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Climate variability and irregular migration to the European Union☆

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A B S T R A C T

The so-called 'European Migrant Crisis' has been blamed on armed conflict and economic misery, particularly in the Middle East and Sub-Saharan Africa. Some have suggested that this process has been exacerbated by climate change and weather events. In this paper, we evaluate these claims, focusing on the role of droughts in influencing irregular migration flows to the European Union. Drawing on temporally disaggregated data on the detection of unauthorized migrants at EU external borders, we examine how weather shocks affect irregular migration. We show that weather events may indeed influence migration. Yet, in contradiction to the findings from recent research, we find no evidence that a drought in a sending country increases unauthorized migration to the EU. If anything, and while not entirely conclusive, the incidence of drought seems rather to exert a negative, albeit moderate, impact on the size of migration flows, in particular for countries dependent on agriculture. Conversely, higher levels of rainfall increase migration. We interpret this as evidence that international migration is cost-prohibitive, and that adverse weather shocks reinforce existing financial barriers to migration.

1. Introduction

Do environmental shocks cause migration from poor countries to the European Union? The well-known push–pull model of international migration suggests that factors in the receiving country such as economic opportunities, political freedom, and family ties "pull" in people seeking a better life, while economic hardships and violence can "push" people out of origin countries (Jenkins, 1977; Zimmermann, 1996). With the accelerating pace of climatic change, it is plausible that disruptions to normal weather patterns serve as an additional push factor as they can disrupt economic activity, particularly in the agricultural sector. Indeed, many observers have linked climate shocks to food insecurity and large-scale movements of people. The Internal Displacement Monitoring Centre (IDMC) estimates that between 2008 and 2018, an average of 24 million people have been displaced by climate and weather-related disasters (IDMC, 2019).

A growing body of research has sought to uncover links between environmental factors and migration. Feng et al. (2010) find that climate change and declining crop yields in Mexico lead, in part, to migration to the United States. Missirian and Schlenker (2017) report that temperature fluctuations in countries of origin lead to additional asylum applications in Europe. In the same vein, Cai et al. (2016) present evidence that rising temperature are associated with higher migration to OECD countries, but only for countries reliant on agriculture. Reuveny and Moore (2009) find that natural disasters are positively linked to migration to developed countries. Looking at internal migration in Indonesia, Bohra-Mishra et al. (2014) demonstrate that province-to-province migration increases significantly with higher temperatures and responds to a lesser extent to precipitation. Others have reported similar results for Pakistan and the United States (Feng et al., 2010; Mueller et al., 2014). In fact, a recent World Bank report predicts that internal migration will increase substantially as a result of climatic change (Rigaud et al., 2018).

Yet, others have found more complex relationships. Cattaneo and Peri (2016) observe that, while higher temperatures in middle-income countries influence both international migration and urban growth, the same temperature rise in countries at the bottom wealth quartile have a negative effect on migration. Koubi et al. (2016a; 2016b), using survey data from six countries, find that slowly-evolving natural disasters such as droughts do not prompt people to leave, as they are able to make necessary adaptations. Thiede and Gray (2017) report that higher temperatures in Indonesia are associated with less, not more migration, but that delays in the onset of the monsoon season increase migration. Gray and Mueller (2012) find that disasters and crop failure

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only have modest and inconsistent effects on migration in Bangladesh. They conclude that, "although mobility can serve as a post disaster coping strategy, it does not do so universally, and disasters can in fact *reduce* mobility by increasing labor needs at the origin or by removing the resources necessary to migrate" (Gray and Mueller, 2012: 4). Thus, while natural disasters may be a push factor in migration decisions, they may also have countervailing effects on the propensity to leave. It is also worth noting that others have reported no association between environmental factors and international migration (see Bohra-Mishra and Massey, 2011; Beine and Parsons, 2015). In addition, data garnered in Tambacounda, a high emigration area in Senegal, show that climatic factors have little influence on migration to Europe (Ribot et al., 2020).

