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On Weather Disasters and International Migration: Empirical Model and Projections to 2060

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ABSTRACT

Weather Disasters (WDs) have played a role in promoting migration in several episodes, but it is unclear if their role is systematic or idiosyncratic. The answer to this public policy question is very important because the intensity, frequency, and scope of WDs are observed growing as climate change progresses in this century under business as usual. Known empirical studies mainly associate essential immigration inflows with violence, economic and institutional development in origin countries. This paper develops a theoretical framework and statistical model that anticipates potential for varied migration responses to WDs across countries and over time, and examines public/economic policy levers that might mitigate or facilitate these responses. Our econometric analysis utilizes unbalanced panel data set for migration flows between 190 origins and 190 destinations across the period from 1980 to 2009.The results suggest that the effect of intensity and incidence of WD on migration flow is nonlinear and may vary in both magnitude and direction due to other factors such as country-specific personal income or international aid, for example. The empirical results are used to estimate projections of migration flows to 2060 under several conservative scenarios. Finally, we discuss implications of our findings for illegal immigration, the possibility of immigration-induced violence, and policies of adaptation to and mitigation of climate change.

INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment finds, among other things, that the incidence and intensity of weather disasters (WDs) such as storms, floods, droughts, sea surges, heat waves, and heavy precipitation, and their adverse impacts on human and natural systems have generally been observed growing since the mid-20th century. This trend of intensification, according to the IPCC, has reflected both the progress of climate change and the growing risk exposures of human settlements. People who are politically, socially, institutionally, economically, or otherwise relegated have been the most vulnerable to WDs, particularly in less developed countries (LDCs), for they are the least able to respond to crisis. The IPCC expects that in the absence of a major mitigation of greenhouse gas emissions (so-called business as usual) the trend will intensify (IPCC, 2013, 2014).

People living in areas affected by more and more intense WDs induced by climate change may respond in several observed ways:

- do nothing and absorb the losses;
- attempt to adapt by reducing their exposure to WDs by changing practices and improving the resilience of structures and livelihoods;
- Adapt by leaving the affected area during and in the aftermath of a disaster and return to rebuild after the disaster has passed and things return to some level of normalcy;
- Adapt by leaving the affected area permanently or migrate; or
- Mitigate causes of climate change with or without adaptation. The particular focus of this paper is WD induced international migration.

Seeking to say something about these possibilities for the future, IPCC (2014a, 2014b, 2013: Ch. 9, 12, 19) examines a large body of recent empirical and theoretical research on WDs and migration. The review concludes that many people hit by WDs migrate elsewhere within their country. On the other hand, people displaced by WDs may attempt to return to their home and rebuild, pulled by place-attachment, inability to migrate due to damages, and aid inflow for rebuilding, and the latter factor, the

IPCC notes, can pull immigrants. Looking forward, the IPCC expects that climate change and WDs will increasingly join other factors in promoting migration at particular times and places. Since the most studies reviewed by the IPCC typically observe rural-urban and internal patterns of international migration worldwide, the IPCC predicts the future migration will be mostly internal, particularly in LDCs (IPCC, 2013: 767-7; 2014b: Box CC-KR).

The IPCC projection of rising internal migration in LDCs in the future is logically clear. But, as noted, LDCs also have great difficulty to respond to crises, so at least some of the people hit by WDs in LDCs may seek to leave their countries, all else being equal. This paper seeks to say something about the latter possibility, but there is really no reason to exclude affected DCs from the analysis. It is conceivable that some of the people from DCs may also seek to go to another country as a result of increasing WDs intensity.

The research question of this paper can be stated as following. The big question is whether or not the WDs increase international migration worldwide in this century. But before we can examine implications for the future, we need to appropriately and reliably recognize, quantify and generalize the role of WDs in international migration so far, assuming, as the IPCC and all of us do, that while the future is unknown, the past could tell us something about the future.

The question of this paper is important regardless of what we may find for the past. If WDs have increased international migration, the pressure may grow in the future since climate change is expected to induce more and more intense WDs. Responding, the destination nations would need to take note and develop appropriate public policies mitigating the consequence. If we find an opposite effect or no effect at all, the nations in harm would need to take a note since it would pose for them fewer adaptation avenues. But our question is important for yet another reason. Violent conflict between international migrants and residents was prevalent throughout the colonial era to its end in the 1970s. This alone should suffice for to motivate our question, but an emerging literature discussed in the last section finds that such conflicts sometimes also occur today, particularly when there are many migrants that differ from natives along racial, ethno-religious, cultural, and/or class line. Indeed, IPCC (2013: Figure 12-3, Ch. 19) suggests that the possibility of migrant-native violent conflicts is an emergent risk of climate change and WDs. But then those native-migrant differences are also sometimes prevalent in modern international migration.

It is the potential for international migration both to rise in WDs and migrant-native violence what motivate this paper. The paper develops a statistical model to describe the yearly bilateral international migration flow between directed pairs (or dyads) of countries.[1] The sample includes 190 origins and 190 destinations and covers the period from 1980 to 2009, containing all the data we could find. The explanatory variables include various measures of WDs and non-weather disasters (NWDs) for both the origin and destination countries and, as controls, typical socioeconomic and political variables. Along the way, we introduce features that heretofore received little attention in the literature, including using three measures of WDs in the same model, interactions between WDs and non-WDs variables, nonlinear Ds and non-WDs terms, fixed effects by directed dyad and by year, north to south migration flows, and some south to south flows.

The findings indicate that WDs in the origin and destination countries have already promoted considerable international migration, and so we proceed to forecast such migration to 2060 based on our model, under several scenarios for the evolutions of the model's variables. The forecasted numbers are impressively large even for the best possible scenario in which the WDs incidence and intensity decline by 2060 to their average levels in the 1990s.

The reminder of this paper is organized as following. The next section positions our study in the body of the related empirical modeling literature on factors of migration. Sections 3 to 5 develop our model, Section 6 presents results,

[1] In this design, each country-pair appears twice in the dataset, depending on data availability. For example, the US-Brazil pair appears once for migration from the US to Brazil in all the years for which there is data, and once for the migration flow from Brazil to the US.

and section 7 employs the model in forecasting. The paper concludes with summary of the findings, and puts the results in the greater context of limiting the scope of climate change impacts on human systems.

PREVIOUS EMPIRICAL MODELS

A large modeling literature examines the role of different socioeconomic and political factors in international migration using samples of various countries and years. The typical unit of analysis is the directed country-pair, or dyad, per year. Given the availability of data, the destinations in these samples are mostly DCs and the origins are DCs and LDCs (e.g., Borda and Mahia; 2010; Mayda, 2010; Belot and Ederveen, 2012). The main findings of these studies indicate that international migration rises when economic and political conditions worsens in the country of origin and improve in the country of destination, when population rises in the origin and (less so) in the destination, when more people in the destination share a language and/or religion with the origin, and when the distance from the origin to the destination declines. These studies do not consider WDs in their list of potential migration factors.

Relatively small though growing literature adds WDs to the list of potential migration factors in two types of modeling approaches, controlling for non-WDs factors. Within the first approach, most micro-level models examine the migration decision at nominal, e.g. to migrate or to stay, or ordinal level, and based on data coming from an individual sample survey collected in some LDC. A smaller body of models utilizes different approach that uses measures of international migration of a higher, ratio or interval, level, - namely, the figures reported by governments and put together by sound international governmental organizations. This paper takes the second, more informative, approach to modeling acknowledging that the survey models are insightful and it is beneficial to discuss their findings.

IPCC (2013: Ch. 9, 12, 19) centers almost entirely on the survey models, so we do not list a full pull of examples here. Atypical model focuses on the area of origin and one type of disaster (e.g., drought, flood). The destination is typically within country, and is either unknown or is listed broadly (e.g., urban/rural). Models for origins (destinations) include only a few or no destination (origin) factors. Most models find WDs raised migration from affected origins and reduced migration to affected destinations. Some models find reverse effect, --that WDs reduced emigration from affected origins (e.g.). Only a few studies, to our knowledge, model migration abroad. For example, Halliday (2006) finds El Salvadorians badly affected by earthquakes were less likely to migrate to the US. Hunter et al. (2013) find Mexicans hit by a recent drought were less likely to migrate to the US, and those with a drought two years earlier and migration in the family were more likely to do so.

To our knowledge, only three published papers have studied the effect of WDs on total international migration figures, namely Reuveny and Moore (2009), Naudé (2010) and Drabo and Mbaye (2014). The explanatory variables for these models also include non-WD controls. The unit of analysis is either the country-period or the directed dyad-period, where period is either the year or the five-year intervals. Since we take the total migration approach to modeling in this paper, we discuss these studies in somewhat greater detail.

Reuveny and Moore (2009) modeled yearly international migration flows for directed dyads between 107 origins and 15 DC destinations in 1986-1995 as a function of the total number of people affected (needed instant help with food, shelter, water, and/or medical treatment) by all WDs. Non-WD variables were measured for both countries, WDs only for the origin, and NWDs were excluded. They found that WDs in an origin raise international migration.

Naudé (2010) modeled net migration flow by country, given as one number defined as the migration inflow to a country from anywhere of the world less outflow from the country to anywhere. The sample includes 45 Sub-Saharan African nations in 1974-2003 in five-year interval. Disasters were measured by the total number of WDs and NWDs in those five-year periods. The estimation results indicated that disasters did not affect the net migration.

Drabo and Mbaye (2014) modeled semi-decadal changes in stocks of migrants from 67 LDCs that reside in each of six DCs (US, Australia, UK, France, Germany, and Canada) for time period from 1975 to 2000. WDs were measured by a variable set to one if the origin countries experienced storms, floods, wet landslides, drought, wildfire, and/or extremely high temperatures in the five years. The non-WDs variables were measured for both the origin and the destination countries. The results indicated that WDs in the origin raised international emigration.

Finally, Marchiori et al. (2012) offer a model of migration at the country level. They find that greater deviations from a country's long term mean for precipitation and temperature were associated with more migration abroad from that country during the period 1960-2000.

Overall, the socioeconomic models of migration offer a measureable framework that is in line with the cost-benefit theory/rational choice, but, recall, they do not consider WDs. The results obtained for the effect of WDs on migration are quite mixed, making generalization hard and policy recommendations useful: many studies find that WDs promote emigration, but others report negative and no effect. Two studies look at WDs in the destination for internal migration, one finding a positive effect and the other a negative effect. As far as we can see, the role of WDs in the destination has not been studied for international migration.

What to make of the mixed picture? The role of disasters in migration may be idiosyncratic, but before we make a determination we need to address a number of issues the existing studies raise. The survey and country-flow models, for example, omit one side of the migration, -- either the origin is modeled or the destination, but not both. Their results may not be general; the survey models examine on single countries, and the country-level models examine Sub-Sahara Africa. Additionally, the role of NWDs is shown to be nontrivial in Halliday (2006) and Naudé (2009, 2010). NWDs ought to be considered in a generalized model, although Halliday only looks at El Salvador and Naudé does not distinguish between WDs and NWDs. Reuveny and Moore (2009) take account for both the origin and destination in a large N sample, but model WDs only for the origin and do not include NWDs at all.

Taking a broader view, the role of WDs in migration may be moderated by socioeconomic forces, but other than Gray and Muller's (2012a) studies do not model interactions. Gray and Muller find little empirical support for interaction at the individual level of analysis, but their result may not be general because it is based on a survey for Ethiopia. Finally, not much is offered in terms of quantified implications for policy aimed at minimizing the role of WDs in motivating migration and in terms of quantified implications for migration in the future. Though almost all of these studies essentially seek to say something about migration and WDs under climate change, they do not offer a forecast.

Of course, there is really no such thing as a "perfect model" and these pioneering studies have already done a lot. We build our model upon their insights and attempt to address some of the issues they raise by developing and testing a statistical model, including quantifying some policy impacts and offering a forecast of migration due to WDs assuming a climate change scenario of business as usual.

Theoretical Setup

The cost-benefit/rational choice theory of migration provides a natural start for this section, for it drives almost all migration research. Potential migrants assumed to estimate the expected net benefits (benefit - cost) for each potential destination on their list, including their current place, and considering all the constraints they face. They migrate to the place with the highest net benefit. Empirical models assume that observed moves maximize the net benefit.

We assume people choose to reside in the country that maximizes their expected net benefits based on factors they deem important. The model explains the migration flow (number per period) from an origin to a destination as a function of these factors, assuming the observed move maximizes the expected net benefit. The unit of analysis in the model is the directed country-pair (or dyad) per period.[2]The key explanatory variables are WDs in the origin and destination and the dependence their effects on countries' copping capacity, the country-specific personal income in a dyad (characterizes both driven or anchoring force), and the foreign aid they receive (as affected countries often get aid, which is a policy variable).Migration may also depend on other factors, which are treated here as observed controls or as fixed effects to account for unobserved country/year specific factors.

Such WDs as floods, storms, and droughts can kill and injure people and damage properties

[2] For example, for the country pair France-Greece each side appears both as an origin and as a destination.

(e.g., homes, farms, industry, infrastructures) and services (e.g., sewage disposal, healthcare, law and order). Health, economic output, and employment may fall and protest and unrest may rise. International migration may rise with WDs occurred in the origin, as people seek for a better standard of living, but may also fall due to associated obstacles to leaving a country(e.g., injury, falling income, assisting family) and rebuilding efforts. The net effect may depend on both the magnitude and occurrence frequency of WDs. For example, migration may first rise with WDs as the desire and opportunity to leave offsets the barriers and rebuilding, and, then, fall after WDs rise above some critical [threshold] level as the latter become dominant (inverted U curve). Other examples of possible behavior may include a fall in migration as WDs rise followed by a rise (U curve), and nonlinear monotonous increase (or decline) in international migration as WDs rise. This logic, with obvious changes, should also apply to the effect of WDs on the migration in the destination.

The effect of WDs on migration may depend on the capacity of the origin and destination to cope with them. This capacity should rise with factors such as

- Preparedness (e.g., levees, water reserves, early warning, evacuation capabilities, disaster insurance);
- Resilience (e.g., strong structures, diversified income sources, crisis healthcare, extra law and order);
- Recovery (e.g., continual operation of computer-based systems); and
- Rebuilding (e.g., funds, knowhow, organizational abilities).

The effect of WDs in the origin on migration may naturally fall with copping capacity, but it may also rise, as more people may be able to leave. Likewise, the same logic (with fitting changes) is also fully applicable in the destination.

Countries hit by WDs often receive foreign aid to help to cope with the impacts. The push effect of WDs on migration in the origin may naturally decline with aid. But the effect of WDs on emigration may also rise with aid. The better situation, more available funding may enable more people to leave. The giving may raise the appeal of a donor as an attractive destination by signaling empathy, and/or the receiving may reduce the appeal of an origin by suggesting greater damages and a smaller copping capacity. In the destination, the pulling effect of WDs may rise with aid by improving conditions and signaling better relations with a donor origin. But the effect may also go in the other direction by signaling greater damages and smaller copping capacity and/or by reducing the need for foreign labor in the rebuilding effort.

Other variables may also play a role, though we obviously cannot include all of factors ever examined in the literature, because of insufficient data coverage in both time and space. We control for effects of NWDs, wage, foreign aid as a standalone variable, population, civil war, and interstate war, and model other unobserved forces by including directed country-pair (dyad) and time-period fixed effects.

Only few international migration models examine NWDs and those that do either look at earthquakes (typically for one country) or combine NWDs with WDs in one measure for a sample of many countries (Belasen and Polachek, 2013). We include NWDs in the model so as not to conflate their impacts with those of WDs. Our speculations suggest WDs effect on migration may go either way.

Turning to socioeconomic variables, higher income in the origin may pull people to stay by signaling a prospect for a higher quality of life and better economic opportunities, but may also enable more people to afford migration abroad. Higher income in the destination may pull migrants for similar reasons, but may also push migrants by signaling a higher cost of living and preference for skilled labor. The net effect may be nonlinear, taking the form of one of the responses noted above.

Civil war in an origin (a militarized conflict between rebel and government forces), may reduce migration as people may not be able to leave or may stay to fight. But it is also possible that people may migrate to flee the fighting and its socioeconomic consequences. Civil war in a destination may deter migrants but, in principle, may also attract people who seek to join the fight. War between the destination and the origin is expected to reduce their migration. People in the origin will likely join the fighting on the side of their country. The destination will most probably view people from the origin it fights as a security risk and refuse to accept them, except, perhaps, in special cases involving asylum seekers and refugees.

Almost all international migration models control for population. The effect of increasing this variable in the origin and destination may go either way. On the one hand, it can facilitate the migration by offering a larger pool of potential migrants and by intensifying competition over jobs in the origin, and by offering more opportunities in the destination and making it easier to go unnoticed and assimilate. On the other hand, a larger population can offer more opportunities in the origin, and increase competition over jobs in the destination, both of which work to reduce migration.

Finally, turning to the policy relevant factors, the foreign aid may also play a role beyond its effect in conjunction with WDs. More aid to the origin may improve economic and social conditions, pulling people to stay. But the better conditions may enable mobility and a rise in aid itself may signal a poorer place in greater need, pushing migration. More aid to the destination may attract migrants but may also signal a poorer place in greater need, deterring migrant, while a rise in aid from a migration partner may increase migration by suggesting better relations. The net effect of these forces is likely to be nonlinear along the patterns discussed above.

