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CDP 09/21

- ▶ Climate Change, International Migration, and Interstate Conflict
- ▶ Cristina Cattaneo and Timothy Foreman

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Climate Change, International Migration, and Interstate Conflict

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Abstract

A number of factors contribute to interstate conflicts. One social element that has received little attention in the literature is the role of international migration. At the same time, the contribution of climate stress on interstate disputes has been under-researched. This paper analyses if climate stress represents a direct driver of interstate disputes and, at the same time, an indirect driver to conflicts through its effect on international migration. To do so, we use climate shocks to instrument for migration flows in a gravity setting in order to study its causal effect on international conflict. We find that a 1% increase in climate-induced migration increases the probability that the destination of the flows initiates conflict against the origin by 0.001 percentage points over a mean incidence of conflict of 0.13 percentage point per year. The results are consistent across different migration datasets and different specifications of defining the initiator in the conflict.

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1 Introduction

Whether economic interdependence between states exacerbates or alleviates tensions is an important question as the world becomes ever more globalized. This topic has received considerable attention in the literature, but the majority of existing studies focus on interdependence generated by trade flows. While scholars have studied the possible pacifying effects of economic ties generated by trade flows (among others Martin et al. (2008)), little attention has been given to the security implications generated by another type of connection, namely flows of individuals. International migration, especially from developing to developed countries and between developing countries, can significantly influence international relations, by eventually affecting the likelihood of interstate conflicts between receiving and sending countries (Weiner, 1992, 1985). Some authors addressed the security consequences associated with refugee flows (Salehyan, 2008; Whitaker, 2003; Martin, 2005). However, refugees come from very specific origin countries and are a different type of flow, compared to voluntary movement of persons, which are flows of people who voluntary chose to move within or outside the borders of the country of origin.

At the same time, there is a large body of literature investigating the impacts of climatic conditions on conflicts. This literature mainly considers intragroup or intranational conflicts, such as civil conflicts, while only a few studies have analyzed a possible causal link between climate and interstate conflicts. To this point, in a meta-analysis on the influence of climate on conflicts, only one study focuses on interstate conflicts (Hsiang et al., 2013). Despite the scant attention to interstate disputes in climate and conflict studies, a possible role of climate stress as a driver of interstate disputes should not be dismissed, given the wide range of impacts that climate produces on societies.

This paper aims to fill in these gaps in research and analyses if climate stress represents a direct driver of interstate disputes and, at the same time, an indirect driver to conflicts through its effect on international migration. Climatic stress in fact, can intensify emigration flows (Cattaneo and Peri, 2016; Beine and Parsons, 2017), and these flows may influence interstate disputes. Reuveny (2007) document that climate-induced migration could be an important pathway for the climate to impact conflict. Burrows and Kinney (2016) review

the research on the climate, migration, and conflict nexus, and report that there are still many uncertainties in the linkages from climate to migration and migration to conflict.

According to the rationalist theory of interstate conflict, states benefit if they resolve their disputes nonviolently (Fearon, 1995). Leaders try to compromise and negotiate in the first instance. However, there are some factors that influence the utility of acting violently or affect the opportunity costs of entering in a conflict. For example, control of rival and excludable good has historically influenced the incidence of interstate militarized conflicts (Caselli et al., 2015). Moreover, Spolaore and Wacziarg (2016) report that the more countries are culturally similar, the more they are prone to fight over rival goods, given that their preferences over these rival resources are similar.

Migration flows might be an additional driver of interstate conflicts. Migrants may compete with locals for jobs and scarce resources, and this can generate a sense of hostility among natives. Labour market concerns are a strong driver of opposition towards migrants in hosting societies (Hainmueller and Hopkins, 2014; Haaland and Roth, 2017). In many cases, this is not a real threat but an “emotional” threat perceived by the hosting population. The literature documents that natives have strong misperceptions of some migrants’ characteristics (Hopkins et al., 2018; Alesina et al., 2018; Grigorieff et al., 2018). These misperceptions can contribute to feeding the “emotional” threat, which can drive interstate conflicts by increasing bargaining failures. In this circumstance, the receiving country of the flows has low incentives to make concessions to avoid escalation toward war. These concerns can be exacerbated when the population flows occur too rapidly to be smoothly absorbed, as it might be the case for climate-induced migrants.

The hypothesis that the existence of these emotional threats might result in a higher risk of tensions finds support in the existing literature, which documents that non-economic factors, such as emotional cues like anger, or fear, can give rise to inter-group violence (Card and Dahl, 2011; Baysan et al., 2019). Card and Dahl (2011) model losses in football games as a trigger of family violence. Baysan et al. (2019) introduce a psychological consumption value of violence, which increases the utility of acting violently and therefore augments the risk that violence occurs between two parties. In our framework, the flows of migrants between two countries can resemble a visceral non-economic factor, that affects the probability of

disputes between these two countries.¹

Conversely, a relationship between climate and inter-country conflicts may arise through an income effect. Warming and rainfall deficits have been shown to lower productivity and income, which in turn reduces the opportunity cost of participating in violence (Baysan et al., 2019; Chassang and Padró i Miquel, 2009). One area that has been empirically considered for a possible connection between climate change and interstate conflict involves water. Devlin and Hendrix (2014) study the link between conflicts and precipitation at the dyad level. In agreement with the income effect story, the author finds that lower precipitation means an increase in international conflicts. However, this relationship only holds between pairs that do not share a water resource or are not geographically contiguous. Moreover, in their paper, precipitation scarcity experienced jointly by the pairs of countries decreases interstate disputes. This indicates that joint water scarcity is associated with cooperative outcomes. Similarly, Gleditsch et al. (2006) find that low average rainfall increases interstate conflicts between dyads, but only if the dyads do not share a river basin. In water scarcity, countries that share basins have higher incentives to invest in water management measures and avoid conflict. Localized scarcity can contribute to technological or social innovations that manage any tendency toward conflict (Gartzke, 2012; Koubi et al., 2013).

The present paper aims to shed light on two little-researched mechanisms through which interstate conflicts arise, namely climate stress and migration inflows. The paper will take into account both mechanisms.² Drawing from Baysan et al. (2019), we employ a conceptual framework where both economic factors (direct impacts of climate change) and non-economic factors (i.e. international migration flows) influence the values of peace and violence. A conflict occurs if the value of conflict exceeds the value of peace.³ The specific mechanism in

¹There is another possible mechanism linking international migration and interstate dispute. If the destination labor market is not be able to absorb an influx of population, this may cause a decline in per capita income. As a consequence, the value of peace may fall below the value of attacking, as in Chassang and Padró i Miquel (2009). However, this hypothesis is quite unlikely, given that international flows of people are generally responsible for mutual advantages to both the host and receiving countries (Battisti et al., 2018; Aubry et al., 2016; Docquier et al., 2015).

²There is an additional (indirect) mechanisms, possibly linking climate change and interstate disputes. Political unrest within states and civil conflicts are found to spark disputes between states (Gleditsch et al., 2008). Therefore, given that there is some evidence that climatic shocks are linked to civil conflict (Burke et al., 2015; Hsiang et al., 2013), the climatic events may constitute a possible driver of interstate disputes through their effect on civil conflicts.

³Baysan et al. (2019) introduce a non-rival psychological consumption value of violence, γ , which is

place may determine which country initiates the conflict. If a country experiences warming or scarcity in one environmental factor, according to the income effect story described above, this country may take action against another country and become the initiator of a conflict. However, if the dispute is connected to the generated migration flows, the country that experiences the resource scarcity may become the target of aggression. If climate shocks (such as water scarcity or soil degradation) boost emigration flows, then the receiving country of the flows may decide to initiate hostile actions against the origin country of the flows (Stalley, 2003), as suggested by the perceived threat hypothesis.

We find that climate exerts both an indirect and a direct effect on interstate disputes. A 1% increase in the inflows of climate-induced migrants leads to 0.001 percentage point increase in the probability that the destination country initiates a conflict against the origin country of the flows, which corresponds to an increase of 0.9% over the observed yearly mean. Second, both excess and scarcity of precipitation in the aggressor country increase the engagement in conflicts. Moreover, the probability of initiating a conflict is influenced by the temperature. It decreases for optimal temperatures, with a minimum at 15.5 °C and it increases after this point. These findings give support to the empirical evidence that documents an influential role of climate on conflicts, even if the research was so far limited to analyses of civil conflicts.

One paper closely related to ours is Docquier et al. (2018), which brings some evidence to bear on the question of how migration affects interstate conflict. They argue that migration is a significant driver of interstate conflicts, using decadal data on migration and conflict. While they establish a link between these two variables, there is the possibility that their estimates are biased by unobserved variables that could drive both conflict and migration, as well as the possibility that conflict itself could be influencing population movements within the same decade. To overcome these challenges, in this paper we exploit exogenous climate shocks that drive migration. Moreover, the present paper is innovative with respect to Docquier et al. (2018) in a second dimension, as it complements decadal with yearly data. The combination of data at different frequencies allows us to capture both short-run and medium-run responses

increasing in temperature $\frac{\partial \gamma(\tau)}{\partial \tau} > 0$. In our setting, γ can proxy for a visceral factor that increases the value of violence, which responds to the inflows of migrants: $\frac{\partial \gamma(m)}{\partial m} > 0$.

to climate threats. While the decadal data for migration gives migration information for all possible pairs of countries globally, thus ensuring extensive geographical coverage, it does not allow to connect yearly variation in interstate disputes with the yearly flows. If bilateral flows peaked in a specific year but reversed later, this dynamic would not be captured by decadal data. Finally, given the possible relevance of water scarcity for interstate disputes, this paper contributes to the existing literature by computing indicators of climatic variability based on the Standardized Precipitation Index (SPI) and allowing varying impact parameters of the SPI on migration as well as interstate conflicts along the SPI distribution.

The rest of the paper is organized as follows. Section 2 presents a description of the data and the variables used to study whether climate stress and climate-induced migration affect interstate disputes. Section 3 describes the empirical approach and presents the findings. Section 4 concludes the paper and discusses possible policy implications.

2 Data description

2.1 Migration Data

2.1.1 OECD Data

The primary migration dataset that we use is the OECD International Migration Database, with additions from Adsera and Pytlikova (2015). This dataset provides the flows of migrants to primarily OECD destination countries from around the world at a yearly frequency. The bilateral nature of the data is necessary for us to match up with bilateral conflict data. The use of yearly data allows us to study how migration evolves around the time of conflict. This data is available from 1980 to 2010. The disadvantage of this dataset is that it does not cover many possible destination countries that may have been involved in interstate disputes.

2.1.2 GBMD data

To allow a wider geographical coverage and include all possible international disputes, we complement the yearly with decadal data, in particular the Global Bilateral Migration Database (Ozden et al., 2011). This dataset provides global bilateral migrant stocks every

10 years from 1960 to 2000. These data are compiled from national censuses, making them more reliable than survey data or estimates of flows. Starting from the bilateral stocks, we compute net bilateral migration flows between each country pair as the difference between bilateral stocks in two consecutive census years as in Beine and Parsons (2015) and Cattaneo and Peri (2016).

2.2 Correlates of War Data

The data on bilateral conflicts come from the Correlates of War Project (COW), Version 4.3 (Maoz et al., 2019), which gives information on Militarized Interstate Disputes (MIDs). This is the most widely referenced measure of interstate conflict and covers all militarized threats, displays, or uses of force up to and including war among internationally recognized states, from 1816-2010. The dyadic dataset tracks each pair of countries involved in military conflicts and provides the level of hostility, which can vary from 1 to 5. Given that we are interested in a broad view of conflict that can be influenced by migration, we use conflicts that correspond to the categories of display of force (= 3), use of force (=4), and war (=5). This has also commonly been used in prior literature (Docquier et al., 2018; Conconi et al., 2014; Baliga et al., 2011; Martin et al., 2008). This generally does not include UN peacekeeping missions, but events where there is a military action taken under the direction of a national government.

As detailed in Chassang and Padró i Miquel (2009) for intergroup conflicts, one agent may choose to attack the other first. This dynamic allows one to distinguish between the country that initiates a conflict from the country that is the target of an attack. In this framework, it is the aggressor's incentives that are important. In this paper, we follow this approach. The Correlates of War project has the advantage that it indicates for each conflict pair the role each country plays: primary initiator, primary target, joiner on the initiator's side, and joiner on the target's side. In our results, we consider both the primary initiator and the joiners on the initiator's side to be the initiator in a dyadic dispute. The data also includes which side seeks a policy change in the conflict. We use this to determine which country is the aggressor in an alternative specification, as the country that takes the first military action is not necessarily the one that starts the conflict in a broader sense of the

term.