In this paper we examine the competing claims that weather shocks—such as droughts and excess precipitation—may either increase or decrease emigration from a country. On one hand, adverse weather events may disrupt livelihoods, especially in agriculture-dependent economies, prompting migration. On the other hand, such shocks may decrease emigration by reducing the financial means to migrate.

Our paper builds upon that of Missirian and Schlenker (2017), but relies on a different measure of migration, irregular migration to the European Union (EU), as well as of environmental shocks, the Standardized Precipitation Evapotranspiration Index (SPEI). In what follows, we use the terms irregular or unauthorized migration interchangeably to denote migration without a visa or other legal travel documents. Understanding the relation between climatic variability and irregular migration is important, both from a scientific and a policy perspective. First, irregular migration from developing countries represents a substantial share of migrants to the EU. More than 2.2 million irregular migrants have been detected at EU external borders between 2009 and 2017, according to data compiled by Frontex, the European Border and Coast Guard Agency (this figure excludes the *Western Balkans Route* and the *Circular Route from Albania to Greece*). By way of comparison, total immigration flows from non-EU countries amounted to over 13 million over the period 2009–2016 (Eurostat, 2018). At its highest, the so-called 2015 "migration crisis" saw more than a million irregular migrants attempt to enter the EU. In addition to war and economic misery, several commentators have claimed that climate change is a key driver of irregular migration to Europe and the United States (e.g., The Guardian, 2015; The New York Times, 2016; Washington Post, 2018).

Second, the political salience of unauthorized migration is high and has arguably fueled the rise of populist parties in Western countries. Third, while prior research has generally focused on aggregate migration flows based on census data, these statistics often exclude irregular migrants. Despite a lack of systematic information, conventional knowledge on Mexican immigration to the US holds that undocumented migrants tend to have lower socioeconomic and educational status, compared to legal migrants (Hanson, 2006). They are also more likely to come from rural areas (Orrenius and Zavodny, 2005). While the validity of these studies to other contexts remains an open question, there are reasons to believe that climatic variability is a driver unauthorized migration (Nawrotzki et al., 2015; Chort and de la Rupelle, 2019). In fact, unauthorized migration is known to be more responsive to the economic cycle than legal immigration (Hanson and Spilimbergo, 1999). By comparison, visa applications typically last for months, and may be subject to stringent requirements. To our knowledge, our study is one of the first to systematically examine the effect of weather shocks on irregular migration across a large number of countries and in the European context.[1]

We contribute to the literature by offering a nuanced account of the effects of environmental change on migration to the EU. We report evidence consistent with the claim that droughts may dampen migration pressure. Conversely, higher than usual rainfall is associated with increased irregular migration to the EU. Furthermore, our results indicate that this dampening effect is primarily driven by agriculturally-reliant countries. While out-of-sample cross-validations suggest that climate variables never substantially improve the predictive ability of the estimated models, our findings nonetheless do not align with prevailing narratives that see droughts and global warming as associated with a rise in migration to the EU.

In the next section, we review the recent literature on weather variability and international migration and formulate a set of observable implications. We then present the Frontex data used to measure irregular migration to the EU and our main indicator of weather shocks, the Standard Precipitation Evapotranspiration Index. Section four discusses the results of the empirical analyses. Finally, section five concludes.

2. Weather shocks and migration theory

Classical models of migration assume that individuals move in response to different wage rates between countries (Massey et al., 1993) as well as within them (Nguyen et al., 2015). An alternative approach views the household unit as the locus of decision-making, with the family choosing to send members to work in more lucrative areas in order to receive remittances and diversify risk (Massey et al., 1993; Taylor, 1999; Stark and Bloom, 1985). Both approaches argue that differences in earnings potential between origin and destination regions are a primary driver of migration. Survey data from China (Zhu, 2002) and Mexico (Quinn, 2006), confirm that wage differences play a large role in migration decisions.