EMPIRICAL MODEL

Having discussed the theoretical framework and expected effects of the explanatory variables on international migration, this section presents the variables, data, and their measures used in the empirical model. The estimation employs an unbalanced panel with 5,345 directed dyads and 50,638 observations for 190 origins and 190 destinations across the period 1980-2009. The summary statistics and list of countries in the sample are presented in the appendix.

Unobserved/unmeasured factors unique to a directed origin-destination pair and time invariant appears may affect migration. Examples of observed included distance, contiguous borders, migration treaty, shared language/religion, colonial link, diaspora in destination, and history as a unified country. Unobserved and unmeasured forces accounted by these effects may include, for example, emotional links to a place, xenophobia, and bias by officials, as well as the so-called multilateral resistance (difficulty) to migration elsewhere (e.g., Feenstra, 2004). We summarize the net impact of these forces by including individual effects per each directed dyad in the sample. The results of the Hausmantest suggest that the country/dyadic specific effects need to be specified as fixed (Appendix).

Unobserved/unmeasured factors unique to a period of time and location-invariant may affect migration for all dyads (e.g., global recession/boom, world war, universal migration treaty, falling transportation cost). We summarize such forces by including individual fixed effects per each time period in the sample.

The dependent variable in our model is the yearly bilateral international migration flow. The independent variables include various measures of WDs, NWDs, copping capacity, foreign aid, population, income, civil war, interstate war, period effects, and directed dyad effects. Model also includes quadratic and interaction terms to allow for nonlinearity.

Data for the migration flow from origin O to destination D in the year T (M_{ODT}) come from the Organization for Economic Cooperation and Development (OECD, 2012a). We improve coverage for 1980-89usingthe OECD's SOPEMI (1990) and the US Government's USINS (1996). The data count people relocating by year, per OECD country, Romania, Bulgaria, Russia, and Lithuania, by nationality. The migration data excludes undocumented and non-OECD to non-OECD flows; the data are not there.

The WD data are from the Emergency Events Dataset (EM-DAT, 2012).This source defines disasters as events in which at least 100 people are affected (e.g., need urgent care, shelter, food, water); or at least 10 people die or are assumed dead; or a government declares a state of emergency; or a government calls for foreign help. Using all the WDs in EM-DAT, we compute the total yearly incidence of droughts, storms, heat and cold waves, floods, wet landslides, extreme temperatures, extreme precipitations, and wildfires in the origin (WDI_{OT}) and destination (WDI_{DT}), and the total numbers of people affected (WDA_{OT}, WDA_{DT}) and killed (WDK_{OT}, WDK_{DT}).WDI senses proneness to WDs, while WDA and WDK reflect intensity, duration, and scope, as well as some ability to cope with WDs. The model includes both linear and quadratic terms for these measures, as discussed above.[3]

[3] EM-DAT also offers disaster damages in money terms. We do not use these data as they are mostly missing and reflect country reports that are inexact and perhaps biased (Kahn, 2005; Raschky, 2008).

Data for copping capacity are not available on a comparative basis for many countries and years, so we employ economic development as a proxy, measured by the gross domestic product per capita (GDPPC). The data in 2005 dollars adjusted for purchasing power parity differences across countries, also known as real international dollars (I$), come from Heston et al. (2011).The variables are $GDPPC_{OT}$ for the origin and $GDPPC_{DT}$ for the destination, and they are included as both linear and quadratic terms.

The theoretical setup suggests WDs in the origin or the destination may affect migration in conjunction with the copping capacity of the hit countries. We model this nexus by including interaction terms between each of the three WD measures (WDI, WDA, and WDK) and GDP per capita, by country.

The model includes aid flows per capita per year from the destination to the origin (AID_{DOT}), from the origin to the destination (AID_{ODT}), from the rest of the donors (international governmental organizations and other countries in the sample) to the origin (AID_{ROT}), and from these donors to the destination (AID_{RDT}). The aid data in millions of constant 2005 dollars come from OECD (2012b).Unless reported by the data, we assume OECD states do not give aid to each other, and non-OECD states do not give aid to either OECD or to non-OECD countries.[4]Quadratic aid flows are also included, as discussed above.

The previous section suggests that WDs may affect migration in conjunction with aid flows to the WD-hit countries. We model this possibility by including interaction terms between each of the three WD measures and the both types of aid (from the migration partner and the test of the donors), by country.

The NWDs data come from EM-DAT (2012), including earthquakes, volcanic eruptions, tsunamis, dry landslides, and infestations. We compute the incidence in a year T in the origin ($NWDI_{OT}$) and destination ($NWDI_{DT}$), and the numbers of affected ($NWDA_{OT}$, $NWDA_{DT}$) and killed (WDK_{OT}, $NWDK_{DT}$).

Civil war is modeled as a binary variable set to 1 if there is a militarized conflict between state forces and forces rejecting the state legitimacy, and set to 0 otherwise. The data come from UCDP/PRIO (2012), which tracks events with at least 25 fatalities and at least 1,000 fatalities, by year. We use the 25-threshold, as these events may too affect in migration. The variable names are $CWAR_{OT}$ and $CWAR_{DT}$.

War between the origin and the destination countries is modeled by a binary variable set to 1 if there is fighting, and set to 0 otherwise. The dyadic war events for 1980-2001 come from Maoz (2005), which codes war based on the usual threshold of at least 1000 fatalities in a year.

We code origin-destination war events for 2002-2009 based on the UCDP/PRIO (2012) compilation of international disputes that kill at least 1000 people.

The variable name is called WAR_{ODT}. In addition, we also coded as “war” the situations in which a foreign country supports of the sides of internal conflict.

The population sizes of the origin and destination countries in a year T are labeled POP_{OT} and POP_{DT}, respectively. The data in thousands of persons come from Heston et al. (2011).

The functional form for the model also reflects four empirical considerations:

- M_{ODT} may affect $GDPPC_{OT}$, $GDPPC_{DT}$, POP_{OT}, and POP_{DT}. The effect is likely weak as M_{ODT} is not so large, but we play it safe and replace the four variables by their first lagged values (e.g., Mayda, 2010).
- Heteroscedasticity is likely to be present in the panel as variables come in markedly different scales and magnitudes, so we use natural logarithms of the level variables, adding 1 to M_{ODT}, WD, NWD, and AID before taking their logs since they possess zero in the sample.
- The quadratic and interaction terms are naturally correlated with their contributors, potentially reducing estimation efficiency, so we center their inputs on their respective means (e.g., Balli and Sørensen, 2013).
- The directed country-pair (dyad) effects can be specified as random or fixed. The choice is empirical, and results in the appendix suggest they need to be specified as fixed.[5]

[4]A few non-OECD states (e.g., China) give aid to LDCs, but these dayds’ migration data are missing.

[5]The directed dyad fixed effects, of course, subsume all the time invariant country effects.

Equation (1) states the model in general form:[6]

$$\ln(M_{ODT}+1)=\alpha_0+\sum_i \alpha_{Oi}\ln(WD_{OTi}+1)+\sum_i \alpha_{Di}\ln(WD_{DTi}+1)+\sum_i \beta_{Oi}(\ln(WD_{OTi}+1)-\ln WDOi+1)2+i\beta Di(\ln(WDDTi+1)-\ln WDDi+1)2+i\gamma Oi\ln XOTi \sum_i \gamma_{Di}\ln(X_{DTi})+\sum_i \delta_{Oi}(\ln(X_{OTi})-\ln(XOi)2+i\delta Di\ln(XDTi)-\ln(XDi)2+\sum_i \pi_{Oi}(\ln(WD_{OTi}+1)-\ln WDOi+1\ln XOTi-\ln XOi+\sum_i \pi_{Di}(\ln(WD_{DTi}+1)-\ln WDDi+1)(\ln XDTi-\ln XDi)\quad i\theta Oi\ln(ZOTi)+\sum_i \theta_{Di}\ln(Z_{DTi})+\sum_i \kappa_{ODi}P_{ODTi}+u_{OD}+\tau_T \quad (1)$$

The Greek symbols are coefficients. Bars denote sample mean. Subscripts O and D denote the origin and destination. For the variables, WD_{Oi} and WD_{Di} are WDI, WDA or WDK; X_{Oi} and X_{Di} are GDPPC or AID measures; Z_{Oi} and Z_{Di} are POP, NWDI, NWDA, NWDK, or CWAR; P_{ODi} is WAR or a directed dyad fixed effect; and Y_t is a yearly fixed effect. The X_{Oi}, X_{Di}, Z_{Oi} and Z_{Di} that take on zero values (AID and NWD) include the plus one, POP and GDPPC are lagged one year, and u_{OD} is the error term.

Finally, the marginal effects (MEs) of the log-transformed WD_{Oi}, WD_{Di}, X_{Oi}, and X_{Di} on M_{OD} are expressions that depend on the variables' values, while those at the logged Z_{Oi} and Z_{Di} are the coefficients. The coefficients at the logged WD_{Oi}, WD_{Di}, X_{Oi}, and X_{Di} terms are their ME, holding their own value and that of the logged variables they interact with at the sample mean (or the unlogged value at the geometric mean; e.g., at $\exp(\overline{\ln(WDI_O+1)})-1$ for WDI_O). The MEs are not elasticities despite the log-log model since we add one to M_{OD} and variables taking zero values in the sample. For variable a V, the V elasticity of M_{OD} is $ME_V(M_{OD}+1)V/(M_{OD}(V+1))$ for a $\ln(V+1)$ variable, and is $ME_V(M_{OD}+1)/M_{OD}$ for a log-transformed variable V, i.e. $\ln(V)$.[7]

Estimation Results

This section presents results, while the appendix shows auxiliary results supporting the model. We estimate (1) using OLS with Huber-White standard errors clustered by directed dyad since there may be autocorrelation in our panel and some residual heteroskedasticity even with logged variables.

Table 1 gives M_{OD} elasticities and changes, holding other factors at the geometric mean. At that point, a relatively poor origin gets twice the aid per capita a richer and more populated destination gets. Both are peaceful with small disaster measures. When WDI_O or WDI_D rise by 1%, M_{OD} rises by 0.02% and 0.017%, respectively.

The WDK elasticities are about 0.01. WDA has an elasticity of 0.004 at the destination and no effect at the origin. M_{OD} rises with WDI and WDK in each site and with WDA in the destination.[8] A 1% rise increases M_{OD} by 0.86% for $GDPPC_D$, 0.47% for POP_O, 0.07% for AID_{OD}, and 0.06% for AID_{DO}; reduces M_{OD} by 0.21% for $GDPPC_O$ and 0.05% for AID_{RD} and AID_{RO}; and changes it by -0.003% to 0.008% for NWDs. M_{OD} rises with NWDI and falls when NWDK, $NWDA_D$, or $NWDA_O$ rise. POP_D changes have no effect. A 0 to 1 rise raises M_{OD} by 8.8%for $CWAR_O$, lowers it by -12.7% for $CWAR_D$.

This rise is a 100% change; stated loosely as a 1% rise, the effects of CWAR are not that large. WAR_{OD} has no effect, which may not be general since missing M_{OD} data drop most of the sample's war years.[9]

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[6]The notation used here allows us to simplify the equation that includes 50+ explanatory variables. In the further presentation we will omit time-subscript T in the sake of simplicity.

[7]For the ln(V+1) variables, $ME_V=\frac{\partial\ln(M_{OD}+1)}{\partial\ln(V+1)}=\frac{\partial M_{OD}/(M_{OD}+1)}{\partial V/(V+1)}=\left(\frac{\partial M_{OD}}{\partial V}\right)\left(\frac{V+1}{M_{OD}+1}\right)=\left[\left(\frac{\partial \mathbf{M_{OD}}}{\partial \mathbf{V}}\right)\left(\frac{\mathbf{V}}{\mathbf{M_{OD}}}\right)\right]\left(\frac{M_{OD}}{V}\right)\left(\frac{V+1}{M_{OD}+1}\right)\rightarrow ME_V=\text{elasticity}_V\left(\frac{M_{OD}}{V}\right)\left(\frac{V+1}{M_{OD}+1}\right)$. For $\ln(V)$, $ME_V=\frac{\partial\ln(M_{OD}+1)}{\partial\ln(V)}=\frac{\partial M_{OD}/(M_{OD}+1)}{\partial V/(V)}=\left(\frac{\partial M_{OD}}{\partial V}\right)\left(\frac{V}{M_{OD}+1}\right)=\left[\left(\frac{\partial \mathbf{M_{OD}}}{\partial \mathbf{V}}\right)\left(\frac{\mathbf{V}}{\mathbf{M_{OD}}}\right)\right]\left(\frac{M_{OD}}{M_{OD}+1}\right)\rightarrow ME_V=\text{elasticity}_V\left(\frac{M_{OD}}{M_{OD}+1}\right)$.

[8]Most of the countries receiving many migrants in the sample are DCs and they tend to rebuild following WDs, in line with a reading that the rebuilding pulls migrants (e.g., as for Hurricane Katrina in the US).

[9] For a binary change, we get $\%\Delta M_{OD}=100(e^{\beta}-1)$, as $\ln(M_{OD\,WAR=1})-\ln(M_{OD\,WAR=0})=\beta(1-0)$.

Table 1: *Point Elasticities and Migration Change at the Sample's Geometric Mean*

Variable	Elasticity	Variable	% ΔM_{OD} for 0→1
$NWDI_O$	0.00767***	$CWAR_O$	8.789**
	(0.00271)		3.922
$NWDA_O$	-0.00155	$CWAR_D$	-12.742***
	(0.00186)		5.336
$NWDK_O$	-0.00184*	WAR_{OD}	37.713
	(0.00105)		(53.794)
$NWDI_D$	0.00810***		
	(0.00301)		
$NWDA_D$	-0.00344*		
	(0.00202)		
$NWDK_D$	-0.00198*		
	(0.00113)		
POP_O	0.46919**		
	(0.20920)		
POP_D	-0.00147		
	(0.23748)		
$GDPPC_O$	-0.20827**		
	(0.10231)		
$GDPPC_D$	0.85944***		
	(0.11683)		
AID_{DO}	0.05843***		
	(0.01099)		
AID_{RO}	-0.05059**		
	(0.02449)		
AID_{OD}	0.06857***		
	(0.00969)		
AID_{RD}	-0.05366***		
	(0.01936)		
WDI_O	0.01982**		
	(0.00891)		
WDA_O	0.00155		
	(0.00177)		
WDK_O	0.00984***		
	(0.00370)		
WDI_D	0.01680*		
	(0.00932)		
WDA_D	0.00410**		
	(0.00188)		
WDK_D	0.01007***		
	(0.00382)		

Note: *Robust standard errors clustered by directed dyad in parenthesis. * p<0.1, ** p<0.05, *** p<0.01*

The results at the geometric mean point do not tell the full story, as the WD elasticities may vary when the WD, income, and aid measures move away from that point.[10] Figures 1-6 present the elasticities by WD measure (columns) and another measure (rows), holding other factors at the geometric means. Unless noted otherwise, we discuss values significant at a 5% level (bolded and highlighted).[11]

In Figure 1, the WDI_O elasticity rises as WDI_O and AID_{DO} rise, and falls as $GDPPC_O$ and AID_{RO}

[10] The GDPpc and aid effects also vary with WD, GDPpc and aid, respectively, but center on WDs.

[11] For example, in Figure 1's top panel, if $GDPPC_O$=3,551 and WDI_O=6, elasticity=0.116: a 1% rise in WDI_O raises migration by 0.116% and the next WD, a rise of 16.6% ($\frac{1}{6}$) by 1.9%.

rise. It is almost always positive (see below). In the top panel, it rises in a growing GDPPC$_O$ range that starts at a smaller level, as WDI$_O$ rises from 2. For GDPPC$_O$> 26,239 $pc, it is nil for all WDI$_O$. In them id panel, the elasticity is positive in a growing range of AID$_{DO}$ that starts from no aid, as WDI$_O$ rises from 2. If AID$_{DO}$≥ 149 $pc, it is nil for all WDI$_O$. The bottom pattern is quite similar, but the elasticity falls with AID$_{RO}$ and is negative for WDI$_O$ = 1 and AID$_{RO}$≥ 3,196 $pc. Excluding the negative cells, this elasticity is nil for all WDI$_O$ if AID$_{RO}$≥ 58$pc.