2.3 Climate Data

Climate data comes from the Climatic Research Unit at the University of East Anglia (Climatic Research Unit, 2013). This data provides temperature and precipitation monthly at a 0.5×0.5 degree resolution. This data utilizes weather station data and interpolation methods to produce a uniform grid for the world (Mitchell and Jones, 2005). It is one of the standard climate datasets used in economic analyses (Auffhammer et al., 2013). This data is aggregated to the country level using population weights from the Gridded Population of the World version 4 using population data from 1970, as this is the earliest population estimate available (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016).

In the analysis, we also employ bilateral geographical variables, namely $\log(\text{distance})$, whether the pairs of countries share a border, whether they share a common colonial history, common language tree, or common water resource. Most of these variables are from the Adsera and Pytlikova (2015) dataset. We use the population-weighted distances between countries from the CEpii GeoDist database (Mayer and Zignago, 2011). The water basin data are from the UNEP Transboundary River Basins Assessment (UNEP-DHI and UNEP, 2016). Language similarity comes from Martin et al. (2008).

Given the importance of water availability in the context of climate change and international disputes (Devlin and Hendrix, 2014; Gleditsch et al., 2006), we use the monthly precipitation values to compute measures of scarcity and excess precipitation. There is little consistency in how precipitation is used in studies of either migration or conflict. For example, within the literature on civil conflicts, Harari and Ferrara (2018) compute the Standardized Precipitation-Evapotranspiration Index (SPEI), which accounts for the joint effects of precipitation, potential evaporation, and temperature.⁴ They use the average monthly SPEI over the growing season months of a cell's main crop in a given year. McGuirk and Burke (2020), in a study of local violence across the African continent, compute the

⁴Ma et al. (2014) however, argue that the SPEI index suffers a potential limitation as it overestimates the influence of temperature.

Standardized Precipitation Index (SPI), which is a frequently used measure of drought based on monthly precipitation, first developed by McKee et al. (1993). Couttenier and Soubeyran (2014) computes the Palmer Drought Severity Index (PDSI) and use the average of the monthly grid cell PDSI values. Within the migration literature, Gröschl and Steinwachs (2017) use the negative mean of the SPEI in a gravity migration equation. Dallmann and Millock (2017), to study interstate migration in India, compute indicators of moderate and severe droughts as well as moderate and severe excess precipitation using thresholds of the SPI. Based on the SPI measure, they also compute the maximum duration in a number of months of drought and excess precipitation. However, these studies either enter the average drought measure linearly or use indicator dummies. In this paper, we use the Standardized Precipitation Index (SPI) and contribute to the existing literature by modelling piecewise linear response functions.

To do so, we first compute the 6-month SPI by fitting a Gamma distribution to the long-run precipitation gridded data from 1902-2018 and convert this into a standard normal distribution (McKee et al., 1993; Guttman, 1999). The measure is then aggregated to the country-year level by averaging within each pixel over the year, then population-weighting across pixels over the country:

$$SPI_{cy} = \sum_{p \in c} W_p \sum_{m=1}^{12} SPI_{pm} \quad (1)$$

where SPI_{pm} is the pixel-month level SPI and $p \in c$ indicates the pixels in country c . The population-weights W_p are normalized for each country such that $\sum_{p \in c} W_p = 1$.

We then compute a measure of drought based on the SPI. We follow McGuirk and Burke (2020) and consider 1.5 standard deviations below the long term levels as a plausible threshold for severely dry situations.⁵ The drought SPI measure is thus defined as follows:

$$D_{cy} = \sum_{p \in c} W_p \sum_{m=1}^{12} (SPI_{pm} + 1.5) \mathbb{1}[SPI_{pm} \leq -1.5] \quad (2)$$

⁵In the empirical session below, we run our regressions at varying cutoffs and find the value that maximizes the goodness of fit to be close to -1.5 and 1.5, so keep these thresholds to maintain consistency with other work. The results of this analysis are available upon request.

This value is the population-weighted drought severity measure.

Similarly, we compute the excess precipitation based on the SPI using the same 1.5 threshold.⁶ The excess precipitation SPI measure is defined:

$$EP_{cy} = \sum_{p \in c} W_p \sum_{m=1}^{12} (SPI_{pm} - 1.5) \mathbb{1}[SPI_{pm} \geq 1.5] \quad (3)$$

By using the three variables jointly in a (migration or conflict) specification, one can model a piecewise linear response of the outcome variable to SPI. Accounting for different regimes in the response function is important, because first, only reasonably large deviations from long term means indicate adverse weather situations, which might cause migration and conflict. Second, responses to positive and negative deviations may be of opposite signs. For example, the literature finds that in most cases, floods-induced migration tends to be temporary and over short distances, making international migration unaffected, while it documents both cases of international departures as well as cases of people trapped *in-situ* as a consequence of droughts (Cattaneo et al., 2019).

The following example describes how these measures interact when included together. An outcome variable Y_{cy} is regressed on SPI_{cy} , D_{cy} , and EP_{cy} .

$$Y_{cy} = \beta_1 SPI_{cy} + \beta_2 D_{cy} + \beta_3 EP_{cy} + \epsilon_{cy} \quad (4)$$

For concreteness, we set $\beta_1 < 0$, $\beta_2 < 0$, and $\beta_3 > 0$. The estimated response function, in the simple case of one country c consisting of only one pixel, will appear as follows:

$$Y = \begin{cases} (\beta_1 + \beta_2) SPI & \text{if } SPI \leq -1.5, \\ \beta_1 SPI & \text{if } -1.5 < SPI < 1.5, \\ (\beta_1 + \beta_3) SPI & \text{if } SPI > 1.5 \end{cases}$$

In the reality, a country consists in multiple pixels. We can assume a case where the country has 10 pixels of equal population, so that the population weight for the single pixel

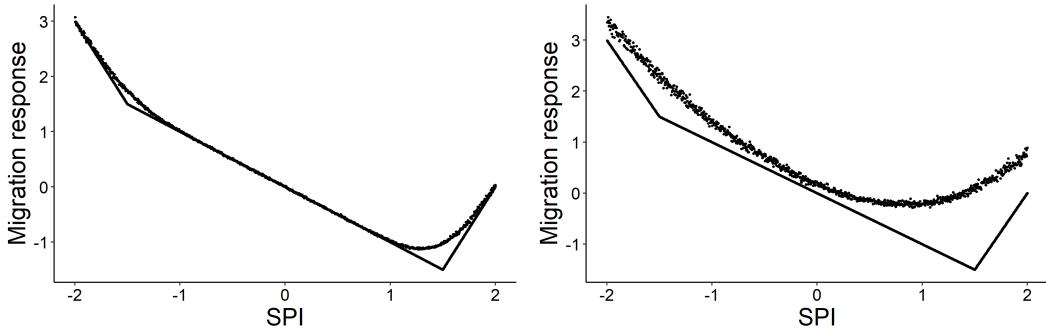
⁶Although the SPI intends to measure drought, it can also be a good indicator of excess precipitation (Seiler et al., 2002).

W_p is 0.1. Then the response to one pixel will be:

$$Y = \begin{cases} .1(\beta_1 + \beta_2)SPI & \text{if } SPI \leq -1.5, \\ .1\beta_1 SPI & \text{if } -1.5 < SPI < 1.5, \\ .1(\beta_1 + \beta_3)SPI & \text{if } SPI > 1.5 \end{cases}$$

While the response for a pixel is straightforward to calculate, it is an empirical question how the outcome will respond to a country-level shift in SPI. If the SPI distribution within the country is very narrow, as the values of the SPI are similar among the different pixels, the country level response will look similar to the pixel-level response. However, if the distribution is wider, with some pixels having SPI values differing from other pixels SPI, the response will be smoothed out.

To see how the single-pixel cases can vary compared to the country case, we simulate an SPI distribution for a country with differing levels of within-country variability. Figure 1 shows the country level response and the comparison to the single-pixel case. As a starting point, consider an SPI distribution that is normal with mean μ that will range from -2 to 2 and standard deviation $\sigma = .3$. The resulting response functions is shown in the left panel of Figure 1. The right panel shows the response with $\sigma = 1$. As the within-country variability increases, the response becomes more smooth, as well as wider for a given value of SPI, since there will be some pixels far from the average.



Notes: Dots display country while line pixel responses. The left panel shows the pixel response with a SPI distribution with $\sigma = 0.3$. The right panel shows the pixel response with $\sigma = 1$.

Figure 1: Response function of migration to SPI for different levels of within-country variation

2.4 Summary Statistics

Table 1 provides summary statistics for the key variables used in the estimations. Panel A is available on a yearly basis, from 1980 to 2010 and includes a total number of 3,675 pairs, representing 160 and 38 source and OECD destination countries for migration, respectively. Panel B, available on a decadal basis, from 1960 to 2000, includes 10,876 pairs, 160 sources and 155 destinations, from all over the world. The incidence of interstate conflicts is 0.13% in the yearly and 0.65% in the decadal sample, respectively. The higher incidence in the latter reflects first that many international disputes occurred between pairs that are both non-OECD countries and second that a decade provides more opportunity for conflict than a single year. A third reason for this higher figure is that more recent years have been characterised by more peace between countries. Nevertheless, the positive percentage in the yearly sample indicates that at least some international disputes involved OECD countries. The average and maximum number of bilateral flows of migrants are also higher in the decadal sample. This is both a result of the cumulative number of migrants arriving over the period of a decade, as well as an indication that OECD countries are not the sole destinations of the flows, and large part of the existing flows involves South-South countries.⁷

Despite the differences in the geographical coverage, the distance variable displays very similar values in the two samples. The table also provides summary statistics for the climatic variables. This data is unilateral information for the OECD and non-OECD countries of the analyses. The higher maximum temperature in the yearly sample indicates that the hottest temperatures were registered between 2000 and 2010. The average value of SPI is negative, suggesting greater precipitation deficit than precipitation excess in the sample compared to the long-run mean.

⁷The comparison of yearly and decadal flows must be done with caution, given the different ways the two statistics have been computed. The yearly data are inflows of migrants from one country to another (OECD) country. The decadal data, being computed as a difference in stocks, represent net migration flows.

Panel A: Yearly sample						
	Mean	Std. Dev.	Min	p10	p90	Max
Starts conflict (%)	0.13	3.65	0.00	0.00	0.00	100.00
Migrants (1000s)	1.22	7.45	0.00	0.00	1.99	946.17
Log(distance)	8.59	0.86	4.39	7.28	9.51	9.88
Temperature	18.98	7.32	-2.69	8.33	27.18	29.73
Precipitation	0.09	0.06	0.00	0.02	0.19	0.35
SPI	-0.03	0.39	-2.81	-0.49	0.45	1.67
Drought SPI	-0.06	0.08	-1.31	-0.17	0.00	0.00
Excess SPI	0.02	0.04	0.00	0.00	0.06	0.62
Observations	77041					

No. of pairs: 3675
 No. of origins: 160
 No. of destinations: 38

Panel B: Decadal sample						
	Mean	Std. Dev.	Min	p10	p90	Max
Starts conflict (%)	0.65	8.06	0.00	0.00	0.00	100.00
Migrants (1000s)	1.82	35.89	0.00	0.00	0.69	4705.68
Log(distance)	8.65	0.82	4.39	7.49	9.52	9.89
Temperature	18.45	7.24	-1.95	7.93	26.81	28.88
Precipitation	0.09	0.06	0.00	0.03	0.18	0.32
SPI	-0.05	0.18	-0.96	-0.26	0.19	0.45
Drought SPI	-0.06	0.06	-0.37	-0.12	-0.01	-0.00
Excess SPI	0.02	0.02	0.00	0.00	0.04	0.15
Observations	48490					

No. of pairs: 10876
 No. of origins: 160
 No. of destinations: 155

Table 1: Summary statistics

3 Empirical Analysis

3.1 Effect of migration on conflict

3.1.1 Empirical strategy

One of the purposes of this study is to examine the effect of international migration on interstate conflicts in a dyadic setting. However, the relationship between migration and conflicts is complex, as migration flows can both cause but also be affected by conflicts.

To address this potential for reverse causality, we employ a two-stage least squares (2SLS) estimation strategy. As our instrument, we construct a predicted migration variable, where

migration flows are predicted based on climate variation. We rely on a “gravity” approach that predicts bilateral migrants based on a variety of origin-destination characteristics, and we augment the specification with climate shocks. This approach, first used in the pioneering works of Frankel and Romer (1999); Rodriguez and Rodrik (2001); Rodrik et al. (2004), has been largely used to instrument trade or migration flows also in a panel setting (Alesina et al., 2016; Ortega and Peri, 2014; Feyrer, 2009b,a). Climate shocks, primarily in the form of elevated temperatures, droughts, or floods, can lead to increased migration flows. In this implementation, while we control for fixed geographic characteristics of migrants’ origin- and destination countries, we use time-varying climatic variables in origin countries to predict changes in the flow of migrants. Hence, we obtain panel-level identification of migration flows associated with changes over time in climatic variables. Another advantage of this estimation strategy is that it also allows us to study the effects of climate migrants in particular on the potential for conflict.