Adverse weather events can lead to disruptions in the local economy, depressing productivity and economic growth (Ahmed et al., 2009; Burke et al., 2015; Dell et al., 2012; Rowhani et al., 2011). Weather shocks—or large deviations from historical weather patterns—can be particularly disruptive to agrarian societies that do not have access to capital improvements such as irrigation, improved seeds and fertilizers, and crop insurance mechanisms (Adger et al., 2003). Thus, weather shocks may threaten food security and exacerbate wage differentials between developing and developed countries leading to increased pressure to emigrate. Previous studies have found that rural–urban migration in Sub-Saharan Africa (Barrios et al., 2006; Marchiori et al., 2012), as well as Vietnam (Nguyen et al., 2015), is partly driven by weather shocks and agricultural decline. Others have found that international migration also responds to adverse climatic events (Backhaus et al., 2015; Cai et al., 2016; Marchiori et al., 2012; Missirian and Schlenker, 2017), and declining crop yields (Feng et al., 2010). While they do not find evidence for a direct association with international migration, Beine and Parsons (2015) report a potential indirect pathway through the effects of rainfall deficits on wage differentials.

Yet, migration to developed countries can be a costly endeavor, with no guarantee of success. Studies have shown that the fees paid to human smugglers along the US-Mexico border have risen dramatically with the trend toward greater immigration enforcement (Roberts et al., 2010). For potential Mexican migrants, financial barriers are a significant impediment to emigration (Angelucci, 2015; see also Stecklov et al., 2005). In fact, recent research indicates that municipalities exposed to lower levels of rainfall and high temperature have sent fewer international migrants (Riosmena et al., 2018). Similarly, irregular migrants to Europe face significant smuggling costs, ranging on average from 3,000 to 6,000 euros (Europol and Interpol, 2016: 8). Dustmann and Okatenko (2014) demonstrate that migration decisions are non-linearly associated with income—relatively wealthy individuals do not have the incentive to migrate, while the very poor face budget constraints in making the journey (see also McKenzie and Rapoport, 2007). Kleemans (2015) finds that, in Indonesia, climatic variability has heterogenous effects with

[1] For a similar, but independent study, see Missirian (2019). She compares UNHCR data on asylum applications with Frontex data on irregular migration flows and examines the correlates of irregular migration, including precipitation and temperature levels. She reports that migration "may respond to temperature over the maize growing area and season, although the relationship is weak and unstable" (p. 19).

adverse weather shocks increasing the frequency of short-distance, rural moves, but decreasing long-distance, urban moves. Evidence from a field experiment in Bangladesh suggests that perceptions of risks associated with migration make poor rural households reluctant to send a migrant to cities, even when benefits are large (Bryan et al., 2014).

Given that weather shocks have the greatest negative consequences in: a) poor countries; b) the agriculture sector; and c) vulnerable people with few resources, climatic events may have the short-term effect of reducing the resources needed to make distant journeys. Weather-related disasters may depress migration rates between poor countries and wealthy ones. In fact, long-distance moves decreased during the 1983–5 drought in Mali (Findley, 1994). Recent findings suggest that rising temperatures in poor countries correlate with lower rates of international migration, due to financial barriers to migration (Cattaneo and Peri, 2016). In addition, Gray and Mueller (2012) note that weather shocks may increase local demand for labor, as poor households must devote greater effort to ensuring minimally-sufficient agricultural yields. Hence, adverse weather shocks could further impoverish poor communities and thereby limit their ability to support the costs of migration (Black et al., 2013).

Therefore, the effect of weather-related shocks on international migration is ambiguous. Climatic events may depress wages, overall economic growth, and threaten food security. This serves as a push factor, leading to increased demand for emigration. However, weather shocks may have the countervailing effect of diminishing the resources necessary for costly migration routes, especially among the most vulnerable. Even if rural–urban migration or migration to proximate countries increases, financial costs associated with illicit entry into rich countries may be prohibitive. We thus have the following hypotheses:

H1: Weather shocks in a sending country increase the level of irregular migration to the European Union.
H2: Weather shocks in a sending country decrease the level of irregular migration to the European Union.