Figure 1: Elasticities of WDs Incidence in the Origin

	WDIo						
GDPPCo	1	2	4	6	11	19	32
1	0.096	0.172	0.234	0.287	**0.333**	**0.373**	**0.411**
3	0.086	0.156	0.215	**0.266**	**0.31**	**0.350**	**0.387**
9	0.076	0.140	0.196	**0.244**	**0.287**	**0.326**	**0.363**
24	0.066	0.125	0.177	**0.223**	**0.265**	**0.303**	**0.339**
65	0.056	0.109	**0.158**	**0.202**	**0.242**	**0.279**	**0.315**
177	0.046	0.093	**0.138**	**0.180**	**0.219**	**0.256**	**0.291**
481	0.037	**0.078**	**0.119**	**0.159**	**0.197**	**0.233**	**0.267**
1,306	0.027	**0.062**	**0.100**	**0.138**	**0.174**	**0.209**	**0.243**
3,551	0.017	**0.046**	**0.081**	**0.116**	**0.151**	**0.186**	**0.219**
9,653	0.007	**0.031**	**0.061**	**0.095**	**0.129**	**0.162**	**0.195**
26,239	-0.003	0.015	0.042	**0.073**	**0.106**	**0.139**	**0.171**
71,325	-0.013	-0.001	0.023	0.052	0.083	0.115	0.147
193,881	-0.022	-0.016	0.004	0.031	0.061	0.092	0.124

	WDIo						
AIDdo	1	2	4	6	11	19	32
0	0.006	**0.029**	**0.06**	**0.093**	**0.126**	**0.16**	**0.193**
2	0.009	**0.034**	**0.065**	**0.099**	**0.133**	**0.167**	**0.200**
6	0.012	0.038	**0.071**	**0.105**	**0.14**	**0.174**	**0.207**
19	0.015	0.043	0.077	0.112	**0.147**	**0.181**	**0.214**
54	0.018	0.048	0.082	0.118	0.153	**0.188**	**0.221**
149	0.021	0.053	0.088	0.125	0.160	0.195	0.229
406	0.024	0.057	0.094	0.131	0.167	0.202	0.236
1,107	0.027	0.062	0.10	0.137	0.174	0.209	0.243
3,010	0.03	0.067	0.105	0.144	0.181	0.216	0.25
8,184	0.033	0.071	0.111	0.150	0.187	0.223	0.257

	WDIo						
AIDro	1	2	4	6	11	19	32
0	**0.027**	**0.062**	**0.100**	**0.138**	**0.174**	**0.21**	**0.244**
2	0.015	**0.043**	**0.076**	**0.111**	**0.146**	**0.18**	**0.213**
7	0.002	**0.023**	**0.052**	**0.084**	**0.117**	**0.15**	**0.183**
21	-0.010	0.003	0.028	0.057	**0.089**	**0.121**	**0.153**
58	-0.023	-0.017	0.003	0.030	0.060	0.091	0.123
158	-0.035	-0.037	-0.021	0.003	0.032	0.062	0.093
432	-0.048	-0.056	-0.045	-0.024	0.003	0.032	0.062
1,175	-0.060	-0.076	-0.069	-0.051	-0.026	0.003	0.032
3,196	**-0.073**	-0.096	-0.094	-0.078	-0.054	-0.027	0.002
8,690	**-0.085**	-0.116	-0.118	-0.105	-0.083	-0.057	-0.028

Figure 1. *WDI$_O$ Elasticity of Migration Functions*

In Figure 2, the WDI$_D$ elasticity is positive, rising as WDI$_D$ rises and falling as GDPPC$_D$, AID$_{OD}$, and AID$_{RD}$ rise. At the top, it is significant for more GDPPC$_D$ values, starting at a smaller GDPPC as WDI_D rises from 2. For WDI_D> 34, it is positive for all GDPPC. In the middle, the elasticity is significant for more AID_{OD} values starting at no aid as WDI_D rises from 4.For AID_{OD}> 7 \$pc, it is nil for all WDI_D. The pattern is similar at the bottom, except that the elasticity is nil for all WDI_D, as AID_{RO} rises above 59 \$pc.

Figure 2: Elasticities of WDs Incidence in the Destination

GDPPCd \ WDId	1	2	4	7	12	20	34
1	0.043	0.098	0.157	0.216	0.272	0.327	**0.380**
4	0.038	0.09	0.147	0.204	0.260	0.315	**0.367**
10	0.032	0.082	0.137	0.193	**0.248**	**0.302**	**0.354**
27	0.027	0.073	0.127	0.182	**0.237**	**0.290**	**0.342**
74	0.022	0.065	0.117	0.171	**0.225**	**0.278**	**0.329**
200	0.017	0.057	0.107	**0.160**	**0.213**	**0.265**	**0.317**
545	0.012	0.049	0.096	**0.148**	**0.201**	**0.253**	**0.304**
1,480	0.006	0.040	**0.086**	**0.137**	**0.189**	**0.241**	**0.292**
4,024	0.001	**0.032**	**0.076**	**0.126**	**0.177**	**0.228**	**0.279**
10,938	-0.004	**0.024**	**0.066**	**0.115**	**0.165**	**0.216**	**0.267**
29,733	-0.009	0.015	**0.056**	**0.103**	**0.153**	**0.204**	**0.254**
80,822	-0.015	0.007	0.046	**0.092**	**0.142**	**0.192**	**0.242**
219,696	-0.020	-0.001	0.036	0.081	**0.130**	**0.179**	**0.229**

AIDod \ WDId	1	2	4	7	11	19	33
0	-0.012	0.012	**0.052**	**0.099**	**0.149**	**0.199**	**0.249**
2	-0.022	-0.005	0.031	**0.076**	**0.124**	**0.174**	**0.224**
7	-0.044	-0.039	-0.010	0.03	0.076	0.124	**0.172**
20	-0.065	-0.072	-0.051	-0.016	0.027	0.073	0.121
55	-0.087	-0.106	-0.093	-0.062	-0.022	0.023	0.069
152	-0.108	-0.140	-0.134	-0.107	-0.070	-0.027	0.018
415	-0.130	-0.174	-0.175	-0.153	-0.119	-0.078	-0.033
1,129	-0.151	-0.208	-0.217	-0.199	-0.168	-0.128	-0.085
3,071	-0.172	-0.242	-0.258	-0.245	-0.216	-0.178	-0.136
5,063	-0.183	-0.258	-0.279	-0.268	-0.241	-0.204	-0.162

AIDrd \ WDId	1	2	4	7	11	19	33
0	0.009	**0.044**	**0.091**	**0.142**	**0.195**	**0.247**	**0.298**
2	-0.005	**0.023**	**0.065**	**0.114**	**0.164**	**0.215**	**0.266**
7	-0.018	0.002	0.040	**0.085**	**0.134**	**0.184**	**0.234**
21	-0.031	-0.019	0.014	0.057	**0.104**	**0.152**	**0.202**
59	-0.045	-0.040	-0.012	0.028	0.073	0.121	**0.170**
163	-0.058	-0.061	-0.038	-0.001	0.043	0.090	0.137
445	-0.072	-0.082	-0.064	-0.029	0.012	0.058	0.105
1,211	-0.085	-0.104	-0.089	-0.058	-0.018	0.027	0.073
3,293	-0.098	-0.125	-0.115	-0.087	-0.048	-0.005	0.041
8,954	-0.112	-0.146	-0.141	-0.115	-0.079	-0.036	0.009

Figure 2. *WDI_D Elasticity of Migration Functions*

In Figure 3, the WDA_O elasticity is negative for small WDA_O and positive for large. It rises as WDA_O, GDP_O and AID_{RO} rise, and falls as AID_{DO} rises. In the top panel, it is negative in a shrinking $GDPPC_O$ range starting at 1 \$pc as WDA_O rises below 1,000 people. It is positive in a growing GDPPC range starting at a declining level as WDA_O rises from 1,000. In the middle, the elasticity is negative in a shrinking AID_{DO} range starting at no aid as WDA_O rises below 20.

It is positive in a growing AID_{DO} range starting at no aid as WDA_O rises from 1,000. For AID_{DO}> 1107 \$pc, it is nil for all WDA_O. In the bottom, the picture is quite similar, but the elasticity rises with AID_{RO} and is positive for all AID_{RO} and WDA_O≥ 200,000 people.

Figure 3: Elasticities of Affected by WDs in the Origin

WDAo

GDPPCo	1.0E+00	1.0E+01	5.5E+01	1.0E+03	1.0E+04	1.0E+05	1.0E+06	1.0E+07	1.0E+08	1.3E+09
1	**-0.049**	**-0.043**	**-0.036**	-0.027	-0.021	-0.012	-0.006	0	0.009	0.015
3	**-0.045**	**-0.039**	**-0.033**	-0.023	-0.017	-0.008	-0.002	0.004	0.013	0.019
9	**-0.041**	**-0.035**	**-0.029**	-0.020	-0.014	-0.004	0.002	0.008	0.017	0.023
24	**-0.037**	**-0.031**	**-0.025**	-0.016	-0.01	-0.001	0.006	0.012	0.021	**0.027**
65	**-0.033**	**-0.027**	**-0.021**	-0.012	-0.006	0.003	0.009	0.015	**0.025**	**0.031**
177	**-0.029**	**-0.023**	**-0.017**	-0.008	-0.002	0.007	0.013	0.019	**0.028**	**0.035**
481	**-0.025**	**-0.019**	**-0.013**	-0.004	0.002	0.011	0.017	**0.023**	**0.032**	**0.038**
1,306	**-0.021**	**-0.015**	**-0.009**	0	0.006	**0.015**	**0.021**	**0.027**	**0.036**	**0.042**
3,551	**-0.018**	**-0.011**	-0.005	0.004	**0.01**	**0.019**	**0.025**	**0.031**	**0.04**	**0.046**
9,653	**-0.014**	**-0.008**	-0.001	**0.008**	**0.014**	**0.023**	**0.029**	**0.035**	**0.044**	**0.05**
26,239	**-0.01**	-0.004	0.002	**0.012**	**0.018**	**0.027**	**0.033**	**0.039**	**0.048**	**0.054**
71,325	-0.006	0	0.006	**0.015**	**0.021**	**0.031**	**0.037**	**0.043**	**0.052**	**0.058**
193,881	-0.002	0.004	0.010	**0.019**	**0.025**	**0.034**	**0.041**	**0.047**	**0.056**	**0.062**

WDAo

AIDdo	1.0E+00	7.0E+00	2.0E+01	1.0E+02	1.0E+03	2.0E+04	2.0E+05	1.0E+06	9.0E+06	2.0E+08
0	**-0.013**	**-0.007**	-0.004	0.002	**0.008**	**0.017**	**0.023**	**0.029**	**0.035**	**0.044**
2	**-0.015**	**-0.008**	-0.005	0.001	**0.007**	**0.016**	**0.022**	**0.028**	**0.034**	**0.043**
6	**-0.016**	**-0.01**	-0.007	-0.001	0.005	**0.014**	**0.021**	**0.027**	**0.033**	**0.042**
19	**-0.017**	-0.011	-0.008	-0.002	0.004	0.013	**0.019**	**0.025**	**0.031**	**0.04**
54	**-0.019**	-0.013	-0.010	-0.003	0.003	0.012	0.018	**0.024**	**0.03**	**0.039**
149	-0.020	-0.014	-0.011	-0.005	0.001	0.010	0.016	0.023	**0.029**	**0.038**
406	-0.021	-0.015	-0.012	-0.006	0	0.009	0.015	0.021	0.027	**0.036**
1,107	-0.023	-0.017	-0.014	-0.008	-0.001	0.008	0.014	0.020	0.026	**0.035**
3,010	-0.024	-0.018	-0.015	-0.009	-0.003	0.006	0.012	0.018	0.025	0.034
8,184	-0.025	-0.019	-0.016	-0.01	-0.004	0.005	0.011	0.017	0.023	0.032

WDAo

AIDro	1.0E+00	7.0E+00	2.0E+01	1.0E+02	1.0E+03	2.0E+04	2.0E+05	1.0E+06	9.0E+06	2.0E+08
0	**-0.014**	**-0.008**	-0.005	0.001	**0.007**	**0.016**	**0.022**	**0.028**	**0.035**	**0.044**
2	**-0.014**	**-0.008**	-0.005	0.001	**0.007**	**0.017**	**0.023**	**0.029**	**0.035**	**0.044**
7	**-0.014**	**-0.007**	-0.004	0.002	**0.008**	**0.017**	**0.023**	**0.029**	**0.035**	**0.044**
21	**-0.013**	**-0.007**	-0.004	0.002	**0.008**	**0.017**	**0.023**	**0.029**	**0.035**	**0.044**
58	**-0.013**	-0.007	-0.004	0.002	**0.008**	**0.017**	**0.023**	**0.029**	**0.036**	**0.045**
158	**-0.013**	-0.007	-0.004	0.002	0.008	**0.018**	**0.024**	**0.030**	**0.036**	**0.045**
432	-0.013	-0.006	-0.003	0.003	0.009	**0.018**	**0.024**	**0.030**	**0.036**	**0.045**
1,175	-0.012	-0.006	-0.003	0.003	0.009	**0.018**	**0.024**	**0.030**	**0.036**	**0.045**
3,196	-0.012	-0.006	-0.003	0.003	0.009	0.018	**0.024**	**0.030**	**0.037**	**0.046**
8,690	-0.012	-0.006	-0.003	0.003	0.010	0.019	**0.025**	**0.031**	**0.037**	**0.046**

Figure 3. *WDA_O Elasticity of Migration Functions*

In Figure 4, the WDA_D elasticity is positive for small WDA_D and negative for large. It falls as WDA_D rises, and rises as $GDPPC_D$, AID_{OD}, and AID_{RO} rise. In the top panel, it is positive in a decreasing $GDPPC_D$ range starting with a growing value as WDA_D rises up to 200 people.

It is negative in a growing $GDPPC_D$ range starting with a falling value as WDA_D rises from 9,000. It is negative for all $GDPPC_D$ if $WDA_D \geq$ 1,000,000. In the middle, the elasticity is positive in a shrinking AID_{OD} range starting with no aid as WDA_D rises below 200. It is negative over a growing AID_{DO} range starting with no aid as WDA_D rises from 9,000. For $AID_{OD} >$ 33 \$pc, it is nil for all WDA_D. In the bottom, the picture is quite similar, but the elasticity is positive for almost all AID_{RD} if $WDA_D \leq$ 200; nil for $WDA_D >$ 200 if $AID_{RD} >$ 445 \$pc; and negative in a growing AID_{RD} range starting with no aid as WDA_D rises from 20,000 people.

Figure 4: Elasticities of Affected by WDs in the Destination

GDPPCd \ WDAd	1.0E+00	2.0E+01	2.0E+02	1.0E+03	9.0E+03	2.0E+05	1.0E+06	9.0E+06	2.0E+08
1	-0.001	-0.011	-0.018	-0.025	-0.031	-0.041	**-0.048**	**-0.055**	**-0.065**
4	0.001	-0.009	-0.015	-0.022	-0.029	**-0.039**	**-0.045**	**-0.052**	**-0.062**
10	0.004	-0.006	-0.013	-0.020	-0.026	**-0.036**	**-0.043**	**-0.05**	**-0.06**
27	0.006	-0.004	-0.010	-0.017	-0.024	**-0.034**	**-0.040**	**-0.047**	**-0.057**
74	0.009	-0.001	-0.008	-0.015	-0.021	**-0.031**	**-0.038**	**-0.045**	**-0.055**
200	0.011	0.001	-0.005	-0.012	-0.019	**-0.029**	**-0.035**	**-0.042**	**-0.052**
545	0.014	0.004	-0.003	-0.009	**-0.016**	**-0.026**	**-0.033**	**-0.039**	**-0.05**
1,480	**0.016**	0.006	0	-0.007	**-0.014**	**-0.024**	**-0.03**	**-0.037**	**-0.047**
4,024	**0.019**	**0.009**	0.002	-0.004	**-0.011**	**-0.021**	**-0.028**	**-0.034**	**-0.044**
10,938	**0.021**	**0.011**	**0.005**	-0.002	**-0.009**	**-0.019**	**-0.025**	**-0.032**	**-0.042**
29,733	**0.024**	**0.014**	**0.007**	0.001	-0.006	**-0.016**	**-0.023**	**-0.029**	**-0.039**
80,822	**0.026**	**0.016**	0.010	0.003	-0.004	-0.014	**-0.020**	**-0.027**	**-0.037**
219,696	**0.029**	**0.019**	0.012	0.006	-0.001	-0.011	**-0.018**	**-0.024**	**-0.034**

AIDod \ WDAd	1.0E+00	2.0E+01	2.0E+02	1.0E+03	9.0E+03	2.0E+05	1.0E+06	9.0E+06	2.0E+08
0	**0.022**	**0.012**	**0.006**	-0.001	**-0.008**	**-0.018**	**-0.024**	**-0.031**	**-0.041**
4	**0.025**	**0.015**	0.008	0.002	-0.005	-0.015	**-0.022**	**-0.028**	**-0.038**
7	**0.026**	0.016	0.010	0.003	-0.004	-0.014	-0.020	**-0.027**	**-0.037**
20	**0.029**	0.019	0.012	0.006	-0.001	-0.011	-0.018	-0.024	**-0.034**
33	**0.030**	0.020	0.014	0.007	0	-0.010	-0.016	-0.023	-0.033
55	0.032	0.022	0.015	0.008	0.002	-0.008	-0.015	-0.022	-0.032
152	0.034	0.024	0.018	0.011	0.004	-0.006	-0.012	-0.019	-0.029
415	0.037	0.027	0.021	0.014	0.007	-0.003	-0.010	-0.016	-0.026
1,129	0.040	0.030	0.023	0.017	0.010	0	-0.007	-0.013	-0.023
3,071	0.043	0.033	0.026	0.019	0.013	0.003	-0.004	-0.011	-0.021
5,063	0.044	0.034	0.027	0.021	0.014	0.004	-0.003	-0.009	-0.019

AIDrd \ WDAd	1.00E+00	2.00E+01	2.00E+02	1.00E+03	2.00E+04	2.00E+05	1.00E+06	9.00E+06	2.00E+08
0	**0.018**	**0.008**	0.002	-0.005	**-0.015**	**-0.022**	**-0.028**	**-0.035**	**-0.045**
2	**0.022**	**0.012**	**0.005**	-0.002	**-0.012**	**-0.019**	**-0.025**	**-0.032**	**-0.042**
7	**0.025**	**0.015**	**0.008**	0.001	**-0.009**	**-0.015**	**-0.022**	**-0.029**	**-0.039**
21	**0.028**	**0.018**	**0.011**	0.005	-0.005	**-0.012**	**-0.019**	**-0.025**	**-0.035**
59	**0.031**	**0.021**	**0.015**	0.008	-0.002	-0.009	**-0.015**	**-0.022**	**-0.032**
163	**0.035**	**0.025**	**0.018**	0.011	0.001	-0.005	-0.012	**-0.019**	**-0.029**
445	**0.038**	**0.028**	**0.021**	0.015	0.005	-0.002	-0.009	-0.015	**-0.025**
1,211	**0.041**	**0.031**	**0.025**	0.018	0.008	0.001	-0.005	-0.012	-0.022
3,293	**0.045**	**0.035**	**0.028**	0.021	0.011	0.005	-0.002	-0.009	-0.019
8,954	**0.048**	**0.038**	**0.031**	0.025	0.015	0.008	0.001	-0.005	-0.015

Figure 4. *WDA_D Elasticity of Migration Functions*

In Figure 5, the WDK_O elasticity falls as WDK_O and AID_{DO} rise, and rises as $GDPPC_O$ and AID_{RO} rise. It is positive for small WDK_O and negative for large. In the top panel, it is positive in a falling range of $GDPPC_O$ starting with a growing value as WDK_O rises up to 8. It is negative in a growing $GDPPC_O$ range starting with a falling value as WDK_O rises from 58. It is negative for all $GDPPC_O$ if $WDK_O \geq 8{,}604$ people. In the middle, the elasticity is positive for small AID_{DO} as WDK_O rises below 21, and is negative for all AID_{DO} as WDK_O rises from 21. In the bottom, the elasticity is positive in a shrinking AID_{RO} range starting with a larger value, as WDK_O rises up to 8. It is negative in a growing AID_{RO} range starting with no aid, as WDK_O rises from 58. For $WDK_O > 23{,}389$ people, the elasticity is negative for all AID_{RO}.

