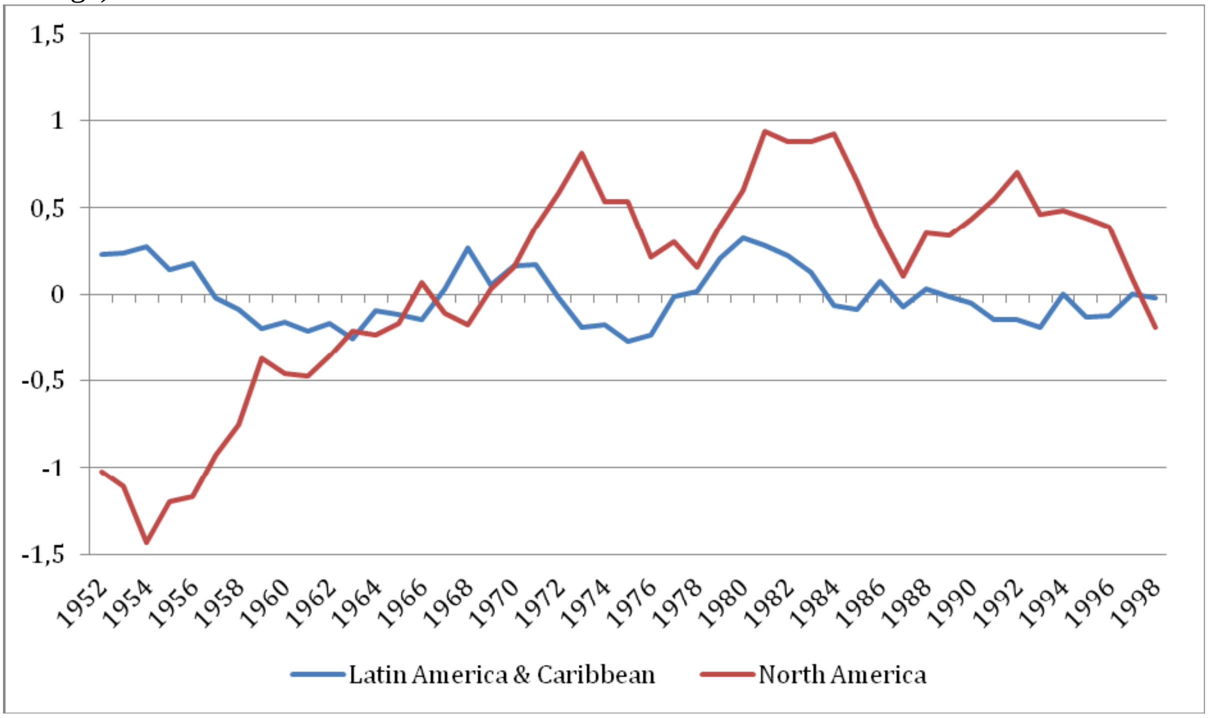

Figure A6. Long run precipitation anomalies: Middle East & North Africa, Sub-Saharian Africa. (5 years moving average)