The earlier discussion also implies that the association between weather shocks and migration might be stronger in countries more reliant on agriculture. Indeed, previous research has documented how droughts and excess rainfall negatively affect agricultural production (Rosenzweig et al., 2002; Schlenker and Roberts, 2009; Lobell et al., 2011). Furthermore, agricultural productivity is widely held to be the primary channel through which climate change may affect international migration. Recent studies have found evidence that agriculturally reliant countries experience higher rates of out-migration (Marchiori et al., 2012; Cai et al., 2016; see also Chort and de la Rupelle, 2019). Mastrorillo et al. (2016) report similar evidence as to the conditional effect of the size of the agricultural sector for internal migration across districts in South Africa. Yet, this assumption has been questioned in the literature. Cattaneo and Peri (2016) show that far from increasing migration, higher temperatures in agricultural societies decrease the rate of emigration. Similarly, Bazzi (2017) finds that negative precipitation shocks depress international migration among land-poor households in Indonesia. Given the lack of clear expectations in the literature with regards to moderating effects of the size of the agricultural sector, we refrain from stating explicit hypotheses about the direction of the conditional relationship, and opt for the following hypothesis:

H3: The (positive or negative) association between weather shocks and the level of irregular migration to the European Union is stronger in countries more reliant on agriculture.

While we focus on the agricultural sector in this paper, it is worth stating that we do not wish to deny the possibility that other channels may also matter. For instance, Hsiang (2010) and Zhang et al. (2018) report evidence for a link between temperature and economic productivity.

3. Data and research design

3.1. Dependent variable: Irregular migration

To measure the size of irregular migration, we use data collected by Frontex from national border authorities. The data provide information on the number of illegal border crossings detected at the external borders of the EU and Schengen Associated Countries (Iceland, Liechtenstein, Norway and Switzerland). Not part of the Schengen area, the United Kingdom and Ireland are not covered. It is available in monthly format from 2009 onwards and is disaggregated by (self-reported) nationality of migrants and migration routes (8 in total, see the Appendix). Aside from its high temporal and spatial granularity, drawing on the Frontex data presents two key advantages compared to alternative sources of data on migration flows, such as from existing databases on migration (Marchiori et al., 2012; Beine and Parsons, 2015; Cattaneo and Peri, 2016; Cai et al., 2016) or UNHCR data on asylum applications (Missirian and Schlenker, 2017). First, the data specifically focus on undocumented migrants, which may evade registration by state bureaucracies, or may opt not to apply for asylum. In fact, migrants who stand little chance of asylum success have incentives not to register with state authorities, and thus are not included in statistics on asylum applications (for a discussion, see Missirian, 2019). Second, there could be a significant time lag between the moment individuals cross a border and when they are added to a population register or apply for refugee status. This is because individuals may apply for asylum only upon detection or arrest by authorities, or after overstaying legal visas. These events may occur several years after entry in the EU. By contrast, the detection of unauthorized migrants is temporally closer to the departure from the home country, and associated weather shocks. While asylum applications and Frontex detections are correlated at the 0.63 level, these are not identical measures (coefficient based on the sample of Table 1 in Section 4).

Fig. 1 presents the total monthly rate of apprehensions aggregated across all irregular migrations routes over the period 2010–2015 (corresponding to the time frame of the empirical analysis conducted in Section 4), along with the number of migrants of unspecified origins. Aggregate trends in the detection of irregular migration were mostly stable over the period 2010–2013, hovering between 60,000 and 130,000 detections/year. From 2014 onwards, irregular migration registered a marked uptick by more than an order of magnitude, peaking in 2015 with more than one million migrants detected. This increase is attributable in large part to three countries: Syria, Iraq, and Afghanistan, although other countries have also witnessed significant increases in irregular migration to the EU over the same period (e.g. Pakistan, Eritrea, and Nigeria). Fig. 1 also reveals that migration patterns present high seasonality, with winter months consistently registering lower migration levels. Fig. 2 displays the distribution of irregular migrants by country of origin. A disproportionate amount of migrants originate from the African continent, the Middle East and South-Asia. In fact, just five countries account for 64% of unauthorized migrants detected (Syria, Afghanistan, Iraq, Eritrea, Nigeria). In the Appendix, we provide additional information on temporal patterns for the eight largest sending countries in the Frontex data, as well report the total number of irregular migrants by country of origin over the period 2010–2015.