Figure 5: Elasticities of Killed by WDs in the Origin

GDPPCo \ WDKo	1	3	8	21	58	158	428	1,164	3,165	8,604	23,389	63,577	172,819
1	0.024	0.012	0	-0.012	-0.025	-0.037	-0.049	-0.061	-0.073	**-0.085**	**-0.098**	**-0.110**	**-0.122**
3	0.025	0.013	0.001	-0.011	-0.024	-0.036	-0.048	-0.060	**-0.072**	**-0.085**	**-0.097**	**-0.109**	**-0.121**
9	0.026	0.014	0.002	-0.011	-0.023	-0.035	-0.047	-0.059	**-0.071**	**-0.084**	**-0.096**	**-0.108**	**-0.120**
24	0.027	0.015	0.003	-0.010	-0.022	-0.034	-0.046	**-0.058**	**-0.071**	**-0.083**	**-0.095**	**-0.107**	**-0.119**
65	0.028	0.016	0.003	-0.009	-0.021	-0.033	**-0.045**	**-0.057**	**-0.070**	**-0.082**	**-0.094**	**-0.106**	**-0.118**
177	0.029	0.017	0.004	-0.008	-0.020	-0.032	**-0.044**	**-0.057**	**-0.069**	**-0.081**	**-0.093**	**-0.105**	**-0.117**
481	0.030	0.017	0.005	-0.007	-0.019	**-0.031**	**-0.043**	**-0.056**	**-0.068**	**-0.08**	**-0.092**	**-0.104**	**-0.116**
1,306	**0.031**	0.018	0.006	-0.006	-0.018	**-0.030**	**-0.042**	**-0.055**	**-0.067**	**-0.079**	**-0.091**	**-0.103**	**-0.116**
3,551	**0.032**	**0.019**	0.007	-0.005	**-0.017**	**-0.029**	**-0.042**	**-0.054**	**-0.066**	**-0.078**	**-0.090**	**-0.102**	**-0.115**
9,653	**0.032**	**0.020**	**0.008**	-0.004	**-0.016**	**-0.028**	**-0.041**	**-0.053**	**-0.065**	**-0.077**	**-0.089**	**-0.102**	**-0.114**
26,239	**0.033**	**0.021**	0.009	-0.003	**-0.015**	**-0.028**	**-0.040**	**-0.052**	**-0.064**	**-0.076**	**-0.088**	**-0.101**	**-0.113**
71,325	**0.034**	**0.022**	0.010	-0.002	-0.014	**-0.027**	**-0.039**	**-0.051**	**-0.063**	**-0.075**	**-0.088**	**-0.100**	**-0.112**
193,881	**0.035**	0.023	0.011	-0.001	-0.014	-0.026	**-0.038**	**-0.050**	**-0.062**	**-0.074**	**-0.087**	**-0.099**	**-0.111**
527,023	0.036	0.024	0.012	0	-0.013	-0.025	-0.037	**-0.049**	**-0.061**	**-0.073**	**-0.086**	**-0.098**	**-0.110**

AIDdo \ WDKo	1	3	8	21	58	158	428	1,164	3,165	8,604	23,389	63,577	172,819
0	**0.036**	**0.024**	**0.012**	0	**-0.013**	**-0.025**	**-0.037**	**-0.049**	**-0.061**	**-0.074**	**-0.086**	**-0.098**	**-0.110**
2	**0.025**	0.013	0.001	**-0.011**	**-0.023**	**-0.036**	**-0.048**	**-0.06**	**-0.072**	**-0.084**	**-0.096**	**-0.109**	**-0.121**
6	0.015	0.002	-0.010	**-0.022**	**-0.034**	**-0.046**	**-0.058**	**-0.071**	**-0.083**	**-0.095**	**-0.107**	**-0.119**	**-0.132**
19	0.004	-0.008	-0.021	**-0.033**	**-0.045**	**-0.057**	**-0.069**	**-0.081**	**-0.094**	**-0.106**	**-0.118**	**-0.13**	**-0.142**
54	-0.007	-0.019	-0.031	**-0.043**	**-0.056**	**-0.068**	**-0.08**	**-0.092**	**-0.104**	**-0.117**	**-0.129**	**-0.141**	**-0.153**
149	-0.018	-0.030	-0.042	**-0.054**	**-0.066**	**-0.079**	**-0.091**	**-0.103**	**-0.115**	**-0.127**	**-0.139**	**-0.152**	**-0.164**
406	-0.028	-0.041	-0.053	**-0.065**	**-0.077**	**-0.089**	**-0.102**	**-0.114**	**-0.126**	**-0.138**	**-0.15**	**-0.162**	**-0.175**
1,107	-0.039	-0.051	-0.064	**-0.076**	**-0.088**	**-0.1**	**-0.112**	**-0.124**	**-0.137**	**-0.149**	**-0.161**	**-0.173**	**-0.185**
3,010	-0.050	-0.062	-0.074	**-0.086**	**-0.099**	**-0.111**	**-0.123**	**-0.135**	**-0.147**	**-0.16**	**-0.172**	**-0.184**	**-0.196**
8,184	-0.061	-0.073	-0.085	**-0.097**	**-0.109**	**-0.122**	**-0.134**	**-0.146**	**-0.158**	**-0.17**	**-0.183**	**-0.195**	**-0.207**

AIDro \ WDKo	1	3	8	21	58	158	428	1,164	3,165	8,604	23,389	63,577	172,819
0	**0.027**	0.015	0.002	-0.01	**-0.022**	**-0.034**	**-0.046**	**-0.058**	**-0.071**	**-0.083**	**-0.095**	**-0.107**	**-0.119**
2	**0.030**	**0.018**	0.006	-0.006	**-0.018**	**-0.031**	**-0.043**	**-0.055**	**-0.067**	**-0.079**	**-0.091**	**-0.104**	**-0.116**
7	**0.034**	**0.022**	**0.010**	-0.003	**-0.015**	**-0.027**	**-0.039**	**-0.051**	**-0.064**	**-0.076**	**-0.088**	**-0.100**	**-0.112**
21	**0.037**	**0.025**	**0.013**	0.001	-0.011	**-0.023**	**-0.036**	**-0.048**	**-0.060**	**-0.072**	**-0.084**	**-0.097**	**-0.109**
58	**0.041**	**0.029**	**0.017**	0.004	-0.008	-0.02	**-0.032**	**-0.044**	**-0.056**	**-0.069**	**-0.081**	**-0.093**	**-0.105**
158	**0.044**	**0.032**	0.020	0.008	-0.004	-0.016	-0.029	**-0.041**	**-0.053**	**-0.065**	**-0.077**	**-0.089**	**-0.102**
432	**0.048**	**0.036**	0.024	0.012	-0.001	-0.013	-0.025	-0.037	**-0.049**	**-0.062**	**-0.074**	**-0.086**	**-0.098**
1,175	**0.052**	0.039	0.027	0.015	0.003	-0.009	-0.021	-0.034	-0.046	**-0.058**	**-0.070**	**-0.082**	**-0.095**
3,196	**0.055**	0.043	0.031	0.019	0.006	-0.006	-0.018	-0.03	-0.042	-0.054	**-0.067**	**-0.079**	**-0.091**
8,690	**0.059**	0.047	0.034	0.022	0.010	-0.002	-0.014	-0.027	-0.039	-0.051	-0.063	**-0.075**	**-0.087**

Figure 5. *WDK_O Elasticity of Migration Functions*

In Figure 6, the WDK_D elasticity rises with WDK_D, $GDPPC_D$, AID_{OD} and AID_{RD}. In the top panel, it is negative in shrinking range of low $GDPPC_D$ starting at 1 as WDK_D rises. It is positive over a growing range of high $GDPPC_D$ starting at a declining level as WDK_D rises. In the middle, the elasticity is positive in a growing range of AID_{OD} starting in no aid as WDK_D rises, and is nil if $AID_{OD} \geq 33$\$pc for all WDKD. In the bottom, the elasticity is nil for all WDK_D when AID_{RD} is zero and for $WDK_D = 1$ when $AID_{RD} < 21$ \$pc. Otherwise, it is always positive.

Figure 6: Elasticities of Killed by WDs in the Destination

GDPPCd \ WDKd	1	3	8	21	56	153	416	1,130	3,072	8,350	22,697	61,698	167,711
1	**-0.210**	**-0.206**	**-0.202**	**-0.198**	**-0.193**	**-0.189**	**-0.185**	**-0.181**	**-0.176**	**-0.172**	**-0.168**	**-0.164**	**-0.159**
4	**-0.187**	**-0.182**	**-0.178**	**-0.174**	**-0.170**	**-0.165**	**-0.161**	**-0.157**	**-0.153**	**-0.148**	**-0.144**	**-0.140**	**-0.136**
10	**-0.163**	**-0.159**	**-0.154**	**-0.150**	**-0.146**	**-0.142**	**-0.137**	**-0.133**	**-0.129**	**-0.125**	**-0.120**	**-0.116**	**-0.112**
27	**-0.139**	**-0.135**	**-0.131**	**-0.126**	**-0.122**	**-0.118**	**-0.114**	**-0.109**	**-0.105**	**-0.101**	**-0.097**	**-0.092**	**-0.088**
74	**-0.115**	**-0.111**	**-0.107**	**-0.103**	**-0.098**	**-0.094**	**-0.090**	**-0.086**	**-0.081**	**-0.077**	**-0.073**	**-0.069**	**-0.064**
200	**-0.092**	**-0.087**	**-0.083**	**-0.079**	**-0.075**	**-0.070**	**-0.066**	**-0.062**	**-0.058**	**-0.053**	**-0.049**	**-0.045**	-0.041
545	**-0.068**	**-0.064**	**-0.060**	**-0.055**	**-0.051**	**-0.047**	**-0.043**	**-0.038**	**-0.034**	-0.030	-0.025	-0.021	-0.017
1,480	**-0.044**	**-0.04**	**-0.036**	**-0.032**	**-0.027**	**-0.023**	-0.019	-0.015	-0.010	-0.006	-0.002	0.002	0.007
4,024	**-0.021**	**-0.016**	-0.012	-0.008	-0.004	0.001	0.005	0.009	0.013	0.018	**0.022**	**0.026**	**0.030**
10,938	0.003	0.007	**0.012**	**0.016**	**0.02**	**0.024**	**0.029**	**0.033**	**0.037**	**0.041**	**0.046**	**0.050**	**0.054**
29,733	**0.027**	**0.031**	**0.035**	**0.04**	**0.044**	**0.048**	**0.052**	**0.057**	**0.061**	**0.065**	**0.069**	**0.074**	**0.078**
80,822	**0.051**	**0.055**	**0.059**	**0.063**	**0.068**	**0.072**	**0.076**	**0.08**	**0.085**	**0.089**	**0.093**	**0.097**	**0.102**
219,696	**0.074**	**0.079**	**0.083**	**0.087**	**0.091**	**0.096**	**0.100**	**0.104**	**0.108**	**0.113**	**0.117**	**0.121**	**0.125**

AIDod \ WDKd	1	3	8	21	56	153	416	1,130	3,072	8,350	22,697	61,698	167,711
0	0.003	0.007	**0.011**	**0.015**	**0.020**	**0.024**	**0.028**	**0.032**	**0.037**	**0.041**	**0.045**	**0.049**	**0.054**
2	0.006	0.011	0.015	**0.019**	**0.023**	**0.028**	**0.032**	**0.036**	**0.040**	**0.045**	**0.049**	**0.053**	**0.057**
4	0.008	0.013	0.017	0.021	0.025	**0.030**	**0.034**	**0.038**	**0.042**	**0.047**	**0.051**	**0.055**	**0.059**
7	0.010	0.015	0.019	0.023	0.027	0.032	0.036	**0.04**	**0.044**	**0.049**	**0.053**	**0.057**	**0.061**
12	0.012	0.017	0.021	0.025	0.029	0.034	0.038	0.042	0.046	**0.051**	**0.055**	**0.059**	**0.063**
20	0.014	0.019	0.023	0.027	0.031	0.036	0.04	0.044	0.048	0.053	0.057	**0.061**	**0.065**
55	0.018	0.023	0.027	0.031	0.035	0.040	0.044	0.048	0.052	0.057	0.061	0.065	0.069
152	0.022	0.027	0.031	0.035	0.039	0.044	0.048	0.052	0.056	0.061	0.065	0.069	0.073
415	0.026	0.031	0.035	0.039	0.043	0.048	0.052	0.056	0.060	0.065	0.069	0.073	0.077
1,129	0.030	0.035	0.039	0.043	0.047	0.052	0.056	0.06	0.064	0.069	0.073	0.077	0.081
3,071	0.034	0.038	0.043	0.047	0.051	0.056	0.060	0.064	0.068	0.073	0.077	0.081	0.085
5,063	0.036	0.040	0.045	0.049	0.053	0.057	0.062	0.066	0.07	0.074	0.079	0.083	0.087

AIDrd \ WDKd	1	3	8	21	56	153	416	1,130	3,072	8,350	22,697	61,698	167,711
0	-0.007	-0.003	0.001	0.005	0.010	0.014	0.018	0.023	0.027	0.031	0.035	0.040	0.044
2	0.003	0.008	**0.012**	**0.016**	**0.020**	**0.025**	**0.029**	**0.033**	**0.037**	**0.042**	**0.046**	**0.050**	**0.054**
7	0.014	**0.018**	**0.023**	**0.027**	**0.031**	**0.035**	**0.040**	**0.044**	**0.048**	**0.052**	**0.057**	**0.061**	**0.065**
21	**0.025**	**0.029**	**0.033**	**0.038**	**0.042**	**0.046**	**0.050**	**0.055**	**0.059**	**0.063**	**0.067**	**0.072**	**0.076**
59	**0.036**	**0.040**	**0.044**	**0.048**	**0.053**	**0.057**	**0.061**	**0.065**	**0.07**	**0.074**	**0.078**	**0.082**	**0.087**
163	**0.046**	**0.051**	**0.055**	**0.059**	**0.063**	**0.068**	**0.072**	**0.076**	**0.08**	**0.085**	**0.089**	**0.093**	**0.097**
445	**0.057**	**0.061**	**0.066**	**0.07**	**0.074**	**0.078**	**0.083**	**0.087**	**0.091**	**0.095**	**0.100**	**0.104**	**0.108**
1,211	**0.068**	**0.072**	**0.076**	**0.081**	**0.085**	**0.089**	**0.093**	**0.098**	**0.102**	**0.106**	**0.110**	**0.115**	**0.119**
3,293	**0.079**	**0.083**	**0.087**	**0.091**	**0.096**	**0.100**	**0.104**	**0.108**	**0.113**	**0.117**	**0.121**	**0.125**	**0.130**
8,954	**0.089**	**0.093**	**0.098**	**0.102**	**0.106**	**0.110**	**0.115**	**0.119**	**0.123**	**0.128**	**0.132**	**0.136**	**0.140**

Figure 6. *WDK_D Elasticity of Migration Functions*

Table 3 summarizes the results from Figures 1-6. For the origin, the WD elasticity of M_{OD} is positive for WDI (except in one case), large WDA, and small WDK. It is negative for WDI=1 and large AID_{RO}, small WDA, and large WDK. For WDI, it rises as WDI and AID_{DO} rise, and falls as GDPPC and AID_{RO} rise. For WDA, it rises as WDA_O, GDPPC and AID_{RO} rise, and falls as AID_{DO} rise. For WDK, it rises as GDPPC and AID_{RO} rise, and falls as WDK and AID_{DO} rise. For the destination, the elasticity is positive for WDI, WDK if GDPPC is large, and small WDA. It is negative for WDK if GDPPC is small or WDA is large. For WDI, it rises as WDI grows and falls as GDPPC, AID_{OD} and AID_{RO} rise; for WDA it rises as GDPPC and AID_{OD}, AID_{RD} rise and falls as WDA rise; and for WDK it always grows.