We estimate the climate-migration relationship using the following equation:

$$\ln(M_{ijt}) = \alpha \mathbf{C}_{it} + \beta \mathbf{C}_{it} \times D_{ij} + \gamma X_{ij} + \theta_{r(i)t} + \delta_i + \eta_j + \epsilon_{ijt} \quad (5)$$

where M_{ijt} is the number of migrants moving from country i to j in year (decade) t , \mathbf{C}_{it} is a matrix of climate variables in country i and year t . Climatic changes in the origin country i represent push factors for out-migration. In our preferred specification, we include average temperature, average precipitation, SPI 6, and measures of drought and excess precipitation, as described in Equations 1, 2, 3. In the decadal specification, SPI, drought and excess precipitation are computed setting $m=1$ up to 120, in Equations 1, 2, 3.

Following Beine and Parsons (2017), we allow heterogeneous response of the climatic variables with respect to a geographical characteristic of the country pair. In particular, we interact the climatic variables of origin i with the log distance between countries i and j (D_{ij}). In a robustness check, we replace the log distance interaction with an interaction with a dummy for common border. The X_{ij} are country-pair time-invariant geographical controls, which include log(distance), shared border, common colonial history, common language tree, or common water resource. $\theta_{r(i)t}$ are origin region-by-year (region-by-decade) fixed effects

which absorb regional, time-varying factors of the sending countries, δ_i are origin fixed effects and η_j destination fixed effects.

The sample of the main yearly regression includes 160 origin countries and 38 (primarily OECD) destination countries. The GBMD decadal data includes 160 origins and 155 destinations, but has many fewer time periods.

We do not expand Equation (5) by explicitly controlling for confounding factors such as GDP or institutional quality, as this approach would introduce an over-controlling bias in the coefficients of the climatic variables. This bias occurs when the equation controls for variables that are themselves affected by climate (Dell et al., 2012). Standard errors are clustered by origin-destination country pairs. We estimate Equation (5) using a Poisson pseudo maximum likelihood (PPML) estimator (Silva and Tenreyro, 2006) to account for a large number of zero observations.⁸

Once we estimate the gravity equation, we generate predicted values for the bilateral flows of migrants, \widehat{M}_{ijt} , for each directed pair of countries ij and year (decade) t . We use these climate-generated flows as an instrumental variable for the flows of migrants from country i to country j in a two-stage least squares (2SLS) estimation for interstate disputes between countries i and j .

The validity of this instrumental approach is satisfied only if the climate in i has no effect on the probability of conflict between i and j , except through its influence on migration from i to j . This is unlikely to hold in our setting, as the climate in i could also affect a number of aspects of country i 's economy and society. While the climate shocks are reasonably exogenous, they will also affect many aspects of society and will not only affect migration patterns, but incomes and other amenities that may affect the propensity of country i to enter an international dispute.

One way to overcome this concern is to identify the country that initiates the conflict (Chassang and Padró i Miquel, 2009). According to the COW classification, the "initiator" is the state which takes the first militarized action against the "target" country. This country should not be directly affected by the climate shock occurring in the target country, which

⁸The gravity equation estimated by PPML takes the form of: $M_{ijt} = \exp[\alpha C_{it} + \beta C_{it} \times D_{ij} + \gamma X_{ij} + \theta_{r(i)t} + \delta_i + \eta_j] + \epsilon_{ijt}$

drives the outflows originated in the target country. Because of this distinction, we are able to utilize directed pairs as our unit of observation. Our dependent variable in the main conflict equation will be whether one country attacks another. Other studies typically use an “undirected” pair as the observation, as they do not assign a direction to the conflict. These studies must combine all migration flows involving the ij pair in some way, often averaging over the flows in both directions (e.g. (Docquier et al., 2018)). Because we distinguish between country i attacking j from j attacking i , we can estimate separately the probability of each of these events happening and specifically identify the role of inflows in the pair. This is implemented by estimating the following regression:

$$MID_{jit} = \beta \hat{m}_{ijt} + \alpha C_{jt} + \gamma X_{ij} + \eta_i + \psi_j + \theta_{r(j)t} + \epsilon_{ijt} \quad (6)$$

Where MID_{jit} captures a conflict initiated by country j against country i in year t and takes the value of 1 or 0 and m_{ijt} denotes the migration flows from country i to country j .⁹

Thanks to this approach, it is plausible that the climatic shock in the sending country i will affect the destination country j , and hence the probability of j initiating a conflict, only through changes in migration level. To further limit potential violation of the exclusion restriction, Equation (6) includes climatic variables - temperature, drought and excess precipitation - of country j (initiator) as controls (C_{jt}).¹⁰ Given that we have in mind an income effect mechanism, whereby warming lowers productivity and income, which in turn reduces the opportunity cost of participating in violence, we allow for non-linearities in the effect of temperature on conflict. The inclusion of climatic controls is important for identification, because climate is correlated across space, and conflicts often occur between neighboring countries. It is possible that the sending and receiving countries experience correlated climate shocks. In Section 3.5, we will conduct some robustness checks, excluding neighbouring countries.

⁹Within the decade, there might be multiple incidents of conflict between a pair of countries, where the same country can be the primary initiator in one year and the primary target in another. We do not allow for both countries in the pair to be the aggressor within a given decade. Therefore, for this decade-pair, we take the first country to initiate a conflict during the decade as the “original” aggressor, consistent with the coding of ongoing conflicts in the COW data.

¹⁰We do not control for socio-economic drivers of conflicts, as this approach would introduce an over-controlling bias in the coefficients of the climatic variables.

By applying this approach, we are also able to test two possible mechanisms from climate to interstate dispute, namely the direct triggering effect and the indirect effect through international migration. It can also be possible that a climatic shock increases the risk of civil conflict in that country, and the civil conflict translates in international disputes, as in Gleditsch et al. (2008) and Most and Starr (2015). This specification is suitable for controlling for this mechanism as well.

The time series variation of the climatic variables allows for the inclusion of country-specific fixed effects (η_i, ψ_j). These fixed effects should capture possible determinants of a country's proneness to be involved in a conflict, as a target or initiator of the conflict. Among other factors, are geography-related characteristics, such as colonisation history, disease environment, geographical accessibility, as well as the country's institutions. The inclusion of these variables addresses the criticism raised by Rodriguez and Rodrik (2001) and Rodrik et al. (2004) to the “gravity” approach used here and first applied by Frankel and Romer (1999).¹¹ Equation (6) also controls for bilateral time invariant characteristics (X_{ij}), such as (log of) distance, whether the pair shares a border, whether they share a common colonial history, and whether they share a common water body. We also include the degree of language closeness, given that cultural similarity between pairs is found to increase interstate disputes (Spolaore and Wacziarg, 2016). $\theta_{r(j)t}$ are region-by-year (region-by-decade) fixed effects of the attacking country, which capture regional trends in conflict involvement. After controlling for time and country fixed effects in the second stage, identification is based on changes over time of the flows of climate-migrants.

In order to construct \widehat{m}_{ijt} , we take the predicted values from the gravity equation, \widehat{M}_{ijt} and set $\widehat{m}_{ijt} = \log(\widehat{M}_{ijt} + 1)$ so that β can be interpreted as the change in probability that j initiates a conflict against i for a 1 percent change in the number of migrants from i to j .

To summarize, Equation (6) takes into account two possible mechanisms, whereby climate change affects interstate disputes. The first through climate-induced migration (Reuveny, 2007), and the second through resource scarcity triggered by climatic shocks (Devlin and Hendrix, 2014; Gleditsch et al., 2006; Gartzke, 2012).

We estimate Equation (6) using a linear probability model in an instrumental variables

¹¹A similar approach is used in Feyrer (2009b,a); Pascali (2017).

regression, for both yearly and decadal specifications. The use of this model with instrumental variables is typically preferred to a non-linear instrumental variable procedure, even in the case of a dichotomous dependent variable in the second stage, such as our measure of interstate disputes. Standard errors are clustered at the country-pair level.¹²

3.2 Climate-Migration Results

The results of the gravity regression, described by Equation (5), for the yearly sample are shown in Table 2. Recall that this high frequency data covers only a limited number of destinations, primarily OECD countries. We estimate a increasingly saturated specifications, with our preferred specification in Column (5). Column (1) introduces only temperature and precipitation. Results indicate that warming and lower precipitation increase emigration towards OECD destinations, but the effect of precipitation is not statistically significant. The magnitude implies that a 1°C increase in temperature increases migration by 6%. Column (2) adds an interaction between the climatic variables and the log distance, to allow a heterogeneous response as in Beine and Parsons (2017). The point estimates indicate that warming increases out-migration, but the impact decreases for increasing distance between origin and (OECD) destination.¹³ This result is consistent with the existing literature that finds that climatic shocks foster emigration mainly to contiguous countries and nearby destinations (Cattaneo and Peri, 2016; Beine and Parsons, 2017).

In Column (3) we replace the precipitation variable, which does not exert a statistically significant effect, with the SPI6 variable. The coefficients of SPI and the interaction are statistically significant. This specification however does not take into account possible varying effects of SPI along its distribution. Substantial deviations from long term precipitation means could have a different effect on migration compared to normal precipitation levels. At the same time, responses to positive and negative deviations may be of opposite signs. In column (4) we add two indicator variables that explicitly measure drought and excess

¹²We do not apply any correction to the standard errors, which is normally employed in the case of a generated variable. The correction is only necessary for generated regressors, while for generated instruments, the 2SLS standard errors and test statistics are asymptotically valid (Wooldridge, 2010).

¹³A test on the joint significance of the coefficients of temperature and of the interaction with distance rejects the hypothesis that the coefficients are jointly equal to zero and thus supports the evidence of an heterogeneous effect of warming (p-value=0.04).

Dependent variable: Migrants	(1)	(2)	(3)	(4)	(5)
Temperature	0.06 (0.03)*	0.19 (0.09)**	0.16 (0.08)**	0.16 (0.08)*	0.16 (0.08)**
Precipitation	-0.69 (0.84)	-7.26 (9.37)			
Temperature x Distance		-0.02 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Precipitation x Distance		0.77 (1.08)			
SPI x Distance			0.07 (0.02)***		0.07 (0.04)**
SPI			-0.59 (0.18)***		-0.50 (0.30)*
Drought (0/1) x Distance				-0.26 (0.15)*	
Drought (0/1)				2.29 (1.20)*	
Excess (0/1) x Distance				0.12 (0.11)	
Excess (0/1)				-0.93 (0.84)	
Drought SPI x Distance					0.02 (0.21)
Drought SPI					-0.84 (1.76)
Excess SPI x Distance					0.06 (0.22)
Excess SPI					-0.71 (1.74)
R2	0.79	0.79	0.79	0.79	0.79
N	77,041	77,041	77,041	77,041	77,041

Notes: The dependent variable is the number of migrants from country i to country j in year t . All specifications include country-pair time invariant controls, origin region-by-year fixed effects, origin fixed effects and destination fixed effects. Method of estimation PPML. Reference periods for the analysis: 1980-2010. Standard errors clustered by origin-destination country pairs; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