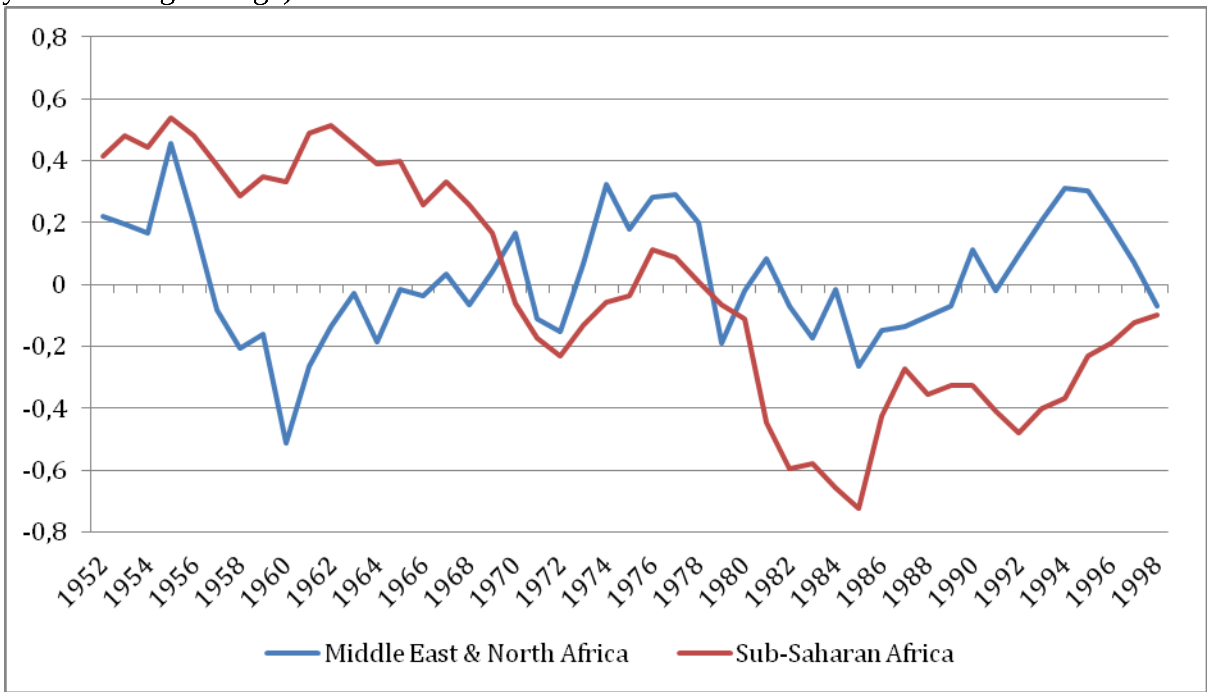

Figure A7. Long run precipitation anomalies: East Asia & Pacific, Europe, Central Asia. (5 years moving average)