Table 3. *Significant WD Elasticities of Migration*

Elasticity			Elasticity Response to Raising			
Measure	**Sign**	**Sign holds for**	**WD**	**GDPPC**	**$Aid_{PARTNER}$**	**Aid_{REST}**
WDI_O	Positive	Almost always	Increase	Decrease	Increase	Decrease
	Negative	WDI=1 &$AID_{RO}\geq$3,196				
WDI_D	Positive	Always	Increase	Decrease	Decrease	Decrease
	Negative	None				
WDA_O	Positive	Large WDA	Increase	Increase	Decrease	Increase
	Negative	Small WDA				
WDA_D	Positive	Small WDA	Decrease	Increase	Increase	Increase
	Negative	Large WDA				
WDK_O	Positive	Small WDK	Decrease	Increase	Decrease	Increase
	Negative	Large WDK				
WDK_D	Positive	Large GDPPC	Increase	Increase	Increase	Increase
	Negative	Small GDPPC				

Note: *$Aid_{PARTNER}$ denotes AID_{DO} or AID_{OD} respectively, and Aid_{REST} AID_{RO} and AID_{RD}*

The WD elasticity of M_{OD} is often insignificant (zero) when the aid inflows are large enough. For example, the elasticity is zero for WDI_O= 11 in Figure 1,if AID_{DO}>$19 per capita (2005 prices), per year (a total of $183.4 million for the geometric mean population of 9,653,829).As another example, the elasticity is zero for WDA_O= 20,000 in Figure 3, the elasticity is zero if the total aid flow larger than$11.3 billion. Yearly aid inflows of this order are perhaps feasible as a policy approach to minimize bilateral migration driven, among other factors, by WDs, on a short term basis. But it may be hard to sustain a policy approach on the sole basis of such large yearly aid inflows in the long run.

PROJECTING WD MIGRATION TO 2060

An projection exercise from a statistical model necessarily assumes the coefficient estimates and the model's structure are applicable for the future, which the essence of the above assumption about the past being able to tell us something about the future.

Looking forward, the IPCC consider three groups of scenarios for this century, assuming, respectively, stringent mitigation of greenhouse gas emissions, rapidly rising emissions, and intermediately rising emissions. Using the 1980-2008 period as a reference period, the intensity, duration, frequency, and scope of extreme weather and climate events is projected to rise the most for the high emissions group, followed by the intermediate rising emissions and stringent mitigation groups (in that order). (IPCC, 2013, 2014).

Computation of WD Migration Projections

In this section we use the model to estimate (forecast) WD migration for the period up to 2060. The procedure involves three steps. We first project M_{OD} for each directed dyad for and year to 2060. Then, we repeat previous step setting WD measures at zero. In the last step, we subtract the second projection from the first by directed dyad and year to get the change in M_{OD} due to WDs per se: $(\Delta M_OD = \left. M_OD \right|_WD - \left. M_OD \right|_(WD = 0))$These computations require as inputs projections of WDI, WDA, WDK, POP, GDPPC, AID per capita from a migration partner, AID per capita from international organizations and all other countries, NWDI, NWDA, NWDK, and CWAR, by country and year; war and directed dyad effects by year; and yearly effects. Clearly, validity and reliability of the input projections will directly define trustfulness and usability of the forecast. In our forecasting we employ reliable exogenous projections for POP and GDPPC, and/or assumed scenarios with respect to other inputs described below. Alternatively, one may use auxiliary, perhaps complex, models to project those forces, which, in turn, requires projecting their factors, and so on, leading to some sort of a world model; this huge endeavor is rarely, if ever, done by one paper[12], and definitely is beyond the scope of our paper. The approach chosen here allows to avoid uncertainty and estimation error generated in the intermediate steps by the axillary models, which themselves are conditioned on certain scenarios and assumptions.

Climatologists expect that the scope, incidence, and intensity of WDs will continue to rise as climate change progresses under business as usual (IPCC, 2013, 2014). To our knowledge no one projected WDs or, for that matter, NWDs

[12]Indeed, even very large world models also treat some variables as exogenous.

for many years by country, let alone our disaster measures. We assume three WDs scenarios:

- WDI, WDA, and WDK decline linearly from their 2009 level to their 1990s' average in 2060 by country, representing some mitigation and adaptation effort (WD1990 scenario);
- The measures linearly rise 100% in the period, representing a worse case (WD100); and
- The measures linearly rise 50% from 2009 to 2060 (WD50). For the NWDs, we assume there are no disasters.

The population projections up to 2060 come from the United Nations (UN, 2013), that offers forecast for a low, medium, and high fertility. We use the medium projection; here population growth falls in most developed countries (to a varying degree) and population size rises the most in LDCs.[13] The GDPPC projections are computed by dividing GDP projections from OECD (2013) by the population projection, by country and year. The OECD projects GDP in 2005 I$ (as it is in our model) and GDP growth to 2060 for 34 OECD and 6 non-OECD countries[14], and the world. We did not find yearly GDP projections to 2060 for other LDCs, so we project their GDPPC by applying the projected world yearly GDP growth to their most recent GDP in the sample and dividing this projection by their population projection from UN (2013).

Projecting aid requires more assumptions. We consider two cases: all the countries (origin and destination) receive no aid, and all the countries continue receiving aid per capita inflows at 2009 level during the whole period up to 2060. Indeed, projections of civil wars and wars for many years and countries are not available. We set these variables to zero (no war) to 2060. The time (year) and dyadic fixed effects, λ_t and u_{OD}, respectively, are coming from our model (1) described in the preceding sections. The year effects, representing dyad invariant events such as world recession, cannot be predicted over long periods of time, so we set them to zero. We assume the estimated directed dyad effects, which account for time invariant unobserved heterogeneity and unmeasured dyad-specific factors, hold the same for the whole forecasting period up to 2060, and migration barriers do not change.[15]

As a base year starting which we forecast migration, we chose 2008 since it has the biggest number of dyads equal 4093 with an aggregated migration flow 6.20 million (with aggregate inflow 4.75 million, and 1.46 million outflows).

Several econometric questions arise here. The first question is whether we need to include migration patterns for all the countries of the world, or to do a forecast only for the countries in our sample is less obvious. On one hand, forecast done for the dyads of countries of our sample only will definitely underestimate the aggregate world migration. On the other hand, an attempt to include as many dyads as possible my create an uncertainty and noise screening the useful effect. Moreover, there is a high probability to end up in the ecological fallacy trap while doing the migration forecast for the whole world. Our approach, instead, is to stay within our sample dyads, and acknowledge that our forecast is rather conservative than unreliable.

The second issue to address is a multiplicative nature of our estimation model (1). Prediction of the response variable requires reverse transformation of $\ln M_{OD,t}$ back to $M_{OD,t}$ and needs to eliminate transformation bias since $\overline{\ln M}_{OD,t} \neq \ln \overline{M}_{OD,t}$. We exploited two approaches to eliminate the bias: parametric and non-parametric. The first, parametric, approach uses properties of the log-normal distribution. The unbiased predicted value of $\widehat{M}_{OD,t}$ for the dyad OD and time t has the following form (see Appendix 2):

$$\widehat{M}_{OD,t} = \exp\left(\widehat{\ln}(M_{OD,t}+1) + \frac{\sigma^2}{2}\right) - 1$$

Here $\widehat{\ln}(M_{OD,t}+1)$ is a predicted value and σ^2 is a variance generated by model (1),.The second approach employs smearing non parametric estimator (Duan, 1983) as following:

$\widehat{M}_{OD,t} = \text{xp}(\widehat{\ln}(M_{OD,t}+1)) \cdot \frac{1}{N_{OD}} \sum_{OD=1}^{N_{OD}} \exp(\ln(M_{OD,t} +$
1−lnMOD,t+1−1

Notably, both approaches give almost the same results.[16]

[13] The low (high) variants give less (more) migration relative to the medium, all else being the same.

[14] These 40 countries account for 98% of the aggregated world GDP in 2008.

[15] The barriers cannot be predicted without more assumptions. Systematic data by directed dyad and year are not readily available. To the extent that they change slowly, if at all, the dyadic effects capture them.

[16] This fact attests homoscedastic error term in model (1), testifying model's validity.

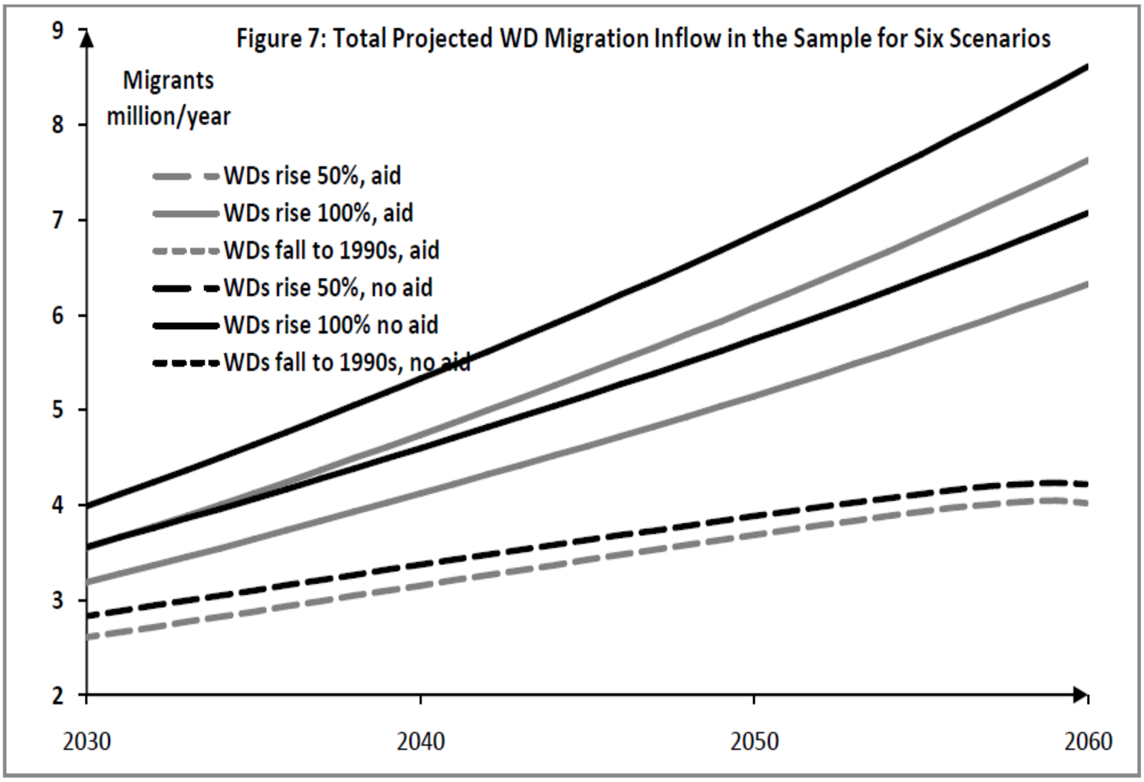

Figure 7. *Total Projected WD Migration Inflow in the Sample for Six Scenarios*

The third issue is to validate of our migration projections since predictions are out-of-sample. We used a rolling validation of the predictions for our model varying ("rolling") our training data from 1980-2003 to 1980-2008 and test data from 2004-2009 to 2009 only, respectively. The procedure performs as following. First, we estimate the model (1) using a training data set. In the next step, we compute unbiased predicted values for $\widehat{M}_{OD,t}$ for the respective test data using the estimates received in the previous step. Since we are primarily interested in the estimation of the projections of aggregate migration (including both inflows and outflows), in the next step, we calculate the aggregated across dyads migration flow $\widehat{M}_t$ for each year t in the test range. Finally, predicted values $\widehat{M}_t$ are compared with the total migrationM_t. The values for absolute percentage error (APE) are presented in Appendix 2. Mean APE varied from 0 to 4% for different training data, and individual years[17], what suggests acceptable validity of our migration projections.

Analysis of WD Migration Projections

Figure 7 presents the projected total WD migration inflow, the sum of all the inflows in the sample, by year, for the WD1990s, WD50, and WD100 scenarios described in the preceding section. The total migration inflow rises in the forecast horizon, except in the last few years for the WD1990s case, ranging from 4.0 million in 2060 for WD1990s with aid to 8.6 million for WD100 without aid. The no-aid migration inflows are larger than those with aid, for the same WDs scenario. By 2060 for the WD100 scenario, for example, aid reduces migration by 1.0 million compared to no aid case.

Figure 8 presents the projected total aggregated WD migration in the sample, by year, defined as the sum over time of Figure 7's inflows from 2010 to year t. The aggregate WD migration rises over time, ranging from 147.1 million in 2060 for the WD1990s scenario with aid, to 247.4 million for the WD100 case with no aid. Aid reduces the aggregate WD migration. For the WD100 scenario in 2060, for example, aid reduces the aggregated WD migration from 247.4 million to 219.7 million.

[17]For 2008, the APE reaches about 17%. We believe this effect is due to the world economic crisis of 2008. Note, that in our working model (1) this effect is accounted by time-fixed effect.

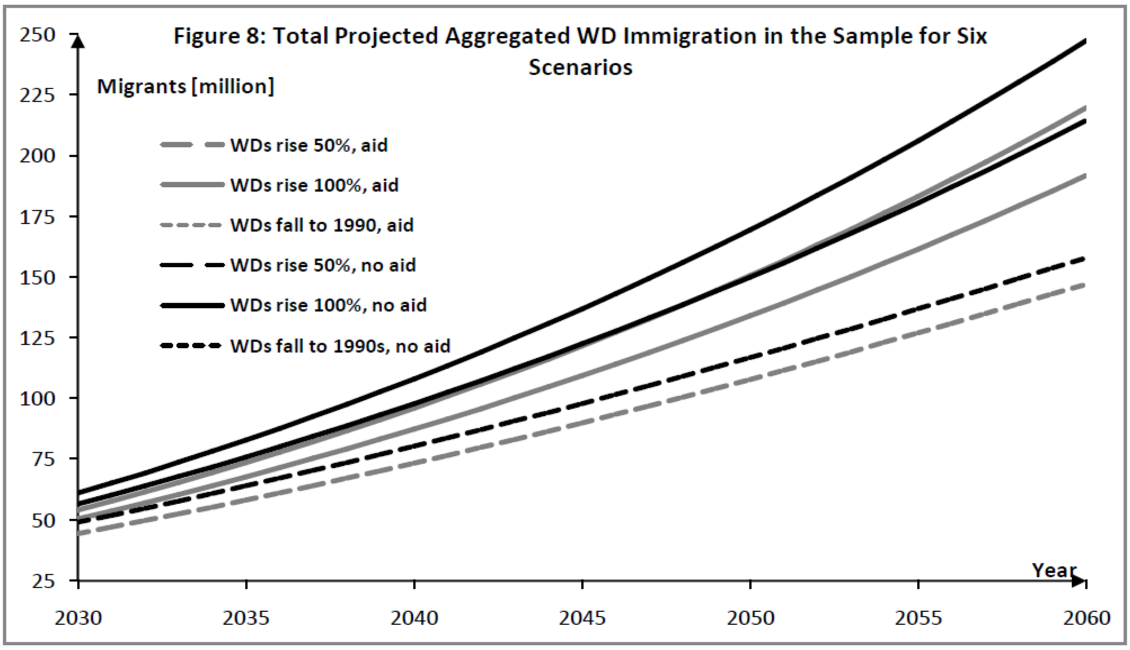

Figure 8. *Total Projected Aggregated WD Migration in the Sample for Six Scenarios*

Figure 9 presents the projected WD migration inflows in 2040and 2060 for the WD50 scenario, by the ten largest inflows in 2060. We list inflows using a log scale by DCs/LDCs origins and aid/no aid. LDCs send more WD migrants than DCs and both inflows rise over time. Aid reduces the inflows relative to no aid by 17-39% for LDCs and less than 4% for DCs, depending on the destination. The US is projected to see the largest inflow of WD migration, with some 1 million from LDCs and 0.5 million from DCs in 2040 for no aid, and 1.5 million and 0.7 million, respectively, in 2060. Germany is next with some 380,000 migrants from DCs in 2060 for no aid, followed by Japan with nearly 335,000 from LDCs. Britain gets the fewest from LDCs in Figure 9, with more than 123,000 in 2060 for no aid, and Switzerland gets the fewest from DCs in Figure 9, with around 70,000 for no aid.