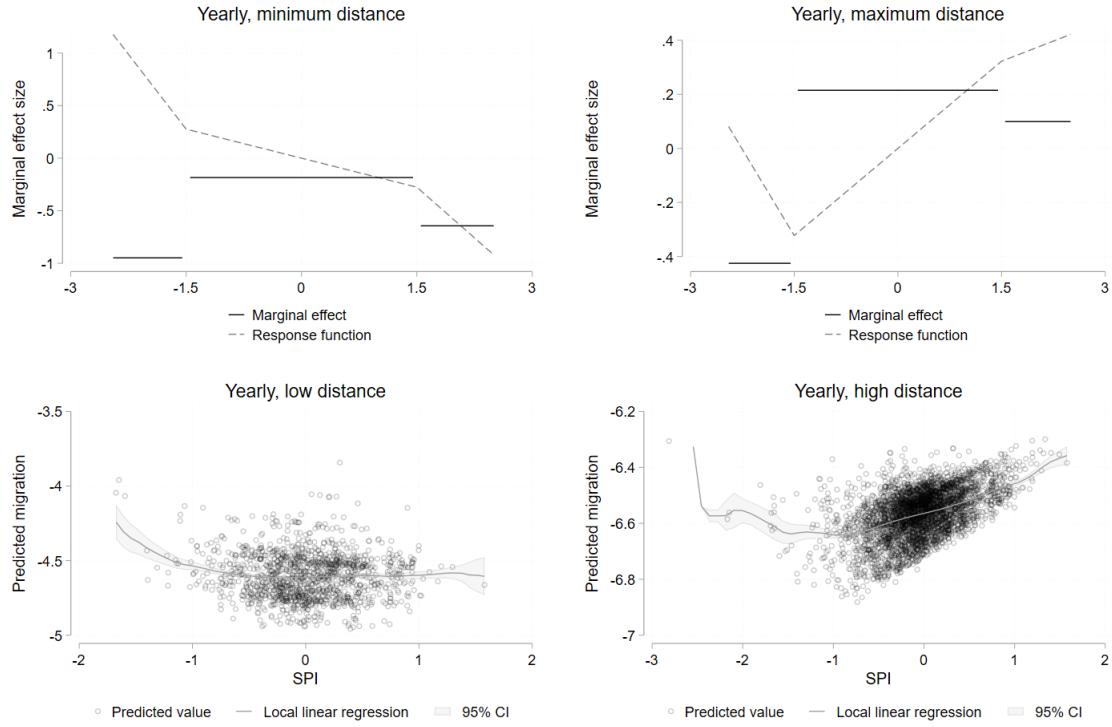
Table 2: Auxiliary regression results of the effect of climate variables on migration. Yearly data

precipitation. One variable takes the value of 1 if the SPI6 is below -1.5, and zero otherwise, and the other that takes the value of 1 if the SPI6 is above 1.5, and zero otherwise. This is however a poor representation of scarcity and excess precipitation. It only models the effect of

being in a situation of scarcity/excess precipitation, and does not take into account that larger deviations from the long term levels might be more detrimental than smaller deviations. Column (5) reports our preferred specification. Rather than using indicator variables that only allow two regimes (0 and 1), we jointly add the variable SPI6, the drought SPI and excess SPI, as described in Section 2, in Equation (4). By adding the three variables jointly, we can model a piecewise linear function of SPI6 on migration. We are able to differentiate between the three regimes (droughts, normal precipitation, excess precipitation) while taking into account the severity of droughts and floods. Responses to drought/floods may intensify if one experiences moderately dry/wet, very dry/wet or extremely dry/wet conditions.

The coefficient of temperature still indicates that warming increases emigration. To ease the interpretation of the parameter estimates of SPI, drought SPI, excess SPI in column (5), Figure 2 shows how migration response varies along the SPI distribution and the distance between origin and destination.¹⁴ The two top panels show the pixel-level response. It plots the marginal effects of SPI for different levels of SPI (solid lines), as well as the shape of the response function (dashed line). The left panel shows the response at the minimum distance in the sample, and the right panel at the maximum distance. Any distance in between will be between these two responses. Points to the left of -1.5 on the x-axis represent situations of drought, points between -1.5 and +1.5 indicate precipitation levels close to the long term mean, and points to the right of +1.5 are indicative of excess precipitation. At small distances (top, left panel), the migration response to SPI within the -1.5 and +1.5 range is flat (dashed line). The corresponding marginal effect (solid line) is close to zero. Consider that within this range of SPI, precipitation is close to the long term mean, and does not constitute an adverse climatic condition. Households likely do not need to adapt through migration. Conversely, the response function to the left of -1.5 is much steeper. In particular, migration to close destinations increases with higher levels of drought, as indicated by the positively sloped dashed line. The negative marginal effect in this regime indicates that increasing deficit of rain boosts emigration. The response function to the right of +1.5 indicates that as a consequence of excess precipitation, migration directed to close destinations slightly shrinks,

¹⁴The coefficients of SPI, drought SPI, excess SPI and their interactions with distance are jointly different from zero. The p-value of the test on the joint significance of the variables is 0.007.



Notes: The Figures use the estimated coefficients from Column (5) in Table 2. The top panels plot (dashed lines) the predicted migration response to changes in SPI, relative to SPI=0 and $\log(\text{distance})=0$, at two different points, one at the minimum $\log(\text{distance})$ in the sample (left panel) and one at the maximum (right panel). Solid lines represent the corresponding marginal effects. The bottom panels show the predicted values from the observed SPI for pairs below the 10th percentile of the distance distribution (left) and above the the 90th percentile (right), along with 95% confidence interval.

Figure 2: Migration response to drought and excess precipitation.

as the marginal effect is indeed negative.

The top right panel shows migration response at the maximum distance within the sample. The dashed response function indicates that migration to far away (OECD) destinations increases with higher levels of drought as well as with higher level of floods. However, the marginal effect for excess precipitation is close to zero.

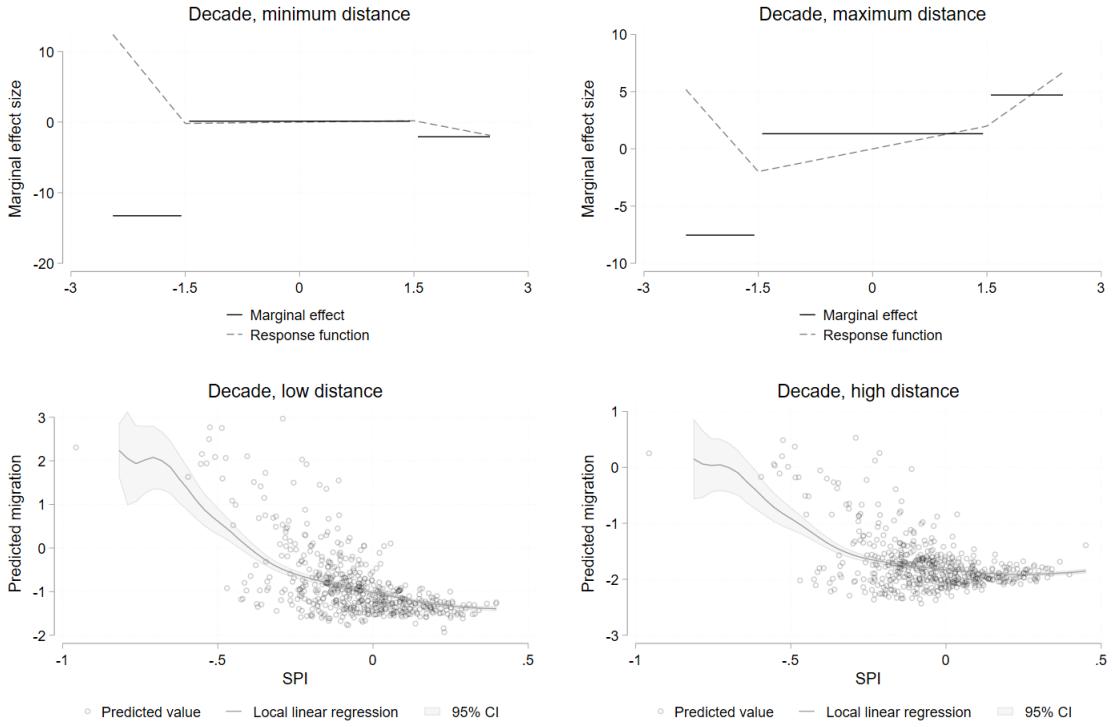
Since these are pixel-level responses, the country-level response will not fall simply along the pixel-level response function represented by the dashed line, but will average over these responses to give a more smoothed response. The predicted migration responses at the country level are plotted in the bottom panels in Figure 2. Since many countries actually experience a wide range of SPI values in a given year, the predicted values become more spread than if they were a single pixel. Here, we take pairs in the bottom 10% and top

10% of the distance distribution for the left and right panels, respectively. The country level representations are consistent with the pixel ones, but demonstrate that a given country will have pixels in different parts of the response during the same time period.

Dependent variable: Migrants	(1)	(2)	(3)	(4)	(5)
Temperature	-0.08 (0.29)	0.31 (0.30)	0.32 (0.29)	0.12 (0.29)	0.20 (0.27)
Precipitation	-23.33 (20.09)	-7.33 (19.85)			
Temperature x Distance		-0.05 (0.01)***	-0.05 (0.01)***	-0.05 (0.01)***	-0.05 (0.01)***
Precipitation x Distance		-2.02 (0.99)**			
SPI x Distance			0.31 (0.21)		0.00 (0.30)
SPI			-2.78 (1.90)		1.02 (2.60)
Drought (0/1) x Distance				-2.29 (1.12)**	
Drought (0/1)				24.17 (12.01)**	
Excess (0/1) x Distance				0.89 (1.18)	
Excess (0/1)				-6.60 (10.06)	
Drought SPI x Distance					1.30 (1.45)
Drought SPI					-22.46 (16.63)
Excess SPI x Distance					2.16 (2.99)
Excess SPI					-20.39 (25.98)
R2	0.74	0.75	0.74	0.75	0.75
N	48,490	48,490	48,490	48,490	48,490

Notes: The dependent variable is the number of migrants from country i to country j in decade d . All specifications include country-pair time invariant controls, origin region-by-decade fixed effects, origin fixed effects and destination fixed effects. Method of estimation PPML. Reference periods for the analysis: 1960-2000. Standard errors clustered by origin-destination country pairs; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Auxiliary regression results of the effect of climate variables on migration. GBMD decadal data



Notes: The Figures use the estimated coefficients from Column (5) in Table 3. The top panels plot (dashed lines) the predicted migration response to changes in SPI, relative to SPI=0 and $\log(\text{distance})=0$, at two different points, one at the minimum $\log(\text{distance})$ in the sample (left panel) and one at the maximum (right panel). Solid lines represent the corresponding marginal effects. The bottom panels show the predicted values from the observed SPI for pairs below the 10th percentile of the distance distribution (left) and above the 90th percentile (right), along with 95% confidence interval.

Figure 3: Migration response to drought and excess precipitation. GBMD decadal data

We also run specifications where we use the interaction with an indicator for sharing a common border rather than distance. The results do not significantly differ and are shown in Table S.I.1. Consistently with results from Table 2, warming increases out-migration, in particular towards near-by countries, bordering countries.

We also run the same specifications using decadal migration data. The data have the advantage to cover all possible destinations, at the cost of lower temporal frequency.

Results are shown in Table 3 and are qualitatively similar to the yearly specification. Warming increases emigration to closer destinations and decreases emigration towards distant destinations. The migration responses along the SPI distribution are illustrated in Figure 3. Consistently with the yearly sample, drought increases out-migration across distances, while we find small effects of SPI near average or at excess levels.

If we replace the distance interaction with an interaction using an indicator for common border, results are again similar (Table S.I.2).

3.3 Main Results

The main objective of the paper is to test the effect of international migration on interstate disputes. The paper also aims to analyse whether climate stress represents a direct driver of interstate disputes, as described in Equation (6). The results using the yearly sample are shown in Table 4. Column (1) presents the OLS estimates of interstate dispute, while Columns (2) to (6) present the 2SLS estimates, which uses the predicted values from the different auxiliary regressions in Table 2, as instruments for migration.¹⁵ Figure S.I.1, left panel reports the predicted bilateral migrants for specifications (5), which is our preferred one, plotted against actual number of migrants. The figure indicates a strong predictive power.

The estimated parameters indicate a positive and statistically significant effect of migration flows on interstate disputes. The effect size estimated by the IV strategy is overall larger than the OLS estimate. The downward bias in the OLS estimate, detected in the majority of the specifications, is likely due to reverse causality between conflicts and migration, with the onset of conflict itself leading to a decrease in actual migration between the pair of countries in conflict.

The 2SLS estimates are fairly stable from specifications (3) to (6). The estimate from the column (6) implies that a one percent increase in the inflows of migrants leads to 0.001 percentage point increase in the probability that the destination country initiates a conflict against the origin country of the flows. This is our preferred specification, where the number of migrants is predicted by temperature and a distance interaction, as well as a flexible SPI measure, also interacted with distance. The resulting 0.001 percentage point increase can be compared to the mean 0.13 percentage point initiation probability, implying an increase in the chance of conflict of 0.9% over the observed mean. Results are comparable in magnitude with those in Docquier et al. (2018).

¹⁵The Kleiberg-Paap F-statistic for weak identification in the 2SLS exceeds 10, which is the standard threshold for a powerful instrument.