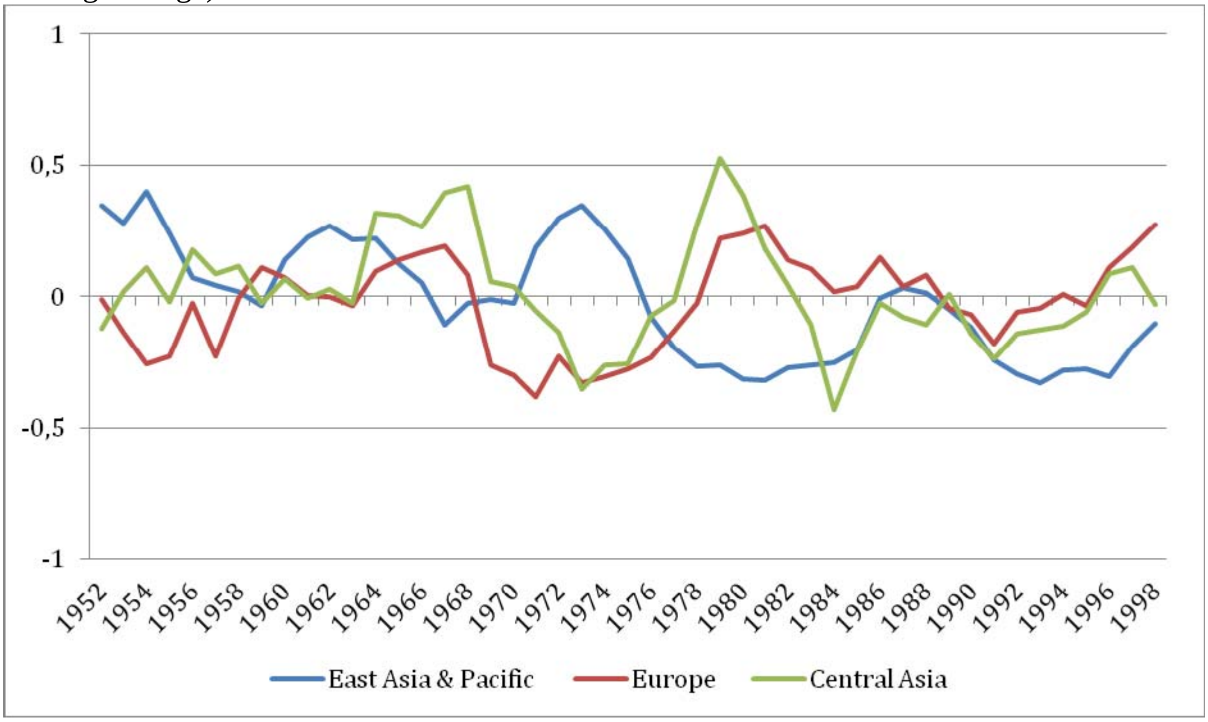

Figure A8. Long run precipitation anomalies: East Asia & Pacific, Europe, Central Asia.

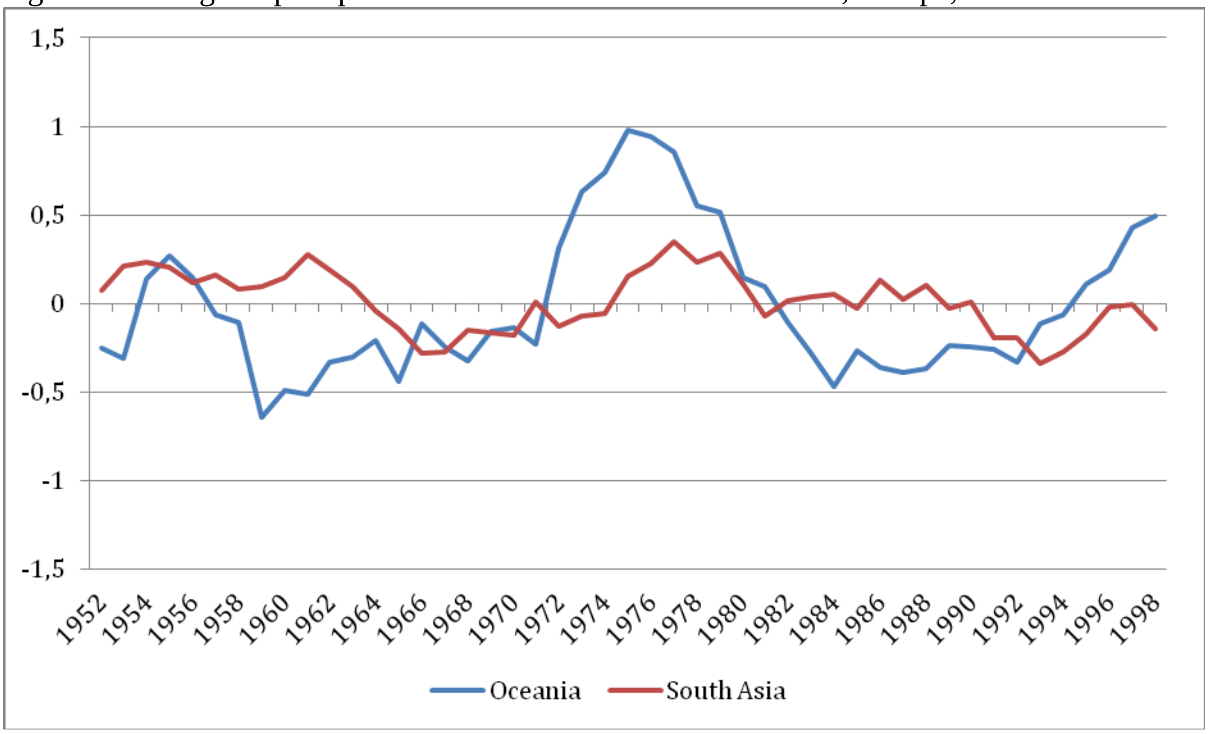

Figure A9. Reported number of people affected by natural disasters, 1900-2010