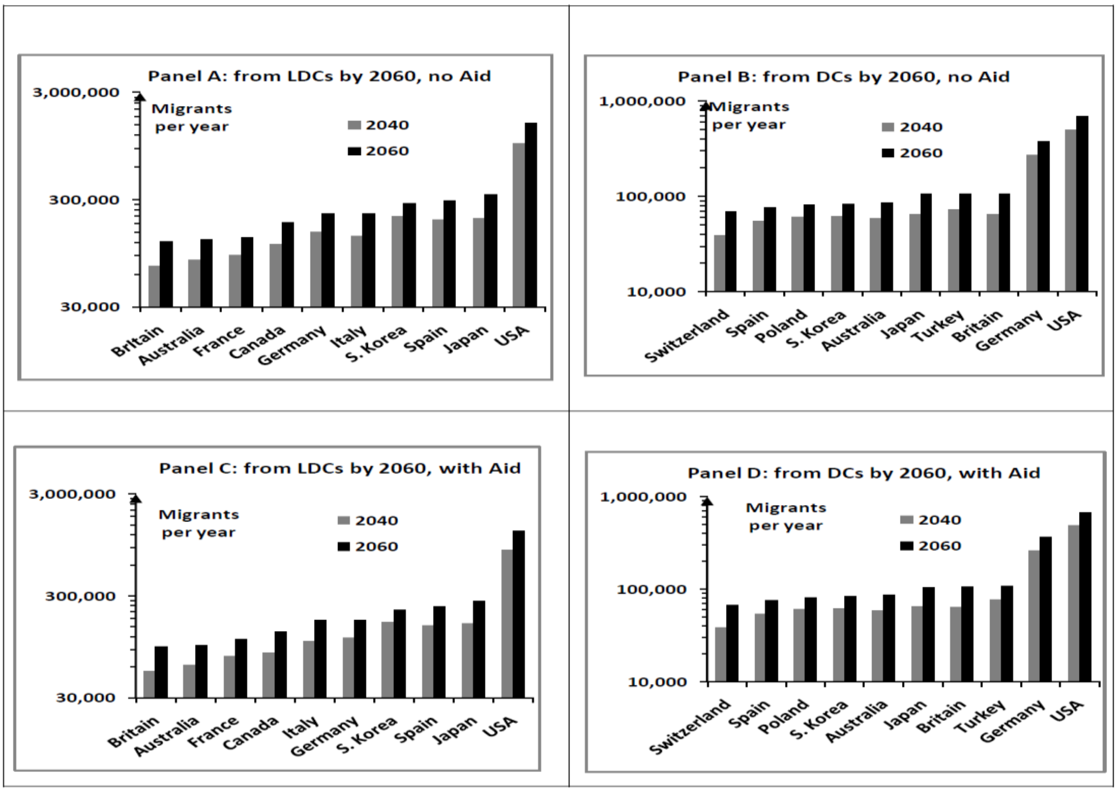

Figure 9. *Ten Largest Projected WD Migration Inflows for the WD50 Scenario*

Figure 10 presents projected aggregated WD immigrations since 2010 for the WD50 scenario in 2040and 2060, by the ten largest aggregates in 2060. The values are smaller with aid than without aid by about the same rates as in Figure 9, and are much larger for LDC origins than for DC origins. The United States sees the largest aggregated immigration with more than 47 million from LDCs in 2060 for no aid and nearly 24 million from DCs. South Korea and Japan are next for LDC origins with around 10 million each by 2060 for no aid, and Germany is next for DC origins with 13 million by 2060. Britain sees the smallest aggregate WD immigration from LDCs, around 3.5 million by 2060 for no aid, while Italy will see the smallest aggregate from DCs, with about 2 million by 2060.

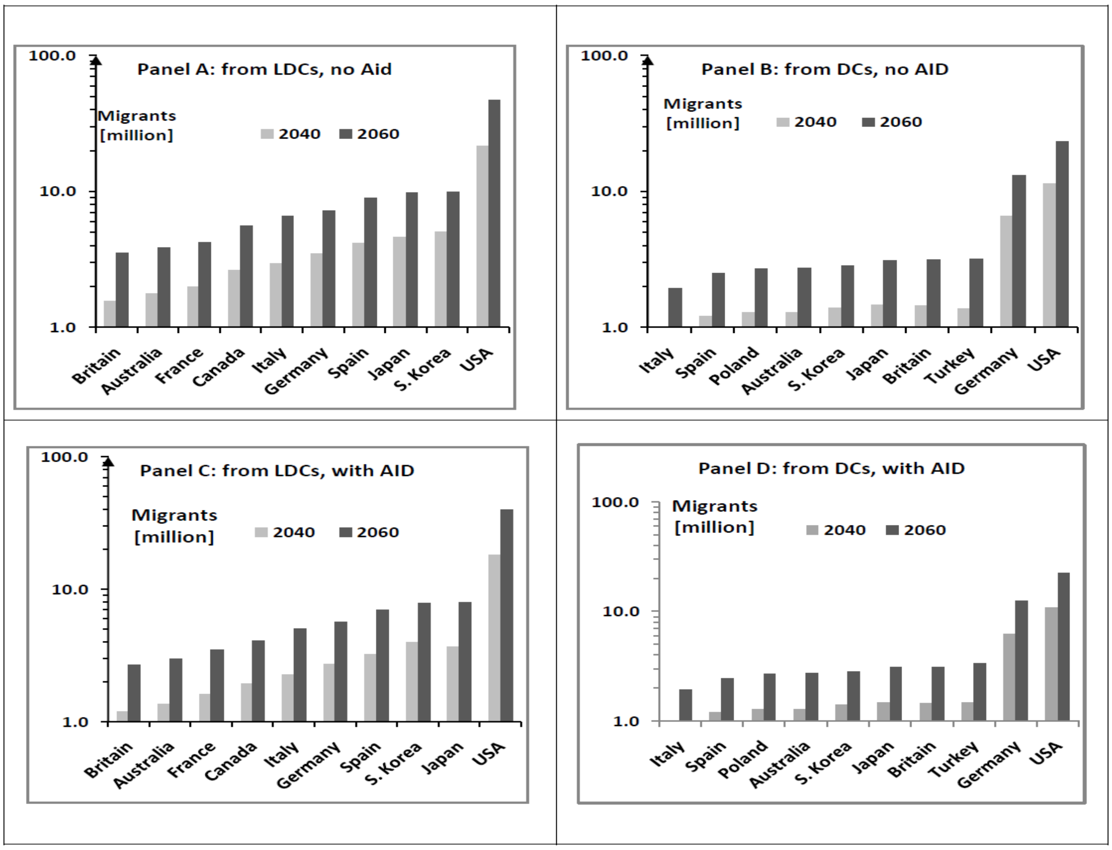

Figure 10. *Ten Largest Projected Aggregated WD Immigrations for the WD50 Scenario*

Finally, the sample excludes almost all the LDC-LDC dyads due to missing migration data. UN (2014) estimates 36% of the landed foreign migrant stock are LDC-LDC migrants. Another 2.6 million per year enter DCs as students, 2 million as short-term workers, and 425,000 seek asylum (OECD, 2013). These extra moves should also apply to LDC, but we did not find data. Some of the extra movers may return home; others may not. The sample's total landed inflow in 2009 is about 5.7, so the non-landed inflow to DCs adds up to 88%. Using the LDC-LDC stock share for flow, and assuming the extra entries reflect WDs (among other factors), one may raise our projections in Figures 7-8 by 36-124% (88% + 36%) and the DC figures in Figures 9-10 by 88%. For example, for WD100 with no aid case, the aggregated global WD migration in 2010-2060 could be 336-554 million, and the United States may see 130 million for WD50 with no aid. To the extent that others may immigrate illegally, these numbers may be even higher.

Implications for Public Policy and Conclusions

A recent worldwide poll suggests that about 630 million people wish to migrate from their countries, and about 130 million would like to migrate to the U.S. only (Gallup, 2013). The predominant reason for this is the seeking for a better life. This figures is a stock, rather than the flow examined in the current study, but they indicate that there is an enormous pent up demand for migration, more than could plausibly be handled by the narrow legal channels we explore. Even so, our analysis uncovers some important tendencies. An increase in WDs in the origin promotes emigration, and a similar increase in the destination promotes immigration. With our conservative estimates show that climate-induced migration may provide from 16 to 35% of total migrants in future 50 years (taking a number or 630 million mentioned above). In addition, those effects work synergistically with one another, as well as with increases in GDP per capita and population in the origin and destination.

However, both the narrow and broader definition figures may in fact understate the difficulty we may face. We did not examine illegal migration as the data are not there, but our findings should apply across the board since excluding criminals and terrorists it is safe to assume that all migrants move because they seek a better life. Whether or not they enter the destination legally or illegally is beside the point for our purpose. Already there is considerable illegal migration. For example, 11-12.4 million illegal migrants are said to live in the US and 500,000-800,000 come each year, and about 8 million illegal migrants live in Europe and 500,000-1 million enter each year,[18] but the issue is in fact much larger than the numbers per se. As discussed, the immigrants are not welcome in many cases and their arrival at times leads to violence[19]. Many residents believe the migrants threaten the local culture, religion, and ethnicity, increase the level of crime, damage the absorbing economy, and harm the national security. In many cases immigrants create their spatial agglomerations which prevent from the adaptation of the migrants within the host country. Hostility toward migrants, particularly from the LDCs, has become common, as are tensions between pro and anti-immigration residents, see for example Sarrazin (2010).

[18]For the US figures, see, e.g., Passell and Cohn (2009, 2008), and Hoefer et al. (2006). For the EU figures, see CEC (2009), Brady (2008), and Addo (2006).

[19]Weiner (1978) is perhaps the first to suggest a general link from contemporary immigration to violence. Dancygier (2010) looks at immigration to Europe since 1945, Salehyan and Gleditsch (2006) and Fearon and Laitin (2011) associate immigration with civil wars, and Reuveny (2007, 2008) and Reuveny and Peterson Allen (2008) provide examples for immigration due to WDs. Media reports cover various episodes, including in Spain (BBC, 2000), UK (MN, 2001), Australia (MIS, 2006; Yale Global, 2010), France (CBS, 2007), Russia (NYT, 2008), South Africa (Time, 2008; Cape Argus, 2009; Guardian, 2010), Greece (BBC, 2009a, 2009b), Italy (CNN, 2010), Indonesia (JG, 2012), US (HP, 2010, 2011; DJ, 2010; NYT, 2012), Israel (Haaretz, 2012; CNN, 2012), and India (NDTV, 2012).

The July 2011 mass murdering in Norway by an anti-immigration extremist is a sort of a natural “bloody” experiment. The German Social Democratic Party leader, Mr. Gabriel, told the public the attacks were fostered by “a trend toward xenophobia and nationalism in” Europe; in such a society “there will be crazy people who feel legitimized in taking harder measures”. Much of what the mass murderer Mr. Breivik wrote in his long manifesto, said Mr. Cohn-Bendit, the European Parliament (EP) Green bloc co-president, “could have been said by any right-wing politician.” Some right wing European politicians essentially sided with Mr. Breivik, calling him an icon (Mr. Coutela, French National Front), saying the killing would not have been happened in a Norwegian Norway (Mr. Ellsborn, Sweden Democrats), and blaming Norway’s disgusting multiracial approach (Mr. Borghezio, EP member, Italian Northern League, which is in coalition with Italian Prime Minister Berlusconi’s party).[20]The most recent example is a wave of violence against migrants in South Africa, where at least six people were killed and as a result, 300 residents were arrested (BBC, 2015)[21]. Indeed, a number of governments, particularly in the developed countries (DCs), increasingly view this prospect as an up and coming threat to national security.[22] For example, Germany’s Chancellor Merkel recognized that multicultural immigration policy fails, not working as intended (2010).

With all this in mind, it thus seems important to develop policy solutions mitigating the problems caused by migration. Consider first unrealistic scenario removing all barriers to migration, enabling the system for self-adjust much along the lines that the free movement within countries works. We suspect that is not likely to happen, but if it were there would have probably been a lot of migrants, which may increase political instability in the destination. One could presumably try to reduce the risk of violence by educating people to accept foreigners and enforcing order, though our model says nothing about the efficacy of this approach and left for a future study.

[20] All the responses are listed in NYT (2011).

[21] BBC: “South Africa anti-immigrant violence: Hundreds held” http://www.bbc.com/news/world-africa-32372501

[22] For example, see Schwartz and Randall (2003), Reuveny (2007, 2008), Smith (2007), Military Advisory Board (2007), High Representative (2008), United Nations (2009), Parsons (2010), Scheffran and Battaglini (2011), and Wright (2012).

An opposite approach would be for the DCs to slow down the pace of economic development in the LDCs (e.g., limit aid flows, limit access to DCs markets), observing our finding that poorer people hit by WDs are less able to migrate than richer people. That would be an unacceptable thing to take out of our model not only because it is obviously unethical, but also because it may be self-defeating in light of the already very large pent up demand to migrate, which we show likely to rise as climate change progresses in the coming decades.

Our study suggests the third option that aid can help countries reduce the propensity of their people to migrate due to WDs. The required amounts, however, can be very large. For example, driving Mexico's marginal effect on emigration to the US to zero requires an aid flow of $6.73 billion per year from the US (which corresponds to about $62 per capita), or $20.3 billion per year from the rest of the world (approximately, $188 per capita), holding the other aid type and GDPPCo at the level of 2008.

This development policy approach may be applied on a case by case basis, though only a few developed countries are likely able to afford it. Equally important, it may backfire, eventually leading to more, not less, migration. To begin with, we find that if the origin's GDP per capita is less than approximately $2,000 (see Fig.3, for example), as in many LDCs, there is a tendency for emigration to rise with development. Countries growing above this level will see a new tendency to stay at home, but there will be side effects. The destinations would need to grow vigorously to afford giving the aid, and the combined origin-destination growth will require more energy, intensifying climate change and WDs and thus increasing the propensity to migrant. A growing destination also attracts more migrants and even more so when hit by WDs.

All of these competing effects reflect the principle of targeting: development policy does not address the root of the problem. The first best approach to address the problem of migration due to the expected increase in WDs is to attack its source: climate change,- that will allow to reduce projected migrants stock by up to one third by 2060. We need a global mitigation program. Unfortunately, efforts to bring it about have so far proved to be illusive. The LDCs argue correctly they have not caused the bulk of the current problem and it is now their turn to develop and emit carbon emission. The DCs reject mitigation if the LDCs reject it and even if the LDCs will accept it seems the US will not get on board anytime soon, making global mitigation unlikely.

The gist of these results holds for directed internal (within country) bilateral migration (e.g., Etzo, 2011 for Italy; Flores et al., 2013 for Mexico). Results for undocumented migration are quite similar, though there are only a few studies and they do not employ a panel of bilateral flow naturally fewer studies and their samples are small; the data are simply not there (e.g., Bratsberg, 1995; Weeks et al., 2011).

A global mitigation plan may be eventually implemented in response to some climate change induced global migration crisis, but then it may be too late. Mitigation, of course, may not solve all of the impending problems, but it seems better to implement an aggressive plan today and hope for the best, than to do nothing. The basic idea, of course, applies across the board and it has served all of us well; it is better to be safe than sorry even in situations where becoming safe is costly in the short run.

REFERENCES

[1] Abramowitz, M., and I.A.Stegun (eds.), 1964, Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables, New York: Dover Publications, 1046p.

[2] Balli, H. O. and B.E. Sørensen (2013), "Interaction Effects in Econometrics", Empirical Economics, 45(1): 583-603.

[3] Bratsberg, B. (1995), "Legal versus Illegal U. S. Immigration and Source Country Characteristics," Southern Economic Journal, 61(3): 715-727.

[4] BBC News (2000), "Mutual Fears Behind Spain's Race Riots," February 8, http://news.bbc.co.uk/2/hi/europe/635514.stm.

[5] BBC News (2009a), "Immigrants Hurt in Greek Violence," May 10, http://news.bbc.co.uk/2/hi/8042409.stm.

[6] BBC News (2009b), "Greek Police Flatten Migrant Camp," July 12, http://news.bbc.co.uk/2/hi/8146597.stm.

[7] Belason, A.B. and S.W. Polachek (2013), "Natural Disasters and Migration," in A.F. Constant and K.F. Zimmerman (eds.), International Handbook on the Economics of Migration, Cheltenham, UK: Edward Elgar.

[8] Belot, M. and S. Ederveen (2012), Cultural barriers in migration between OECD countries, Journal of Population Economics, 25 (3): 1077–1105.

[9] Borda, R.D. A., and R. Mahia (2010), Determinants of Migration Flows Between the EU and MPC: The Case of Algeria, Egypt,

Morocco, Tunisia, and Turkey, Saarbrücken, Germany: LAP Lambert Academic Publishing.

[10] Cape Argus (2009), "Media: Tension Brewing in Townships over Foreigners," June 1, Daily, Cape Town, South Africa, in www.antieviction.org.za/2009/06/02/media-tension-brewing-in-townships-over-foreigners/#more-2566.