Dependent variable: Pr(Conflict) (%)	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Log(migrants+1)	0.046 (0.018)**	0.047 (0.066)	0.140 (0.078)*	0.125 (0.068)*	0.123 (0.067)*	0.114 (0.068)*
Temperature	-0.121 (0.069)*	-0.121 (0.069)*	-0.129 (0.069)*	-0.128 (0.069)*	-0.128 (0.069)*	-0.127 (0.069)*
Temperature ²	0.003 (0.003)	0.003 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)
SPI	0.012 (0.048)	0.012 (0.048)	0.012 (0.048)	0.012 (0.048)	0.012 (0.048)	0.012 (0.048)
Drought SPI	0.354 (0.343)	0.354 (0.342)	0.361 (0.341)	0.360 (0.341)	0.359 (0.341)	0.359 (0.341)
Excess SPI	0.836 (0.441)*	0.837 (0.442)*	0.855 (0.443)*	0.852 (0.442)*	0.851 (0.442)*	0.849 (0.442)*
N	77,041	77,041	77,041	77,041	77,041	77,041
Dependent variable mean	0.134	0.134	0.134	0.134	0.134	0.134
First stage F-stat	.	412	367	428	428	426

Notes: The dependent variable is equal to one if country j initiated a conflict against i and 0 otherwise. All specifications include country-pair time invariant controls, destination region-by-year fixed effects, origin fixed effects and destination fixed effects. Reference periods for the analysis: 1980-2010. Standard errors clustered at the country-pair level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Second stage results with destination aggressor, different specifications of climate effects on migration. Yearly data

The conflict estimates using the decadal data are shown in Table 5. In agreement with yearly sample, they are positive and statistically significant.¹⁶ They show that a one percent increase in migrants increases the probability of conflict by 0.012 percentage points, with the average decadal probability of one country attacking another at 0.65 percentage point per decade. This is an increase of 1.8% over the mean.

These results may indicate that non-economic, visceral factors, such as the "perceived" threats connected to the inflows of migrants, can give rise to inter-group violence. The receiving countries of the flows have low incentives to avoid escalation toward conflicts against the sending countries of the flows.

The second objective of the paper is to estimate a possible direct triggering effect of climatic shocks on the risk of conflict. To meet this objective, we include climate variables for country j (the destination country) in the regression. The coefficients of temperature

¹⁶The plot of the predicted bilateral migrants against actual number of migrants is displayed in the right panel of Figure S.I.1.

Dependent variable: Pr(Conflict) (%)	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Log(migrants+1)	0.009 (0.027)	0.624 (0.282)**	1.141 (0.222)***	1.063 (0.208)***	1.035 (0.210)***	1.158 (0.216)***
Temperature	0.406 (0.317)	-0.504 (0.542)	-1.270 (0.467)***	-1.154 (0.450)**	-1.113 (0.452)**	-1.295 (0.465)***
Temperature ²	-0.028 (0.009)***	-0.008 (0.013)	0.008 (0.012)	0.006 (0.011)	0.005 (0.011)	0.009 (0.012)
SPI	-0.447 (0.415)	-0.375 (0.418)	-0.314 (0.435)	-0.323 (0.433)	-0.327 (0.432)	-0.312 (0.436)
Drought SPI	-0.391 (2.268)	-1.147 (2.289)	-1.784 (2.399)	-1.688 (2.381)	-1.654 (2.375)	-1.805 (2.411)
Excess SPI	5.644 (2.950)*	6.108 (3.007)**	6.499 (3.107)**	6.440 (3.086)**	6.419 (3.079)**	6.512 (3.108)**
N	48,490	48,490	48,490	48,490	48,490	48,490
Dependent variable mean	0.654	0.654	0.654	0.654	0.654	0.654
First stage F-stat	.	176	341	380	380	359

Notes: The dependent variable is equal to one if country j initiated a conflict against i and 0 otherwise. All specifications include country-pair time invariant controls, origin region-by-decade fixed effects, origin fixed effects and destination fixed effects. Reference periods for the analysis: 1960-2000. Standard errors clustered at the country-pair level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Second stage results with destination aggressor, different specifications of climate effects on migration. Decadal data

and its square in Tables 4 and 5, confirm the income-effect hypothesis. The probability of initiating a conflict decreases for optimal temperature level and increases when temperature gets too hot. In the yearly sample, specification (6), the turning point occurs for temperature at 15.5 °C, which corresponds to minimum risk of conflict.

As for the effect of SPI, drought SPI, excess SPI on conflicts, to ease interpretation, we plot the yearly (top panels) and decadal (bottom panels) results in Figure 4. The graphs again show the marginal effects for the different regimes as solid lines and the corresponding response function as a dashed line. The pixel level (left panel) and country level (right panel) representations display consistent response functions. Changes in precipitation near average values do not strongly influence the probability that a country initiates a conflict against another, as indicated by the flat line between -1.5 and +1.5 in both samples and the corresponding marginal effect close to zero. Conversely, excess precipitation is found to influence engagement in conflicts. In particular, both in the yearly data and the decadal data, the probability of initiating a conflict increases with excess precipitation. The drought response is of different sign across the two samples. Rain deficit decreases conflict in the

Revisionist Aggressor	0	1	Frequency
0	216,599	250	
1	408	484	0.54
Frequency		0.66	

Table 6: Number of country pairs for which a given country is the aggressor and for which it is revisionist.

yearly sample, albeit the marginal effect is close to zero, while it increases the probability of initiating a conflict in the decadal sample. The result in the decadal sample is in agreement with Gleditsch et al. (2006); Devlin and Hendrix (2014), which report increased risks of international conflicts connected to low precipitation means.

In the previous specifications, the dependent variable takes the value of 1 if a conflict is initiated by country j , with country j being coded as the aggressor or primary initiator in the COW dataset (and 0 otherwise). The COW data provides an additional classification of the parties in the dispute and identifies "revisionist" as those countries that seek some policy change, usually a change in the border. Since there may be escalating tensions between two countries in a border or other interstate disputes, the country that takes a military action, and is therefore coded as the aggressor, may not be the same as the country seeking a change in policy. Table 6 provides the probability of being revisionist and initiator of a conflict. Given 734 country-pairs in which country j is coded as revisionist, in 484 cases it is also responsible for the first attack. Given 892 country-pairs in which country j is coded as initiator, in about half of these events country j is coded as revisionist and seek some policy change. So, while the initiator and revisionist measures are certainly correlated, as expected, they are not capturing all the same countries as initiators.

Tables 7 and 8, columns (3) and (4) show the OLS and 2SLS estimates of a specification where the dependent variable takes the value of 1 if country j is coded as the revisionist in an international dispute between country j and i (and 0 otherwise), for the yearly and decadal samples. In columns (1) and (2) we present the corresponding estimates from Tables 4 and 5.

The point estimates in both the yearly and decadal samples are positive and statistically significant. In the yearly sample, the estimates are slightly larger than the results where

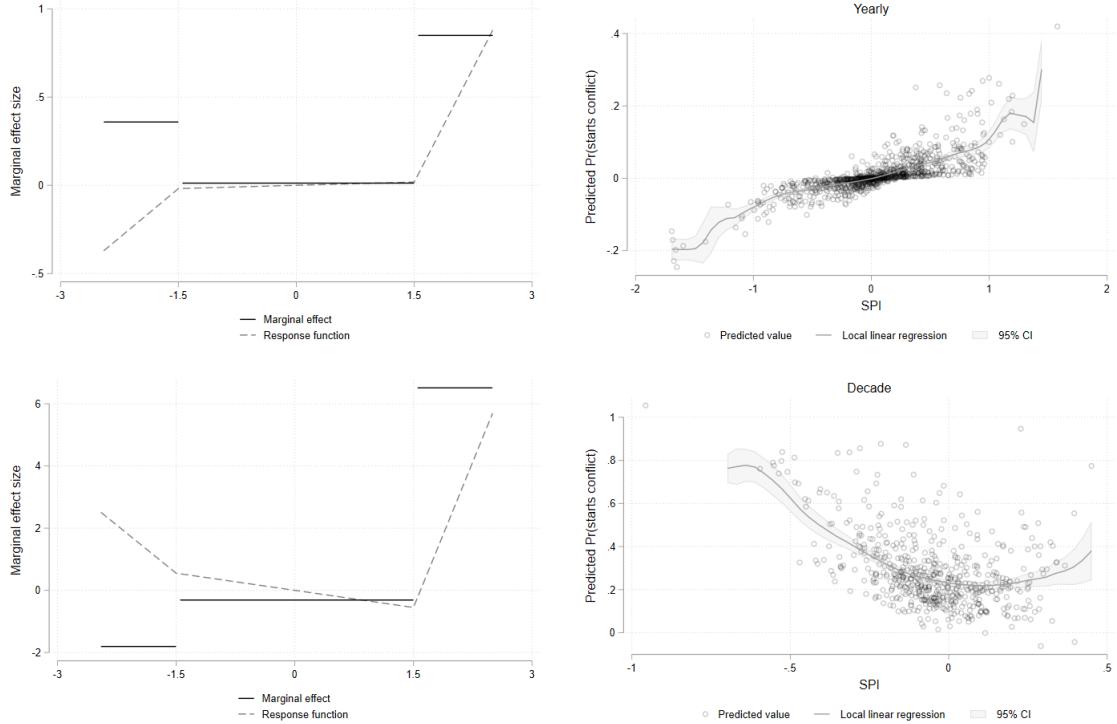
Dependent variable: Pr(Conflict) (%)	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Log(migrants+1)	0.046 (0.018)**	0.114 (0.068)*	0.052 (0.016)***	0.169 (0.077)**	0.063 (0.026)**	0.327 (0.106)***
Temperature	-0.121 (0.069)*	-0.127 (0.069)*	-0.069 (0.051)	-0.079 (0.051)	-0.131 (0.113)	-0.155 (0.113)
Temperature ²	0.003 (0.003)	0.004 (0.003)	0.001 (0.003)	0.002 (0.003)	0.002 (0.005)	0.004 (0.005)
SPI	0.012 (0.048)	0.012 (0.048)	-0.067 (0.054)	-0.066 (0.054)	-0.092 (0.069)	-0.090 (0.069)
Drought SPI	0.354 (0.343)	0.359 (0.341)	0.396 (0.331)	0.404 (0.331)	0.908 (0.529)*	0.928 (0.529)*
Excess SPI	0.836 (0.441)*	0.849 (0.442)*	0.907 (0.424)**	0.930 (0.425)**	1.298 (0.504)**	1.349 (0.508)***
N	77,041	77,041	77,041	77,041	77,041	77,041
Dependent variable mean	0.134	0.134	0.129	0.129	0.227	0.227
First stage F-stat	.	426	.	426	.	426

Notes: The dependent variable is equal to one if country j initiated a conflict against i , for different definition of initiator: (1) and (2) if destination j is the aggressor; (3) and (4) if destination j is revisionist; (5) and (6) any type of interstate conflict; it is equal to 0 otherwise. All specifications include country-pair time invariant controls, origin region-by-year fixed effects, origin fixed effects and destination fixed effects. Reference periods for the analysis: 1980-2010. Standard errors clustered at the country-pair level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Second stage results for different consideration of initiator. Yearly data

we define the aggressor to be the first country to take military action. When the revisionist country is considered the aggressor, in the yearly sample, a 1% increase in migration increases the conflict probability by 0.002 percentage points over a mean of 0.129 percentage points, an increase of 1.3% over the mean. In the decadal sample, a 1% increase in migration increases the conflict probability by 0.012 percentage points, which also corresponds to an increase of 1.3% over the decadal mean.

The identification of parties as initiator and revisionist implies some subjective judgments, which may result in codification errors, as described in Caselli et al. (2015); Conconi et al. (2014). For this reason we employ a specification where the dependent variable is equal to one if an interstate dispute occurs between countries i and j (and zero otherwise), regardless of which side is the initiator. Estimates are in columns (5) and (6) of Tables 7 and 8. The results show a larger-sized effects of climate-induced migration on the probability of being part of an interstate dispute, though a similar increase over the mean occurrence. However, we should interpret the results of these specifications with caution, given that the exclusion restriction is not satisfied in this case.



Notes: The top panels use the estimated coefficients from Column (6) in Table 4. The bottom panels use the estimated coefficients from Column (6) in Table 5. The left panels plot (dashed lines) the predicted conflict response to changes in SPI, relative to SPI=0. Solid lines represent the corresponding marginal effects. The right panels show the predicted values from the observed SPI for country pairs, along with 95% confidence interval.

Figure 4: Conflict response to drought and excess precipitation in the aggressor country.