Nevertheless, there are potential limitations to using these data. First, the number of irregular migrants detected is not only a function of the true number of crossing attempts, but also of "the amount of effort spent […] on detecting migrants" by national authorities (Frontex, 2017a: 13, see also Hanson and Spilimbergo, 1999). Thus, year-to-year increase in the number of migrants detected could either reflect a rise in the number of migrants, or a higher rate of detection resulting from stricter enforcement. Second, the country of origin is self-reported by the migrants. Some irregular migrants may practice "nationality swapping" if they have reasons to believe that this will increase their chance of staying in Europe (Frontex, 2017b: 19). Third, aggregating data from

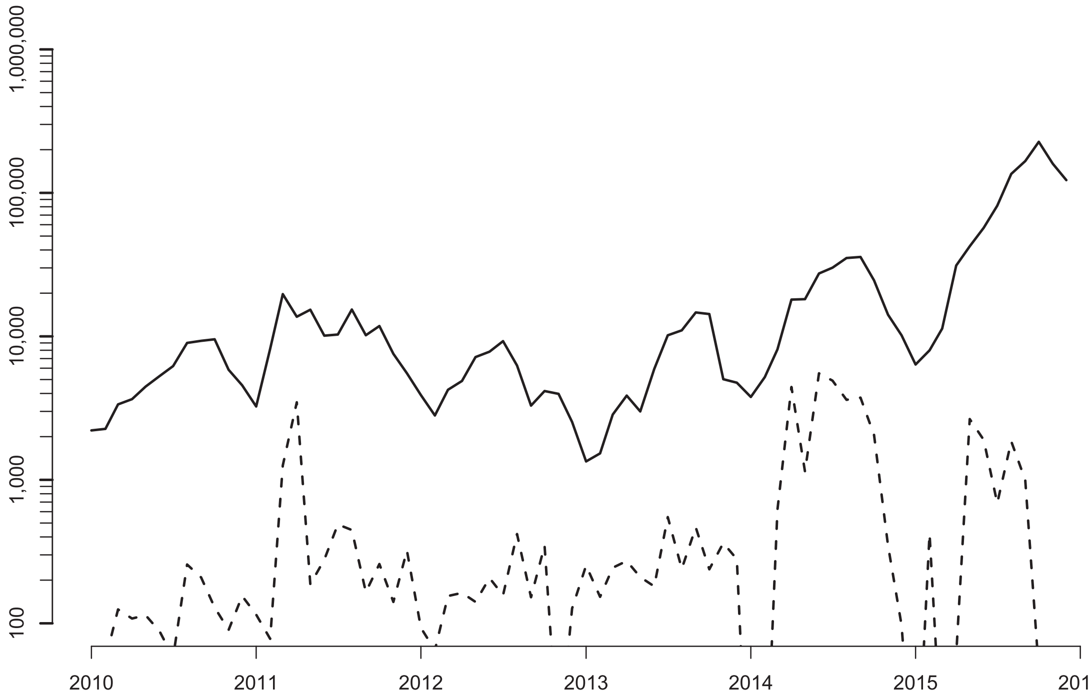

Fig. 1. Monthly irregular migration flow to the EU (2010–2015). The solid line displays the total number of migrants on a log scale, while the dashed line indicates the monthly number of migrants, of which the nationality is not specified in the Frontex data. The graph excludes the *Western Balkan Route* and the *Circular Route from Albania to Greece* (as well as the residual migration route). Note the log scale on the y axis.