[11] CBC News (2007), "In Depth, France Riots: Understanding the Violence," November 28, Canada. http://www.cbc.ca/news/background/paris_riots/.

[12] CNN (2010), "Migrants Leave Italian Town amid Violence," January 11, http://articles.cnn.com/2010-01-11/world/italy.migrant.violence _1_migrants-italian-town-interior-minister-roberto-maroni?_s=PM:WORLD.

[13] CNN (2012), "Why did anti-immigration sentiment boil over in Israel? May 31, http://www.cnn.com/2012/05/31/world/meast/israel-anti-immigration-sentiment.

[14] COW (2011), Correlates of War , "State System Membership List, v2011," http://correlatesofwar.org.

[15] Dancygier, R.M. (2010), Immigration and Conflict in Europe, Cambridge, UK: Cambridge University Press.

[16] DJ (2010), "Rioting, Violence, Mar Protests of Arizona Immigration Laws," May 3, Digital Journal, Toronto, www.digitaljournal.com/article/291517.

[17] Duan, N. (1983). "Smearing Estimate: A Nonparametric Retransformation Method." Journal of the American Statistical Association. 78 (383): 605-610

[18] EM-DAT (2012), "EM-DAT Database Advanced Search," Emergency Events Database, Centre for Research on the Epidemiology of Disasters, Université catholique de Louvain, Belgium. http://www.emdat.be/Database/AdvanceSearch/advsearch.php.

[19] Etzo, I. (2011), "The Determinants of the Recent Interregional Migration Flows in Italy: A Panel Data Analysis," Journal of Regional Science, 51(5): 948-966.

[20] Fearon, J.D. and D.D. Laitin (2011), "Sons of the Soil, Migrants, and Civil War," World Development, 39 (2): 199-211.

[21] Flores, M., M. Zey, and N. Hoque (2013), "Economic Liberalization and Contemporary Determinants of Mexico's Internal Migration: An Application of Spatial Gravity Models," Spatial Economic Analysis, 8(2): 195-214.

[22] Gallup, 2013. http://www.gallup.com/poll/161435/100-million-worldwide-dream-life.aspx?utm_source=position8&utm_medium=related&utm_campaign=tiles

[23] Keating, J. (2012), "Fear Factor: Why is distrust of immigrants so universal?" Foreign Policy, 192 (March/April), http://www.foreignpolicy.com/articles/2012/02/27/fear_factor.

[24] Haaretz (2012), "Violence Erupts at Anti-African Rally in Tel Aviv," Israel, http://forward.com/articles/156744/violence-erupts-at-anti-african-rally-in-tel-aviv/

[25] Heston, A., R. Summers and B. Aten (2011), Penn World Table Version 7.0, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, May 2011.

[26] High Representative (2008), Climate Change and International Security, Paper from the High Representative and the European Commission to the European Council, S113/08, http://www.consilium.europa.eu/uedocs/cms_data/docs/pressdata/en/reports/99387.pdf

[27] HP (2010), "Report: An 'Astonishing' Rise in Anti-Immigrant, Anti-Government Groups," March 2, Huffington Post, http://www.huffingtonpost.com/2010/03/02/report-an-astonishing-ris_n_482409.html.

[28] HP (2011), "Anti-Latino Hate Crimes Rise As Immigration Debate Intensifies," December 17, Huffington Post, http://www.huffingtonpost.com/2011/10/17/anti-latino-hate-crimes-rise-immigration_n_1015668.html?view=print&comm_ref=false

[29] IPCC (2013), "Summary for Policymakers, Stocker," T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)Climate Change 2013: The Physical Science Basis. Contribution ofWorking Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge UK: Cambridge University Press.

[30] JG (2012), "Three Sri Lankan Immigrants Arrested Over Mob Violence in Bogor," Jakarta Glob, July 12, Jakarta Indonesia, http://www.thejakartaglobe.com/home/three-sri-lankan-immigrants-arrested-over-mob-violence-in-bogor/530080

[31] Kahn, M.E. (2005), "The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions," The Review of Economics and Statistics, 87(2): 271-284.

[32] Maoz, Z. (2005), Dyadic MID Dataset V. 2.0, University of California, Davis, http://psfaculty.ucdavis.edu/zmaoz/dyadmid.html.

[33] Mayda, A. M. (2010), "International Migration: A Panel Data Analysis of the Determinants of Migration Flows," Journal of Population Economics, 23(4): 1249-1274.

[34] Migration News (2001), "UK: Ethnic Violence," August, Vol. 8(8).

[35] Military Advisory Board (2007), National Security and the Threat of Climate Change, The

CNA Corporation, Alexandria, VA, http://www.cna.org/reports/climate.

[36] MIS (2006), "On the Beach: Racial Confrontation in Australia," Migration Information Source, Migration Policy Institute, Washington, DC, http://www.migrationinformation.org/USFocus/display.cfm?ID=377.

[37] Naudé, W. (2009), "Natural Disasters and International Migration from Sub-Saharan Africa," Migration Letters, 6(2):165-176.

[38] Naudé, W. (2010), "The Determinants of Migration from Sub-Saharan African Countries," Journal of African Economies, 19 (3): 330-356.

[39] NTDV (2012), "Assam violence: A history of conflict rooted in land," July 27, India, http://www.ndtv.com/article/india/assam-violence-a-history-of-conflict-rooted-in-land-248039

[40] NYT (2008), "Moscow's Immigrants Face Wave of Skinhead Violence," New York Times, February 19, New York, http://thelede.blogs.nytimes.com/2008/02/19/moscows-immgrants-face-rash-of-skinhead-violence/

[41] NYT (2011), "Shift in Europe seen in Debate on Immigrants," New York Times, July 27, New York, http://www.nytimes.com/2011/07/ 28/world/europe/28europe.html?pagewanted=all

[42] NYT (2012), "After a New Immigrant's Killing, Conflict in a Coal Town," New York Times, August 10, New York, http://lens. blogs.nytimes.com/2012/08/10/after-a-new-immigrants-killing-conflict-in-a-coal-town/

[43] OECD (2012a), International Migration Database, Organization for Economic Cooperation and Development, Paris, France, http://stats.oecd.org/.

[44] OECD (2012b), DAC2a ODA Disbursements, Organization for Economic Development and Cooperation, Paris, France, http://stats.oecd .org/.

[45] OECD (2013), International Migration Outlook, Organization for Economic Cooperation and Development (OECD), Paris, France.

[46] Parsons, R. J. (2010), Climate Change: The Hottest Issue in Security Studies?" Risk, Hazards & Crisis in Public Policy, 1(1): 87-116.

[47] Raschky, P.A. (2008), "Institutions and the Losses from Natural Disasters," Natural Hazards and Earth System Sciences, 8(4): 627-634.

[48] Reuveny, R. (2007), "Climate Change-induced Migration and Violent Conflict," Political Geography, 26(6): 656-673.

[49] Reuveny, R. (2008), "Ecomigration and Violent Conflict: Case Studies and Public Policy Implications," Human Ecology, 36(1): 1-13.

[50] Reuveny, R., and A. Peterson Allen (2008), "On Environmental Refugees and Implications for the Future," Ecología Política, Vol. 33: 21-36, 2007.

[51] Reuveny, R., and W.H. Moore (2009), "Does Environmental Degradation Influence Migration? Emigration to Developed Countries in the Late 1980s and 1990s," Social Science Quarterly, 90(3): 461-479.

[52] Salehyan, I. and K. S. Gleditsch (2006), "Refugees and the Spread of Civil War," International Organization, 60: 335-366.

[53] Sarrazin, Th (2010). Deutschland schafftsich ab. DVA Dt.Verlags-Anstalt.

[54] Scheffran, J. and A. Battaglini (2011), "Climate and Conflicts: The Security Risks of Global Warming," Regional Environmental Change, 11(Suppl 1): S27-S39.

[55] Schwartz, P., and D. Randall (2003), "An Abrupt Climate Change Scenario and Its Implications for United States National Security," Global Business Network, San Francisco, http://www.gbn.com/consulting/article_details.php?id=53

[56] Smith, P. J. (2007), "Climate Change, Mass Migration, and the Military Response," Orbis, 51(4):617-633.

[57] SOPEMI (1990), "Continuous Reporting System on Migration: SOPEMI." Paris: Organization for Economic Co-operation and Development, Directorate for Social Affairs, Manpower, and Education.

[58] Starr, P. (2010), "Arizona Sheriff Says Cops Are Being Killed by Illegal Aliens; Joins Call for U.S. Troops at Border," CNSNews.com, April 20, Alexandria, VA,http://www.cnsnews.com/news/article/64385.

[59] The Economist (2008a), "The Politics of the Gun," Special Report: Migration, January 3, London: UK.

[60] The Economist (2008b), "Keep Out," Special Report: Migration, January 3, London: UK.

[61] Time (2008), South Africa Violence: Beyond Racism, May 30, Cape Town, South Africa, www.time.com/time/world/article/0,8599,1810805,00.html

[62] The Guardian (2010), "Warning of xenophobic Violence in South Africa After World Cup: Foreign Migrants and Refugees Fear Attacks after Tournament, "May 17, United Kingdom, http://www.guardian.co.uk/world/2010/may/17/south-africa-world-cup-xenophobic-violence.

[63] UCDP/PRIO (2012), Armed Conflict Dataset v.4-2012, 1946 – 2011, Uppsala Conflict Data Program, Uppsala University, Sweden, and International Peace Research Institute, Oslo, Norway, http://www.pcr.uu.se/research/ucdp/datasets/ucdp_prio_armed_conflict_dataset/.

[64] UN / WB (2010), Natural Hazards, Unnatural Disasters: The Economics of Effective Prevention, The United Nations and the World

Bank, Washington, D.C.: The International Bank for Reconstruction and Development / The World Bank.

[65] United Nations (2009), Climate change and its Possible Security Implications: Report of the Secretary-General, A/64/350, New York: UN General Assembly http://www.unhcr.org/refworld/docid/4ad5e6380.html

[66] USINS (1996), Statistical Yearbook of the Immigration and Naturalization Service, U.S. Department of Justice, Washington, DC, http://www.dhs.gov/files/statistics/publications/archive.shtm.

[67] Weiner, M. (1978), Sons of the soil, Princeton: Princeton University Press.

[68] Wright, S. (2012), "Policing Borders in a Time of Rapid Climate Change," in Jürgen Scheffran, Michael Brzoska, Hans Günter Brauch, Peter Michael Link, Janpeter Schilling (eds.) Climate Change, Human Security and Violent Conflict: Challenges for Societal Stability, 351-370, Berlin: Springer.

[69] YaleGlobal (2010), "Anti-Immigration Backlash Roils Ties Between Australia and India," Online Magazine, March 5, New Haven, CT, www.yaleglobal.yale.edu.

[70] Weeks, J. R., J. Stoler, and P. Jankowski (2001), "Who's Crossing the Border: New Data on undocumented Immigrants to the United States," Population, Space, and Place, 17(1): 1–26.

[71] World Bank (2013), Data, "How we Classify Countries," http://data.worldbank.org/about/country-classifications, accessed on Sept 26, 2013.

Appendix 1

This appendix provides auxiliary details and results for the model development. Table 1a list the countries in the estimation sample, and Table 2a the summary statistics.

Table 1a. *Countries in the Estimation Sample*

Afghanistan	Dominican Rep.	Liberia	Samoa
Albania	Ecuador	Libya	Sao Tome & Principe
Algeria	Egypt	Lithuania	Saudi Arabia
Angola	El Salvador	Luxembourg	Senegal
Antigua & Barbuda	Equatorial Guinea	Macedonia	Serbia
Argentina	Eritrea	Madagascar	Serbia & Montenegro
Armenia	Estonia	Malawi	Seychelles
Australia	Ethiopia	Malaysia	Sierra Leone
Austria	Fiji	Maldives	Singapore
Azerbaijan	Finland	Mali	Slovakia
Bahamas	France	Malta	Slovenia
Bahrain	French Guiana	Marshall Islands	Solomon Islands
Bangladesh	Gabon	Mauritania	Somalia
Barbados	Gambia, The	Mauritius	South Africa
Belarus	Georgia	Mexico	Spain
Belgium	Germany	Micronesia	Sri Lanka
Belize	Ghana	Moldova	Sudan
Benin	Greece	Mongolia	Suriname
Bermuda	Grenada	Montenegro	Swaziland
Bhutan	Guatemala	Morocco	Sweden
Bolivia	Guinea	Mozambique	Switzerland
Bosnia & Herzegovina	Guinea-Bissau	Myanmar	Syria
Botswana	Haiti	Namibia	Taiwan
Brazil	Honduras	Nepal	Tajikistan
Brunei Darussalam	Hong Kong	Netherlands	Tanzania
Bulgaria	Hungary	New Zealand	Thailand
Burkina Faso	Iceland	Nicaragua	Timor-Leste
Burundi	India	Niger	Togo
Cambodia	Indonesia	Nigeria	Tonga
Cameroon	Iran	Norway	Trinidad & Tobago
Canada	Iraq	Oman	Tunisia
Cape Verde	Ireland	Pakistan	Turkey
Central African Republic	Israel	Palau	Turkmenistan
Chad	Italy	Panama	Uganda
Chile	Ivory Coast	Papua New Guinea	Ukraine
China	Jamaica	Paraguay	United Arab Emirates

Colombia	Japan	Peru	United Kingdom
Comoros	Jordan	Philippines	United States
Congo, Dem.	Kazakhstan	Poland	Uruguay
Congo, Rep.	Kenya	Portugal	Uzbekistan
Costa Rica	Kiribati	Puerto Rico	Vanuatu
Croatia	Korea, Rep.	Qatar	Venezuela
Cuba	Kuwait	Romania	Viet Nam
Cyprus	Kyrgyzstan	Russian Federation	Yemen
Czech Republic	Lao People's Democratic Republic	Rwanda	Zambia
Denmark	Latvia	Saint Kitts & Nevis	Zimbabwe
Djibouti	Lebanon	Saint Lucia	
Dominica	Lesotho	Saint Vincent & The Grenadines	

Table 2a. *Summary Statistics*

Variable	**Description**	**Units**	**Mean**	**St. Dev.**	**Min**	**Max**	[a]$\overline{\ln(X+1)}$ [b]$\overline{\ln(X)}$	**Geometric Mean**
M_{OD}	migration flow	Persons	1781.81	9060.86	0	946167	[a]4.44403	84.1173
WDI_O	WD incidence, origin	Events	2.17356	3.72390	0	35	[a]0.80345	1.23324
WDA_O	affected by WDs, origin	Persons	1426359	1.44E07	0	3.42E08	[a]5.01661	149.899
WDK_O	killed by WDs, origin	Persons	253.302	3218.28	0	139343	[a]1.76117	4.81926
$NWDI_O$	NWD incidence, origin	Events	0.19353	0.73570	0	11	[a]0.10120	0.10649
$NWDA_O$	affected by NWDs, origin	Persons	45914.8	109424	0	4.74E07	[a]0.89357	1.44383
$NWDK_O$	killed by NWDs, origin	Persons	194.905	4101.71	0	165818	[a]0.24207	0.27390
POP_O	population, origin	thousands	44963.1	137985	17.788	1317066	[b]9.35674	11576.6
$GDPPC_O$	GDP p.c., origin	2005 I$	19627.9	17003.1	1.3349	89832.9	[b]9.17511	9653.83
$CWAR_O$	civil war origin	Binary	0.03256	0.17750	0	1	0.03256	--
WDI_D	WD incidence, destination	Events	3.20797	5.69555	0	35	[a]0.97391	1.64827
WDA_D	affected by WDs, destination	Persons	1011813	1.18E07	0	3.42E08	[a]5.24586	188.780
WDK_D	killed by WDs, destination	Persons	284.396	2941.71	0	139343	[a]1.99522	6.35389
$NWDI_D$	NWD incidence, destination	Events	0.20169	0.72431	0	11	[a]0.10678	0.11268
$NWDA_D$	affected by NWDs, destination	Persons	34023.4	896735	0	4.74E07	[a]0.91362	1.49333
$NWDK_D$	killed by NWDs, destination	Persons	145.792	3443.77	0	165818	[a]0.21582	0.24089
POP_D	population, destination	thousands	52969.5	122660	17.302	1317066	[b]9.72417	16716.8
$GDPPC_D$	GDP p.c., destination	2005 I$	24052.2	16021.2	1.3349	89832.9	[b]9.58638	14565.1
$CWAR_D$	civil war, destination	Binary	0.02680	0.16149	0	1	0.02680	--
WAR_{OD}	war origin-destination	Binary	0.00026	0.01602	0	1	0.00026	--
AID_{DO}	aid p.c. destination→origin	2011 $	2.70643	39.6889	0	5531.64	[a]0.34850	0.41694
AID_{RO}	Aid p.c. others→origin	2011 $	31.3166	96.1051	0	6312.06	[a]1.68432	4.38878
AID_{OD}	Aid p.c. origin→destination	2011 $	0.98983	10.7352	0	750	[a]0.18645	0.20496
AID_{RD}	Aid p.c.others→destination	2011 $	20.1712	85.2568	0	6312.06	[a]1.07399	1.92703

Note: *p.c. denotes per capita; I$ denotes international dollars.*

In Table 3a, the correlations between the disaster measures when the incidence is not zero are significant, though small, indicating the information contents of these measures are related but are not similar. We therefore estimate a model for each measure and a model using all of the measures.