Dependent variable: Pr(Conflict) (%)	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Log(migrants+1)	0.009 (0.027)	1.158 (0.216)***	0.046 (0.037)	1.175 (0.268)***	0.056 (0.046)	1.493 (0.392)***
Temperature	0.406 (0.317)	-1.295 (0.465)***	-0.244 (0.353)	-1.914 (0.556)***	-0.724 (0.485)	-2.852 (0.796)***
Temperature ²	-0.028 (0.009)***	0.009 (0.012)	-0.018 (0.010)*	0.017 (0.013)	-0.023 (0.014)	0.023 (0.019)
SPI	-0.447 (0.415)	-0.312 (0.436)	0.149 (0.474)	0.282 (0.490)	-0.251 (0.574)	-0.082 (0.604)
Drought SPI	-0.391 (2.268)	-1.805 (2.411)	-1.756 (2.816)	-3.144 (2.957)	-4.864 (3.554)	-6.633 (3.801)*
Excess SPI	5.644 (2.950)*	6.512 (3.108)**	-1.326 (3.176)	-0.474 (3.317)	6.448 (4.291)	7.533 (4.444)*
N	48,490	48,490	48,490	48,490	48,490	48,490
Dependent variable mean	0.654	0.654	0.891	0.891	1.604	1.604
First stage F-stat	.	359	.	359	.	359

Notes: The dependent variable is equal to one if country j initiated a conflict against i , for different definition of initiator: (1) and (2) if destination j is the aggressor; (3) and (4) if destination j is revisionist; (5) and (6) any type of interstate conflict; it is equal to 0 otherwise. All specifications include country-pair time invariant controls, destination region-by-decade fixed effects, origin fixed effects and destination fixed effects. Reference periods for the analysis: 1960-2000. Standard errors clustered at the country-pair level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Second stage results for different consideration of initiator. Decadal data

The decadal estimates provide the risk that a conflict occurs in any of the ten years of the decade as a consequence of migration. Taking into account the different length of the time horizon, the decadal estimate from the main specification, is a somewhat lower increase over the mean (1.8%) compared to the yearly increase (0.9%). In addition, if we assume that each year there is a probability of 0.13 percentage point that a conflict is initiated and that the occurrence of conflict is independent across years, this would correspond to a conflict probability of 0.99 percentage points, somewhat higher than the decadal conflict measure in the data, which is 0.65 percentage point. This difference gives some indication that the use of low frequency decadal data might not capture the whole dynamic in place, with years of upticks in migration and eventual reverse later which washes out using averages over the decade. The consequence of using the decadal data is likely to lead to an underestimation of the risks of interstate conflicts in general, and of the impact of climate-induced migration on disputes in particular.¹⁷

However, we should note that the two samples used for the analyses differ in the

¹⁷Correlation across years within a pair could be in part responsible for this difference.

time coverage, but also in the set of country pairs included. While the GBMD data includes essentially all country pairs, the OECD data primarily includes OECD countries as destinations, while most countries are included as origins. It is therefore interesting to explore how much these discrepancies contribute to the slightly different results. To try to isolate the effect of the time period and geographical coverage, we run the auxiliary regression and the corresponding conflict regression with the GBMD data restricted to the sample which is included in the OECD data. Table S.I.4 provides the second stage conflict estimates. First, one should notice that the mean decadal risk of conflict in this reduced sample, which restricts such that one of the two parties of the dispute is an OECD country (0.41), is lower than the conflict measure in the full sample (0.65 percentage point). This probability is much lower than the theoretical conflict probability, computed from the yearly figure, which is 0.99 percentage points. Given the geographically comparable samples, this confirms the previous evidence that the low frequency decadal data could underestimate the dynamic in place.

As for the impact of climate-induced migration in this restricted sample, we find that the coefficient remains positive, with an effect size highly comparable to the result with the full sample of decadal data. However, the estimate represents an increase of 2.8% over the mean, which is larger than 1.8%, detected using the full decadal sample. These findings indicate that, even if OECD countries are less likely to be involved in inter-conflict disputes, they tend to react more strongly to the inflows of migrants, compared to non-OECD countries.

3.4 Interpretation

Given the direct connection of climate to conflict and the indirect link through migration, it is relevant to explore how changes in climate translate to changes in conflict through these two specific channels. One way to assess this is to consider some counterfactual climate scenarios. In particular, we can consider what would happen to conflict in a world without precipitation extremes, and compare this to the probability of conflicts, given the actual precipitation existing in the world. We do this by setting the variables of SPI, Drought SPI, and Excess SPI to 0, corresponding to setting the precipitation value for each country to its long-run average value. We manipulate the amount of precipitation in origin country i only, and in both origin country i and destination country j . Given the influence of precipitation

extremes on migration, the first manipulation takes into account the indirect effect of climate on interstate conflicts through migration, while the second manipulation takes into account the additional direct effect.

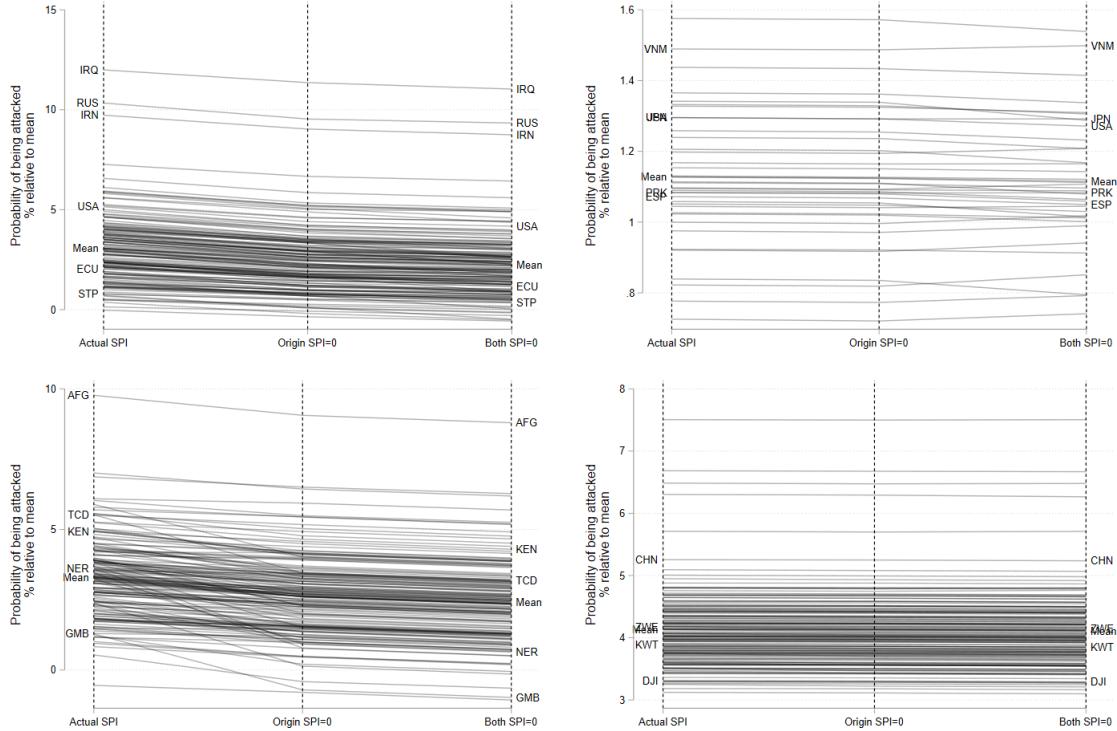
Figure 5, top panels, shows how the average conflict initiation probability for each country j changes, when going from the experienced precipitation (left axis), to a counterfactual with no precipitation extremes at origin i but experienced precipitation at destination j (middle axis), to a world with no extremes in either origin i or destination j (right axis). These comparisons are computed using both the decadal (left panel) and the yearly data (right panel).

We find that removing origin country extremes in precipitation leads to lower initiation probability (averaged across all potential targets) for each country. This result is driven by lower levels of immigration. The effect of additionally removing destination extremes are not as straightforward, with different results in the decadal and yearly samples. In the decadal sample, removing destination precipitation extremes further decreases the probability of initiating conflicts, while in the yearly sample, the effects are mixed depending on the country, and generally smaller than the indirect effects.

The bottom panel shows the effect by origin country i , namely the effect of removing precipitation extremes on the probability of being attacked. For countries with a large amount of precipitation extremes (such as Chad, Niger, and Gambia), there is a clear decrease in the probability that they are attacked when moving to a world with no precipitation extremes. The big drop in the risk of being attacked mainly results from lower climate-driven emigration.

3.5 Robustness

According to our conceptual framework, migration flows are correlated with higher risks of disputes because the inflows generate hostility among natives, and this translates into lower incentives to avoid escalation toward conflicts between the receiving and the origin country of the flows. One could question that non-economic, emotional factors can represent a convincing argument for engaging in international disputes. However, if our hypothesis is correct, we would expect a differential impact of migration on conflicts, depending on



Notes: The Figures show the average conflict probability for observed level of precipitation in both origin and destination countries of the flows (left axis), for no precipitation extremes at origin (middle axis), for no extremes in either origin or destination (right axis). Left panels use decadal and right panels use yearly data. The top panel shows destinations, averaged over origins, and the bottom panel shows origins, averaged over destinations. In the decadal data, the mean conflict probability decreases by 19% when setting the origin SPI=0 and by 27% when both are set to 0. In the yearly data, it decreases by 0.2% and 0.3%

Figure 5: Counterfactual conflict probabilities

some characteristics of the migration flows. For example, natives display larger preferences for high-skilled migrants compared to low-skilled ones (Hainmueller and Hopkins, 2014). Unfortunately, the migration data do not allow us to distinguish the flows by skill levels.

We could however exploit the evidence of a differential sorting of distinct types of migration across distance. Hatton and Williamson (2006) for example, document that Mexican migrants, who are mainly directed towards the neighbouring US are less skilled than African migrants, who get access to distant OECD countries. Given the high costs of distant international migration, low skilled migrants may sort themselves into low cost migration towards neighboring destinations or internal migration. To give support to our hypothesis, we drop neighboring dyads from the analysis. This strategy would likely select the most skilled flows, given the stylized evidence of sorting across distance. This strategy might reduce the number of possible interstate disputes, as many conflicts occur between neighbouring countries, over shared resources for example. It is also true however, that countries that share resources have higher incentives to invest in resource management measures, technological and social innovations to avoid conflict (Gartzke, 2012; Koubi et al., 2013). In Gleditsch et al. (2006), for example, rainfall scarcity increases interstate conflicts between dyads but only if the dyads do not share a river basin.

The results of this exercise are shown in Tables S.I.5 and S.I.6 for the yearly and decadal data, respectively. By excluding neighbouring pairs, the mean conflict probabilities shrunk to 0.11% and 0.37% in the yearly and decadal samples, respectively, which are suggestive of higher risks of conflicts over shared resources. The impact of climate-induced migration turned not statistically significant in the yearly sample, while it remains positive and highly statistically significant in the decadal sample.¹⁸ Interestingly, the point estimates halved both in the yearly and decadal samples, indicating that the impact of long-distance migration on conflicts slightly differ from the impact of close distance migration. This result provides a suggestive evidence that (high skilled) distant migration is perceived as less threatening in

¹⁸A threat to identification could arise if climatic conditions in country i are correlated with climatic conditions in country j . If i and j are neighbouring countries, country j may be experiencing the same climatic shock of country i . The inclusion of climatic shocks of country j should address a possible threat to identification posed by correlation in climate between close by countries. However, the positive a statistical significant coefficient of climate-induced migration when we exclude neighboring dyads represents an additional check on the validity of the empirical strategy.

destinations, compared to (low skilled) migration that connect nearby countries. In case of low-skilled immigration, receiving countries may display lower effort to mediate on existing unsolved disputes, compared to high-skilled migration.

Another way to support our hypothesis, is to check if lower risks of escalation towards conflicts occur when the flows are accompanied by lower perceived threat among natives. Public opinion on migration can shape and influence migration and foreign strategies. To test the validity of the non-economic mechanism, we interact the migration variable with a measure of public perception towards migration in receiving countries. We use a globally comparable acceptance index, created from the Gallup World Poll survey. The index varies from 9, for the highest migrant acceptance, to 1, for low acceptance. As indicated by the negative coefficients of the interaction variable in Columns (1) and (2) of Tables S.I.7 and S.I.8, the impact of immigration on the risk of conflict shrinks in the presence of more favourable attitudes towards migrants.

One could argue that migration and attitude are strongly correlated, thereby invalidating our identification. Populations in countries that attract larger flows might display larger hostility. To overcome this issue, we exploit some characteristics of the origin country of the flow, rather than the destination. Valentino et al. (2019) analyses cultural drivers of attitudes towards immigrants in eleven countries located in four continents. In particular, they explore whether migrant characteristics, such as their level of education, skin tone, or religion, drive natives' attitudes. They find that religious cues strongly influence attitude, and immigrants from Muslim-majority countries elicit significantly lower support than other immigrants. Given this evidence that an important dimension of the perceived threat is linked to religion, we complement the previous analysis by interacting the migration variable with a dummy equal to one for flows originated by Muslim-majority countries. Results are reported in Columns (3) and (4) of Tables S.I.7 and S.I.8. A piece of complementary evidence emerges: reactions to immigrants from Muslim-majority countries are greater than those from non-Muslim nations. Moreover, in the yearly specification, the impact of climate-induced migrants from non-Muslim nations shrinks substantially and is no longer statistically significant.

These final results highlight the benefits that welcoming receiving societies bring to international relations. Societies characterised by a more positive attitude towards migrants

display lower involvements in international disputes. Moreover, the evidence that the impact of international migration on conflict depends on the type of migration - low-skilled versus high-skilled, or migration of people of a certain religious affiliation- give some credit to our hypothesis that non-economic, emotional factors can represent drivers of international disputes.

4 Conclusion

This paper studies the effect on inter-country disputes of two underestimated drivers: international migration and climatic shocks. To meet the paper's objective and address endogeneity concerns for migration, we investigate both the direct role of climatic shocks and their indirect role through migration. The empirical analyses complement decadal with yearly data to capture both short-run and medium-run responses to climate threats and assess the comparability of analyses that use data of different temporal frequencies. Finally, we compute indicators of climatic variability based on the Standardized Precipitation Index (SPI) and allow varying impact parameters of the SPI along the SPI distribution.

We find that climatic shocks have both a direct and an indirect triggering effect on the risk of conflict. First, the probability of initiating a conflict decreases for optimal temperature level and increases when the temperature gets too hot. Excess and scarcity of precipitation increase the engagement in conflicts, although this result is not robust to the sample used. Second, climate, through its effect on international migration, contributes to increased probabilities of initiating a conflict. This empirical result is robust across different specifications, different datasets, different codifications of the parties' role in the disputes and checks for identification. These findings are consistent with a conceptual framework where both economic factors – triggered by climate change – and non-economic factors – triggered by international flows – influence the values of peace and violence.

Our findings finally suggest that low-frequency data may underestimate the dynamic of conflicts in place.

We do not claim that international migration should be constrained. Rather than preventing emigration flows, the root causes of climate-induced migration should be

addressed. Protecting vulnerable populations from the impact of climate change should be of paramount importance. It is crucial on the one hand to mitigate and reduce climate change and the connected shocks, and on the other, facilitate alternative ways to cope with climate change for the number of people at risk, which may not involve migration. Given that climate change is an important direct and indirect driver of country-level social tensions and conflicts, climate change mitigation would result in lower risks of international disputes.

In many destination countries, natives' opinion towards immigration is generally negative. The prevailing narrative presents migrants as a challenge to natives' jobs and security and as a threat to the values of the hosting societies. However, a supportive approach towards immigrants can secure many advantages, for both the immigrant population and the receiving societies. Given that public opinion on migration influences different types of policies, a more favourable attitude can ultimately facilitate an efficient management of the migration flows, improve the integration of migrants in societies and, according to the present study, reduce the risks of international disputes.

Finally, while climate-induced migrants may raise the probability of disputes in some cases, in many other circumstances an escalation of violence did not occur. Future research should take into account which conditions are more prone to give rise to interstate disputes.

References

Adsera, A. and M. Pytlikova (2015). The role of language in shaping international migration. *The Economic Journal* 125(09), 49–82.

Alesina, A., J. Harnoss, and H. Rapoport (2016). Birthplace diversity and economic prosperity. *Journal of Economic Growth* 21(2), 101–138.

Alesina, A., A. Miano, and S. Stantcheva (2018). Immigration and Redistribution. National Bureau of Economic Research 24733, National Bureau of Economic Research.

Aubry, A., M. Burzyński, and F. Docquier (2016). The welfare impact of global migration in OECD countries. *Journal of International Economics* 101(C), 1–21.

Auffhammer, M., S. M. Hsiang, W. Schlenker, and A. Sobel (2013). Using Weather Data and Climate Model Output in Economic Analyses of Climate Change. *Review of Environmental Economics and Policy* 7(2), 181–198.

Baliga, S., D. O. Lucca, and T. Sjöström (2011). Domestic Political Survival and International Conflict: Is Democracy Good for Peace? *The Review of Economic Studies* 78(2), 458–486.

Battisti, M., G. Felbermayr, G. Peri, and P. Poutvaara (2018). Immigration, Search and Redistribution: A Quantitative Assessment of Native Welfare. *Journal of the European Economic Association* 16(4), 1137–1188.

Baysan, C., M. Burke, F. González, S. Hsiang, and E. Miguel (2019). Non-economic factors in violence: Evidence from organized crime, suicides and climate in Mexico. *Journal of Economic Behavior & Organization* 168, 434–452.

Beine, M. and C. Parsons (2015). Climatic Factors as Determinants of International Migration. *The Scandinavian Journal of Economics* 117(2), 723–767.

Beine, M. and C. R. Parsons (2017). Climatic Factors as Determinants of International Migration: Redux. *CESifo Economic Studies* 63(4), 386–402.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Climate and Conflict. *Annual Review of Economics* 7, 577–617.

Burrows, K. and P. L. Kinney (2016). Exploring the Climate Change, Migration and Conflict Nexus. *International Journal of Environmental Research and Public Health* 13(443), 1–17.

Card, D. and G. B. Dahl (2011). Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior*. *The Quarterly Journal of Economics* 126(1), 103–143.

Caselli, F., M. Morelli, and D. Rohner (2015). The Geography of Interstate Resource Wars. *The Quarterly Journal of Economics* 130(1), 267–315.

Cattaneo, C., M. Beine, C. J. Frohlich, D. Kniveton, I. Martinez-Zarzoso, M. Mastrorillo, K. Millock, E. Piguet, and B. Schraven (2019). Human Migration in the Era of Climate Change. *Review of Environmental Economics and Policy* 13(2), 189–206.

Cattaneo, C. and G. Peri (2016). The migration response to increasing temperatures. *Journal of Development Economics* 122, 127–146.

Center for International Earth Science Information Network - CIESIN - Columbia University (2016). Gridded Population of the World, Version 4 (GPWv4): Administrative Unit Center Points with Population Estimates.

Chassang, S. and G. Padró i Miquel (2009). Economic Shocks and Civil War. *Quarterly Journal of Political Science* 4, 211–228.

Climatic Research Unit (2013). CRU Time Series (TS) high resolution gridded datasets 3.2.

Conconi, P., N. Sahuguet, and M. Zanardi (2014). Democratic Peace and Electoral Accountability. *Journal of the European Economic Association* 12(4), 997–1028.

Couttenier, M. and R. Soubeyran (2014). Drought and Civil War In Sub-Saharan Africa*. *The Economic Journal* 124(575), 201–244.

Dallmann, I. and K. Millock (2017). Climate variability and inter-state migration in India. *CESifo Economic Studies* 63(4), 560–594.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature Shocks and Economic Growth : Evidence from the Last Half Century. *American Economic Journal: Macroeconomics* 4(3), 66–95.

Devlin, C. and C. S. Hendrix (2014). Trends and triggers redux: Climate change, rainfall, and interstate conflict. *Political Geography* 43, 27–39.

Docquier, F., J. Machado, and K. Sekkat (2015). Efficiency Gains from Liberalizing Labor Mobility. *Scandinavian Journal of Economics* 117(2), 303–346.

Docquier, F., I. Ruyssen, and M. W. Schiff (2018). International Migration: Pacifier or Trigger for Military Conflicts? *The Journal of Development Studies* 54(9), 1657–1679.

Fearon, J. D. (1995). Rationalist Explanations for War. *International Organization* 49(3), 379–414.

Feyrer, J. (2009a). Distance, Trade, and Income - The 1967 to 1975 Closing of the Suez Canal as a Natural Experiment. Technical Report 15557, National Bureau of Economic Research, Inc.

Feyrer, J. (2009b). Trade and Income – Exploiting Time Series in Geography. Working Paper 14910, National Bureau of Economic Research.

Frankel, J. A. and D. H. Romer (1999). Does Trade Cause Growth? *American Economic Review* 89(3), 379–399.

Gartzke, E. (2012). Could climate change precipitate peace? *Journal of Peace Research* 49(1), 177–192.

Gleditsch, K. S., I. Salehyan, and K. Schultz (2008). Fighting at Home, Fighting Abroad: How Civil Wars Lead to International Disputes. *Journal of Conflict Resolution* 52(4), 479–506.

Gleditsch, N. P., K. Furlong, H. Hegre, B. Lacina, and T. Owen (2006). Conflicts over shared rivers: Resource scarcity or fuzzy boundaries? *Political Geography* 25(4), 361–382.

Grigorieff, A., C. Roth, and D. Ubfal (2018). Does Information Change Attitudes Towards Immigrants? Representative Evidence from Survey Experiments. SSRN Scholarly Paper, Social Science Research Network, Rochester, NY.

Gröschl, J. and T. Steinwachs (2017). Do natural hazards cause international migration? *CESifo Economic Studies* 63(4), 445–480.

Guttman, N. B. (1999). Accepting the Standardized Precipitation Index: A Calculation Algorithm. *Journal of the American Water Resources Association* 35(2), 311–322.

Haaland, I. and C. Roth (2017). Labor Market Concerns and Support for Immigration. SSRN Scholarly Paper, Social Science Research Network, Rochester, NY.

Hainmueller, J. and D. J. Hopkins (2014). Public Attitudes Toward Immigration. *Annual Review of Political Science* 17(1), 225–249.

Harari, M. and E. L. Ferrara (2018). Conflict, Climate, and Cells: A Disaggregated Analysis. *The Review of Economics and Statistics* 100(4), 594–608.

Hatton, T. J. and J. G. Williamson (2006). International Migration in the Long Run: Positive Selection, Negative Selection, and Policy. In R. J. Langhammer and F. Foders (Eds.), *Labor Mobility and the World Economy*, pp. 1–31. Berlin, Heidelberg: Springer.

Hopkins, D. J., J. Sides, and J. Citrin (2018). The Muted Consequences of Correct Information about Immigration. *The Journal of Politics* 81(1), 315–320.

Hsiang, S. M., M. Burke, and E. Miguel (2013). Quantifying the Influence of Climate on Human Conflict. *Science* 341(6151), 1235367–1235367.

Koubi, V., G. Spilker, T. Böhmelt, and T. Bernauer (2013). Do natural resources matter for interstate and intrastate armed conflict? *Journal of Peace Research* 51(2), 227–243.

Ma, M., L. Ren, F. Yuan, S. Jiang, Y. Liu, H. Kong, and L. Gong (2014). A new standardized Palmer drought index for hydro-meteorological use. *Hydrological Processes* 28(23), 5645–5661.

Maoz, Z., P. L. Johnson, J. Kaplan, F. Ogunkoya, and A. P. Shreve (2019). The Dyadic Militarized Interstate Disputes (MIDs) Dataset Version 3.0: Logic and Comparisons to Alternative Datasets. *Journal of Conflict Resolution* 63(3), 811–835.

Martin, A. (2005). Environmental Conflict Between Refugee and Host Communities. *Journal of Peace Research* 42(3), 329–346.

Martin, P., T. Mayer, and M. Thoenig (2008). Make Trade Not War? *Review of Economic Studies* 75, 865–900.

Mayer, T. and S. Zignago (2011). The GeoDist Database on Bilateral Geographical Information. *Cepii*, 18.

McGuirk, E. and M. Burke (2020). The Economic Origins of Conflict in Africa. *Journal of Political Economy*, forthcoming.

McKee, T. B., N. J. Doesken, and J. Kleist (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the Eighth Conference on Applied Climatology*, Boston, MA: American Meteorological Society.

Mitchell, T. D. and P. D. Jones (2005). An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal of Climatology* 25, 693–712.

Most, B. A. and H. Starr (2015). *Inquiry, Logic, and International Politics: With a New Preface by Harvey Starr*. University of South Carolina Press.

Ortega, F. and G. Peri (2014). Openness and income: The roles of trade and migration. *Journal of International Economics* 92(2), 231–251.

Ozden, C., C. R. Parsons, M. Schiff, and T. L. Walmsley (2011). Where on Earth is Everybody? The Evolution of Global Bilateral Migration 1960 – 2000. *The World Bank Economic Review* 25(1), 12–56.

Pascali, L. (2017). The Wind of Change: Maritime Technology, Trade, and Economic Development. *American Economic Review* 107(9), 2821–2854.

Reuveny, R. (2007). Climate change-induced migration and violent conflict. *Political Geography* 26, 656–673.

Rodriguez, F. and D. Rodrik (2001). Trade Policy and Economic Growth: A Skeptic's Guide to the Cross-National Evidence. *NBER Macroeconomics Annual* 15, 261–338.