Table 3a. *Correlations between Measures of Disasters when Incidence > 0*

	Incidence	**Affected**	**Killed**
Weather Disasters			
Incidence	1		

Affected	0.352***	1	
Killed	0.056***	0.071***	1
Non-weather Disasters			
Incidence	1		
Affected	0.254***	1	
Killed	0.312***	0.435***	1

Note: ****p < 0.01, **p < 0.05, *p < 0.1, N=2,111.*

The Robust Hausman test in Table 4a supports specifying the directed dyad effects as fixed, rather than random. The yearly and dyad fixed effects, respectively, are jointly significant. A model with country fixed effects is rejected in favor of a model with dyad fixed effects (to be expected, as the dyad effects subsume any unobserved and observed time-invariant country factors).

Table 4a. *Specification Tests for the Individual Effects*

	Incidence	**Affected**	**Killed**	**All Aspects**
Robust Hausman	497.207***	618.23***	491.449***	863.667***
Joint Significance yearly FE	44.61***	43.96***	43.04***	44.98***
Joint Significance directed dyad FE	36.84***	36.66***	36.99***	36.44***
Directed dyads FE versus country FE	27.654***	22.641***	22.639***	22.724***

Note: ****p < 0.01, **p < 0.05, *p < 0.1, FE denotes fixed effects, N=50,638.*

In Table 5a, the estimates for the four models are similar for the controls and exhibit some differences for WDs. This suggests including all the disaster measures in one model.

Table 5a. *Coefficient Estimates*

	Incidence	**Affected**	**Killed**	**All Aspects**
ln WDI_O	0.05133***			0.03546**
	(0.01208)			(0.01595)
ln WDI_Oxln WDI_O	0.03920***			0.03060***
	(0.01015)			(0.01110)
ln WDI_Oxln $GDPPC_O$	-0.00429			-0.02465
	(0.01455)			(0.01978)
ln WDI_Oxln AID_{DO}	-0.02612*			0.00736
	(0.01539)			(0.02242)
ln WDI_Oxln AID_{RO}	-0.01755			-0.03113**
	(0.01090)			(0.01471)
ln $NWDI_O$	0.04157***			0.07871***
	(0.01606)			(0.02786)
ln WDA_O		0.00491***		0.00154
		(0.00162)		(0.00176)
ln WDA_Oxln WDA_O		0.00128***		0.00152***
		(0.00029)		(0.00032)
ln WDA_Oxln $GDPPC_O$		0.00241		0.00389**
		(0.00147)		(0.00196)
ln WDA_Oxln AID_{DO}		-0.00283*		-0.00136
		(0.00162)		(0.00225)
ln WDA_Oxln AID_{RO}		-0.00161		0.00026
		(0.00114)		(0.00149)
ln $NWDA_O$		0.00230		-0.00260
		(0.00154)		(0.00311)
ln WDK_O			0.01862***	0.01174***
			(0.00373)	(0.00441)
ln WDK_Oxln WDK_O			-0.00676***	-0.00609***
			(0.00086)	(0.00100)
ln WDK_Oxln $GDPPC_O$			-0.00167	0.00092
			(0.00413)	(0.00466)
ln WDK_Oxln AID_{DO}			-0.01192**	-0.01076*
			(0.00468)	(0.00559)
ln WDK_Oxln AID_{RO}			-0.00118	0.00355

			(0.00346)	(0.00397)
ln $NWDK_O$			-0.00198	-0.00844*
			(0.00344)	(0.00481)
ln POP_O	0.50264**	0.47096**	0.46843**	0.46372**
	(0.20593)	(0.20550)	(0.20540)	(0.20676)
ln $GDPPC_O$	-0.20142**	-0.23641**	-0.20859**	-0.20584**
	(0.10101)	(0.10148)	(0.10055)	(0.10111)
ln $GDPPC_O$xln $GDPPC_O$	-0.06124***	-0.06738***	-0.06644***	-0.06030***
	(0.01985)	(0.01970)	(0.01995)	(0.01989)
$CWAR_O$	0.07763**	0.06684*	0.08173**	0.08420**
	(0.03870)	(0.03829)	(0.03844)	(0.03847)
ln WDI_D	0.06532***			0.02668*
	(0.01296)			(0.01480)
ln WDI_Dxln WDI_D	0.03132***			0.04754***
	(0.00861)			(0.00917)
ln WDI_Dxln $GDPPC_D$	0.05103***			-0.01292
	(0.01483)			(0.02252)
ln WDI_Dxln AID_{OD}	-0.02679			-0.05292
	(0.02674)			(0.03851)
ln WDI_Dxln AID_{RD}	0.01142			-0.03303*
	(0.01149)			(0.01826)
ln $NWDI_D$	0.00664			0.07903***
	(0.01584)			(0.02933)
ln WDA_D		0.00564***		0.00407**
		(0.00180)		(0.00186)
ln WDA_Dxln WDA_D		-0.00108***		-0.00167***
		(0.00029)		(0.00029)
ln WDA_Dxln $GDPPC_D$		0.00587***		0.00252
		(0.00166)		(0.00234)
ln WDA_Dxln AID_{OD}		-0.00115		0.00270
		(0.00307)		(0.00439)
ln WDA_Dxln AID_{RD}		0.00256**		0.00331*
		(0.00126)		(0.00184)
ln $NWDA_D$		-0.00100		-0.00568*
		(0.00173)		(0.00334)
ln WDK_D			0.01364***	0.01152***
			(0.00388)	(0.00437)
ln WDK_Dxln WDK_D			0.00119	0.00213***
			(0.00074)	(0.00082)
ln WDK_D xln $GDPPC_D$			0.02277***	0.02372***
			(0.00419)	(0.00511)
ln WDK_Dxln AID_{OD}			-0.00229	0.00397
			(0.00852)	(0.00966)
ln WDK_Dxln AID_{RD}			0.00847**	0.01072**
			(0.00346)	(0.00420)
ln $NWDK_D$			-0.00908*	-0.01008*
			(0.00480)	(0.00576)
ln POP_D	-0.00987	-0.07679	-0.07437	-0.00146
	(0.23496)	(0.23418)	(0.23219)	(0.23471)
ln $GDPPC_D$	0.87616***	0.83812***	0.85096***	0.84940***
	(0.11621)	(0.11547)	(0.11515)	(0.11547)
ln $GDPPC_D$xln $GDPPC_D$	0.09037***	0.08467***	0.08767***	0.09207***
	(0.01996)	(0.01998)	(0.01990)	(0.01993)
$CWAR_D$	-0.15564***	-0.13624**	-0.14236***	-0.13630***
	(0.05445)	(0.05368)	(0.05326)	(0.05199)
ln AID_{DO}	0.18545***	0.19019***	0.18641***	0.19625***
	(0.03684)	(0.03656)	(0.03660)	(0.03692)
ln AID_{DO}xln AID_{DO}	-0.03460***	-0.03466***	-0.03477***	-0.03604***
	(0.00998)	(0.00983)	(0.00999)	(0.00987)
ln AID_{RO}	-0.05909**	-0.06421**	-0.05976**	-0.06138**

	(0.02976)	(0.02979)	(0.02956)	(0.02971)
$\ln AID_{RO} x \ln AID_{RO}$	0.00874	0.01047*	0.00940	0.00864
	(0.00640)	(0.00634)	(0.00631)	(0.00641)
$\ln AID_{OD}$	0.41506***	0.41991***	0.40962***	0.39837***
	(0.05698)	(0.05498)	(0.05503)	(0.05630)
$\ln AID_{OD} x \ln AID_{OD}$	-0.04609***	-0.04483***	-0.04295***	-0.04506***
	(0.01486)	(0.01480)	(0.01483)	(0.01469)
$\ln AID_{OD}$	-0.08037***	-0.08057***	-0.07968***	-0.08054***
	(0.02909)	(0.02898)	(0.02913)	(0.02906)
$\ln AID_{RD} x \ln AID_{RD}$	0.01305**	0.01246*	0.01298**	0.01152*
	(0.00657)	(0.00650)	(0.00655)	(0.00659)
WAR_{OD}	0.30350	0.36147	0.39581	0.32017
	(0.42143)	(0.41751)	(0.41386)	(0.43044)
Constant	3.90166***	3.74409***	3.78094***	3.88608***
	(0.22492)	(0.21804)	(0.21838)	(0.22581)
Observations	50,638	50,638	50,638	50,638
R-squared	0.92173	0.92165	0. 92174	0. 92215

Notes: *ln denotes natural log; logged variables centered at sample means; 1 is added to the disaster and aid variables before taking logs.Robust standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1; Table 6a: Variance Inflation Ratios*

In Table 6a, the individual VIFs are smaller than 10 for all but one case in the single measure models and 10 cases in the all measures model. The mean VIFs are smaller than 10 and the condition numbers are smaller than 30, so the models do not have a multi collinearity problem and any estimation impreciseness will likely be limited to variables with VIFs larger than 10.

Table 6a

	Incidence	Affected	Killed	All Aspects
$\ln WDI_O$	2.08			6.89
$\ln WDI_O$ x $\ln WDI_O$	1.75			2.73
ln WDIO x ln GDPPCO	2.75			14.63
ln WDIO x ln AIDDO	2.34			9.19
$\ln WDI_O$ x $\ln AID_{RO}$	3.87			17.69
$\ln NWDI_O$	1.25			6.41
$\ln WDA_O$		1.97		4.21
$\ln WDA_O$ x $\ln WDA_O$		2.09		2.98
$\ln WDA_O$ x $\ln GDPPC_O$		3.00		9.04
$\ln WDA_O$ x $\ln AIDd_O$		1.72		4.99
$\ln WDA_O$ x $\ln AID_{RO}$		3.00		9.75
$\ln NWDA_O$		1.24		7.68
$\ln WDK_O$			2.91	5.59
$\ln WDK_O$ x $\ln WDK_O$			2.43	3.38
$\ln WDK_O$ x $\ln GDPPC_O$			2.63	7.93
$\ln WDK_O$ x $\ln AIDd_O$			1.97	4.14
$\ln WDK_O$ x $\ln AID_{RO}$			3.51	8.98
$\ln NWDK_O$			1.14	2.5
$\ln POP_O$	2.97	2.56	2.68	3.1
$\ln GDPPC_O$	8.39	8.62	8.31	8.99
$\ln GDPPC_O$ x $\ln GDPPC_O$	2.93	2.74	2.76	2.96
$CWAR_O$	1.08	1.08	1.09	1.1
$\ln WDI_D$	2.48			7.17
$\ln WDI_D$ x $\ln WDI_D$	1.70			2.7
$\ln WDI_D$ x $\ln GDPPC_D$	3.28			17.44
$\ln WDI_D$ x $\ln AID_{OD}$	3.13			11.95
$\ln WDI_D$ x $\ln AID_{RD}$	4.99			22.47
$\ln NWDI_D$	1.25			6.58
$\ln WDA_D$		1.82		3.61
$\ln WDA_D$ x $\ln WDA_D$		1.55		2.21
$\ln WDA_D$ x $\ln GDPPC_D$		3.42		10.61
$\ln WDA_D$ x $\ln AID_{OD}$		1.91		5.37
$\ln WDA_D$ x $\ln AID_{RD}$		3.69		11.58
$\ln NWDA_D$		1.24		7.62

$\ln WDK_D$			2.85	4.98
$\ln WDK_D \times \ln WDK_D$			2.01	2.65
$\ln WDK_D \times \ln GDPPC_D$			3.02	9.19
$\ln WDK_D \times \ln AID_{OD}$			2.36	4.78
$\ln WDK_D \times \ln AID_{RD}$			4.14	10.21
$\ln NWDK_D$			1.16	2.47
$\ln POP_D$	3.18	2.54	2.64	3.32
$\ln GDPPC_D$	9.48	9.07	8.89	10.31
$\ln GDPPC_D \times \ln GDPPC_D$	3.46	3.08	3.17	3.55
$CWAR_D$	1.09	1.09	1.11	1.13
$\ln AID_{DO}$	5.53	5.73	5.51	6.32
$\ln AID_{DO} \times \ln AID_{DO}$	4.50	4.46	4.29	4.56
$\ln AID_{RO}$	9.17	9.29	9.17	9.54
$\ln AID_{RO} \times \ln AID_{RO}$	2.64	2.51	2.64	2.76
$\ln AID_{OD}$	6.54	6.76	6.41	8.47
$\ln AID_{OD} \times \ln AID_{OD}$	5.39	5.39	5.12	5.52
$\ln AID_{RD}$	13.66	13.54	13.31	14.58
$\ln AID_{RD} \times \ln AID_{RD}$	5.99	5.69	5.99	6.27
WAR_{OD}	1.00	1.00	1.00	1.01
Mean VIF	4.06	3.85	3.94	6.90
Condition Number	11.50	11.36	11.27	19.06

Notes: *logged variables centered at sample means; 1 is added to the disaster and aid variables before taking logs.*

Table 7a shows that one cannot exclude disaster measures of any type from the model for any exclusion combination, supporting including all the disaster measures in the model.

Table 7a. *Testing Restrictions for the Disaster Terms*

Restrictions	F-statistics
Incidence	7.72***
Affected	6.34***
Killed	14.55***
Incidence + Affected	6.25***
Affected + Killed	9.75***
Incidence + Killed	10.58***

Note: **** significant at the level of 0.0001.*

Appendix 2. Bias Correction and Model Validation

We applied a smearing non-parametric retransformation method developed by Duan (1983). It allows to account for both multiplicative character of log-log model as well as for heteroskedastic error structure. We estimate a model of the form $\ln y = X\beta + \varepsilon$, reverse transformation of which returnsy = expXβ+ε. Clearly, expected value $E[y|X] = \exp(X\hat{\beta})E[\exp(\varepsilon)]$, where $X\hat{\beta} \equiv \widehat{\ln y}$ is a predicted value and $E[\exp(\varepsilon)] > 0$.Duan's method estimates the bias $E[\exp(\varepsilon)]$and calculate it as following:

$$E[\exp(\varepsilon)] = \frac{1}{N}\sum_{i=1}^{N}\exp(\hat{\varepsilon}_i) = \frac{1}{N}\sum_{i=1}^{N}\exp(\ln y_i - X\beta) = \frac{1}{N}\sum_{i=1}^{N}\exp(\ln y_i - \widehat{\ln y_i})$$

, where N is a number of observations in the sample in the case of homoscedastic error term or is a number of observation in the cross-section if the error is heteroskedastic. Applying this logic to our model (1), the unbiased predicted value $\widehat{M}_{OD,t}$ in the dyad OD at time t takes the following form:

$\widehat{M}_{OD,t} = \exp(\widehat{\ln}(M_{OD,t} + 1)) \cdot \frac{1}{N_{OD}} \sum_{OD=1}^{N_{OD}} \exp(\ln(M_{OD,t} +$ 1−lnMOD,t+1−1.

To validate our out-of-sample forecast we employ a "rolling" validation of the predictions for our model varying ("rolling") our training data from 1980-2003 to 1980-2008 and test data from 2004-2009 to 2009 only, respectively, (See the description in Section 7.1). The values for absolute with average error (APE) are presented below.

Bias Correction[23]	$$\widehat{M}_{OD,t} = \exp(\widehat{\ln}(M_{OD,t} + 1)) \cdot \frac{1}{N_{OD}} \sum_{OD=1}^{N_{OD}} \exp(\ln(M_{OD,t} + 1) - \widehat{\ln}(M_{OD,t} + 1)) - 1$$
	Test data

[23] *The unbiased estimate is factored by 1.016 (corrected by 1.6%) that minimizes APE*

Training data	2004	2005	2006	2007	2008	2009	APE(%)
1980-2003	-8.03	-0.54	3.95	-4.21	-15.72	-4.83	-3.93
1980-2004		-3.32	-1.12	-7.22	-19.13	-7.50	-3.54
1980-2005			1.65	-2.93	-13.88	-1.11	-1.48
1980-2006				2.93	-8.22	7.51	0.25
1980-2007					-7.77	7.16	-0.24
1980-2008						-0.11	-0.11
APE(%)	-8.03	-1.93	1.49	-2.86	-12.94	0.19	

Bias Correction[24]	$\widehat{\mathbf{M}}_{\mathbf{OD,t}} = \mathbf{exp}\left(\widehat{\mathbf{ln}}\left(\mathbf{M}_{\mathbf{OD,t}} + \mathbf{1}\right) + \frac{\boldsymbol{\sigma}^{\mathbf{2}}}{\mathbf{2}}\right) - \mathbf{1}$						
	Test data						
Training data	2004	2005	2006	2007	2008	2009	APE(%)
1980-2003	-8.61	-1.07	3.57	-4.95	-15.98	-5.60	-3.84
1980-2004		-2.04	0.56	-5.98	-17.84	-6.19	-3.21
1980-2005			2.29	-2.61	-13.39	-0.74	-1.66
1980-2006				1.96	-8.85	6.53	-0.36
1980-2007					-7.77	5.66	-0.60
1980-2008						0.31	0.31
APE	-8.61	-1.56	2.14	-2.90	-12.77	0.00	

[24] *The unbiased estimate is factored by 1.04 (corrected by 4%) that minimizes APE*