Rodrik, D., A. Subramanian, and F. Trebbi (2004). Institutions Rule: The Primacy of Institutions Over Geography and Integration in Economic Development. *Journal of Economic Growth* 9(2), 131–165.

Salehyan, I. (2008). The Externalities of Civil Strife: Refugees as a Source of International Conflict. *American Journal of Political Science* 52(4), 787–801.

Seiler, R. A., M. Hayes, and L. Bressan (2002). Using the standardized precipitation index for flood risk monitoring. *International Journal of Climatology* 22(11), 1365–1376.

Silva, J. M. C. S. and S. Tenreyro (2006). The Log of Gravity. *The Review of Economics and Statistics* 88(November), 641–658.

Spolaore, E. and R. Wacziarg (2016). War and relatedness. *The Review of Economics and Statistics* 98(5), 925–939.

Stalley, P. (2003). Environmental Scarcity and International Conflict. *Conflict Management and Peace Science* 20(2), 33–58.

UNEP-DHI and UNEP (2016). Transboundary River Basins: Status and Trends. Technical report, United Nations Environment Programme, Nairobi.

Valentino, N. A., S. N. Soroka, S. Iyengar, T. Aalberg, R. Duch, M. Fraile, K. S. Hahn, K. M. Hansen, A. Harell, M. Helbling, and et al. (2019). Economic and cultural drivers of immigrant support worldwide. *British Journal of Political Science* 49(4), 1201–1226.

Weiner, M. (1985). On International Migration and International Relations. *Population and Development Review* 11(3), 441–455.

Weiner, M. (1992). Security, Stability, and International Migration. *International Security* 17(3), 91–126.

Whitaker, B. E. (2003). Refugees and the Spread of Conflict: Contrasting Cases in Central Africa:. *Journal of Asian and African Studies* 38(2-3), 211–231.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*, (Second Edition, The MIT Press ed.).

Supplementary Tables

Dependent variable: Migrants	(1)	(2)	(3)	(4)	(5)
Temperature	0.06 (0.03)*	0.04 (0.03)	0.03 (0.03)	0.04 (0.03)	0.04 (0.03)
Precipitation	-0.69 (0.84)	0.17 (0.90)			
Temperature x Border		0.12 (0.04)***	0.11 (0.04)***	0.10 (0.04)***	0.10 (0.04)***
Precipitation x Border		-16.83 (6.45)***			
SPI x Border			-0.29 (0.09)***		0.08 (0.18)
SPI			0.05 (0.03)*		0.06 (0.05)
Drought (0/1) x Border				1.79 (0.40)***	
Drought (0/1)				-0.09 (0.13)	
Excess (0/1) x Border				-0.59 (0.34)*	
Excess (0/1)				0.18 (0.15)	
Drought SPI x Border					-2.50 (0.83)***
Drought SPI					-0.14 (0.27)
Excess SPI x Border					-2.48 (1.12)**
Excess SPI					0.16 (0.27)
R2	0.79	0.79	0.79	0.79	0.79
N	77,041	77,041	77,041	77,041	77,041

Notes: The dependent variable is the number of migrants from country i to country j in year t . All specifications include country-pair time invariant controls, origin region-by-year fixed effects, origin fixed effects and destination fixed effects. Method of estimation PPML. Reference periods for the analysis: 1980-2010. Standard errors clustered by origin-destination country pairs; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S.I.1: Auxiliary regression results of the effect of climate variables on migration. Yearly data

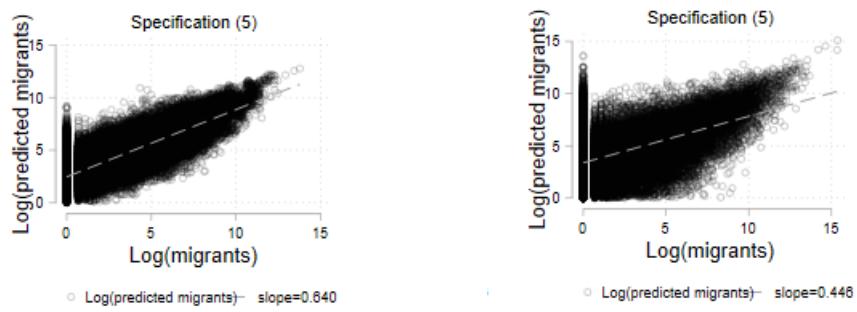


Figure S.I.1: Predicted migrants plotted against actual number of migrants for specifications (5) of Tables 2 (left Panel) and 3 (right Panel).

Dependent variable: Migrants	(1)	(2)	(3)	(4)	(5)
Temperature	-0.08 (0.29)	-0.09 (0.29)	-0.08 (0.28)	-0.24 (0.29)	-0.20 (0.26)
Precipitation	-23.33 (20.09)	-26.57 (20.80)			
Temperature x Border		0.08 (0.02)***	0.11 (0.02)***	0.07 (0.03)**	0.08 (0.03)***
Precipitation x Border		9.24 (2.70)***			
SPI x Border			-0.97 (1.13)		0.64 (1.08)
SPI			-0.08 (0.34)		0.84 (0.66)
Drought (0/1) x Border				11.59 (5.49)**	
Drought (0/1)				2.70 (2.81)	
Excess (0/1) x Border				2.00 (4.87)	
Excess (0/1)				-0.16 (2.13)	
Drought SPI x Border					-8.34 (6.22)
Drought SPI					-9.35 (5.22)*
Excess SPI x Border					-1.10 (10.58)
Excess SPI					-3.41 (6.21)
R2	0.74	0.75	0.74	0.75	0.75
N	48,490	48,490	48,490	48,490	48,490

Notes: The dependent variable is the number of migrants from country i to country j in decade d . All specifications include country-pair time invariant controls, origin region-by-decade fixed effects, origin fixed effects and destination fixed effects. Method of estimation PPML. Reference periods for the analysis: 1960-2000. Standard errors clustered by origin-destination country pairs; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table S.I.2: Auxiliary regression results of the effect of climate variables on migration. GBMD decadal data

Dependent variable: Migrants	(1)	(2)	(3)	(4)	(5)
Temperature	-0.56 (0.44)	-0.51 (0.46)	-0.41 (0.48)	-0.41 (0.48)	-0.29 (0.43)
Precipitation	18.75 (10.72)*	35.84 (17.43)**			
Temperature x Distance		-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Precipitation x Distance		-2.05 (1.86)			
SPI x Distance			0.32 (0.27)		0.34 (0.46)
SPI			-1.84 (2.19)		-1.72 (3.73)
Drought (0/1) x Distance				-0.79 (1.08)	
Drought (0/1)				2.95 (9.02)	
Excess (0/1) x Distance				1.16 (1.73)	
Excess (0/1)				-10.64 (15.08)	
Drought SPI x Distance					-0.15 (2.41)
Drought SPI					2.82 (20.74)
Excess SPI x Distance					-0.02 (4.43)
Excess SPI					-5.74 (39.41)
R2	0.63	0.63	0.63	0.63	0.63
N	11,509	11,509	11,509	11,509	11,509

Notes: The dependent variable is the number of migrants from country i to country j in decade d . All specifications include country-pair time invariant controls, origin region-by-decade fixed effects, origin fixed effects and destination fixed effects. The sample only includes the pairs that exist in the OECD data. Method of estimation PPML. Reference periods for the analysis: 1960-2000. Standard errors clustered by origin-destination country pairs; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table S.I.3: Auxiliary regression results of the effect of climate variables on migration. GBMD decadal data. Subset of the GBMD data for which yearly data exists

Dependent variable: Pr(Conflict) (%)	(1) OLS	(2) 2SLS
Log(migrants+1)	0.004 (0.040)	1.126 (0.418)***
Temperature	-0.278 (0.479)	-1.038 (0.615)*
SPI	0.153 (0.539)	0.534 (0.586)
Drought SPI	-2.485 (4.599)	1.209 (5.356)
Excess SPI	-1.834 (4.871)	-11.136 (6.652)*
N	11,509	11,509
Dependent variable mean	0.408	0.408
First stage F-stat	.	45

Notes: The dependent variable is equal to one if country j initiated a conflict against i and 0 otherwise. All specifications include country-pair time invariant controls, origin region-by-decade fixed effects, origin fixed effects and destination fixed effects. The sample only includes the pairs that exist in the OECD data. Reference periods for the analysis: 1960-2000. Standard errors clustered at the country-pair level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S.I.4: Second stage results with destination aggressor. Decadal data.

Dependent variable: $\text{Pr}(\text{Conflict}) (\%)$	(1) OLS	(2) 2SLS
Log(migrants+1)	0.027 (0.016)*	0.059 (0.046)
Temperature	-0.101 (0.070)	-0.104 (0.068)
Temperature ²	0.002 (0.003)	0.003 (0.003)
SPI	0.005 (0.046)	0.000 (0.046)
Drought SPI	0.399 (0.335)	0.417 (0.336)
Excess SPI	0.809 (0.431)*	0.825 (0.430)*
N	75,458	75,458
Dependent variable mean	0.105	0.105
First stage F-stat	.	531

Notes: The dependent variable is equal to one if country j initiated a conflict against i and 0 otherwise. All specifications include country-pair time invariant controls, destination region-by-year fixed effects, origin fixed effects and destination fixed effects. The sample only excludes neighboring country pairs. Reference periods for the analysis: 1980-2010. Standard errors clustered at the country-pair level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S.I.5: Second stage results with destination aggressor. Excludes neighboring country pairs. Yearly data.

Dependent variable: Pr(Conflict) (%)	(1) OLS	(2) 2SLS
Log(migrants+1)	0.027 (0.018)	0.641 (0.151)***
Temperature	0.807 (0.267)***	-0.120 (0.327)
Temperature ²	-0.033 (0.007)***	-0.014 (0.008)*
SPI	-0.126 (0.350)	-0.106 (0.355)
Drought SPI	-0.733 (1.879)	-1.047 (1.911)
Excess SPI	2.819 (2.433)	3.416 (2.493)
N	47,184	47,184
Dep var mean	0.367	0.367
	.	439

Notes: The dependent variable is equal to one if country j initiated a conflict against i and 0 otherwise. All specifications include country-pair time invariant controls, destination region-by-decade fixed effects, origin fixed effects and destination fixed effects. Excludes neighboring country pairs. Reference periods for the analysis: 1960-2000. Standard errors clustered at the country-pair level in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table S.I.6: Second stage results with destination aggressor. Decadal data.

Dependent variable: Pr(Conflict) (%)	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
	Attitude		Religion	
Log(migrants+1)	0.194 (0.097)**	0.423 (0.191)**	0.005 (0.015)	0.076 (0.071)
Log(migrants+1) Interaction	-0.021 (0.013)	-0.036 (0.020)*	0.118 (0.041)***	0.155 (0.058)***
N	72,143	72,143	77,041	77,041
F-stat	.	197	.	221

Notes: The dependent variable is equal to one if country j initiated a conflict against i and 0 otherwise. Attitude measures the destination country level of acceptance of migrants, from 1.69 (low acceptance) to 8.26 (high acceptance). Religion is an indicator equal to one for the origin country of the flows being majority-Muslim, and 0 otherwise. All specifications include country-pair time invariant controls, region-by-year fixed effects, country j fixed effects and country i fixed effects. Reference periods for the analysis: 1980-2010. Columns (2) and (4) use predicted bilateral migrants from specifications (5) in Table 2, as instrument for migration. Standard errors clustered at the country-pair level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S.I.7: Second stage results with destination aggressor, heterogeneous impact. Yearly data

Dependent variable: Pr(Conflict) (%)	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Attitude				
Log(migrants+1)	0.198* (0.108)	2.960*** (0.669)	-0.015 (0.028)	1.088*** (0.215)
Log(migrants+1) Interaction	-0.028* (0.017)	-0.265*** (0.074)	0.128** (0.059)	0.289*** (0.096)
N	38,953	38,953	48,490	48,490
F-stat	.	85	.	177

Notes: The dependent variable is equal to one if country j initiated a conflict against i and 0 otherwise. Attitude measures the destination country level of acceptance of migrants, from 1.69 (low acceptance) to 8.26 (high acceptance). Religion is an indicator equal to one for the origin country of the flows being majority-Muslim, and 0 otherwise. All specifications include country-pair time invariant controls, region-by-decade fixed effects, country j fixed effects and country i fixed effects. Reference periods for the analysis: 1960-2000. Columns (2) and (4) use predicted bilateral migrants from specifications (5) in Table 3, as instrument for migration. Standard errors clustered at the country-pair level in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S.I.8: Second stage results with destination aggressor, heterogeneous impact. Decadal data