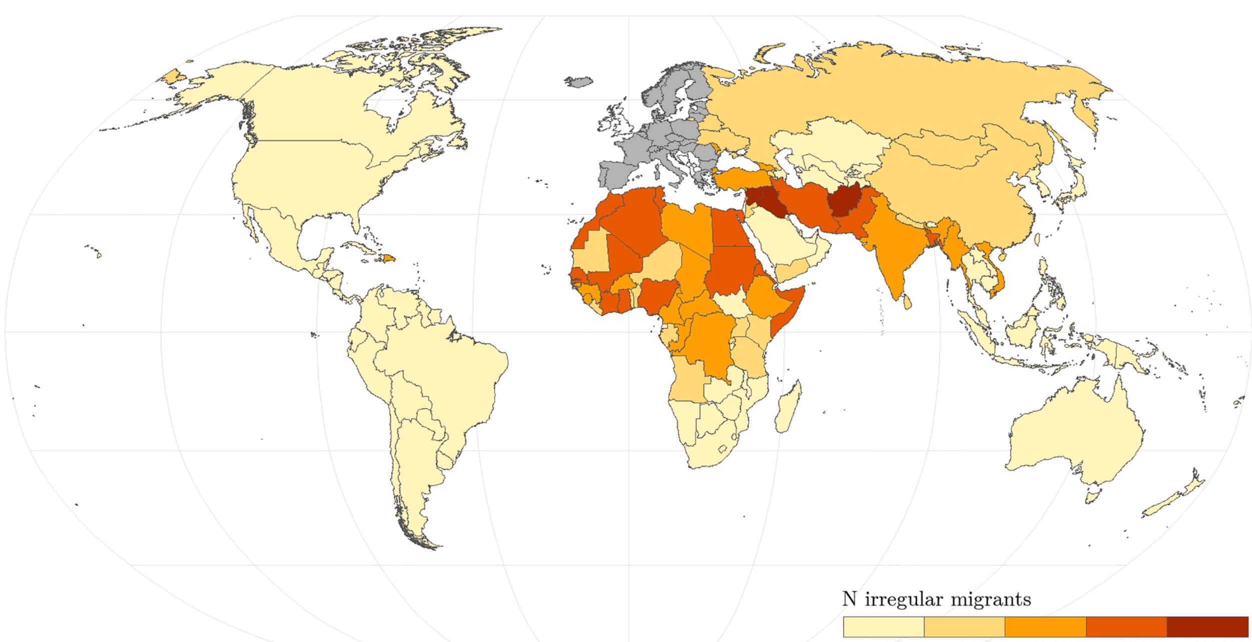

Fig. 2. Number of irregular migrants (2010–2015). The plot is based on Frontex data on the detection of irregular migrants between border-crossing points but exclude estimates from the *Western Balkan Route* and the *Circular Route from Albania to Greece* (as well as the residual migration route). Countries depicted in in grey are EU member states, as well as Schengen-associated countries. Countries depicted in white are non-EU Balkan countries, as well as Ireland and the United Kingdom, which are not part of the Schengen area. The map uses a Robinson projection.

separate migration routes may result in counting the same individual multiple times. This is a concern for the *Western Balkan Route*. Migrants arriving in Greece by land or sea via the *Eastern Mediterranean Route* tend to continue towards Western European countries via the Balkans, and thus potentially be detected a second time at the borders with Slovenia, Croatia, and Hungary. For this reason, we exclude the *Western Balkan Route* and the *Circular Route from Albania to Greece* (thus, we also remove Balkan countries from the sample, as well as the residual migration route). Fourth, as depicted in Fig. 1, while the share of unspecified nationality is generally low (on average 4.7% per month), it exhibits considerable variation, reaching about 25% in April 2011 and 2014.

To compute the dependent variable, we aggregate all migration routes and take the natural logarithm. We add unity to the dependent variable to avoid taking the log of zero. About 7.6% of the observations for Model 1 record zero migrants.

3.2. Independent variable: Weather shocks

Our primary indicator of weather shocks is the 3-month Standardized Precipitation Evapotranspiration Index (SPEI v.2.0), a probability drought index (Vicente-Serrano et al., 2010; Beguería et al., 2014). The SPEI is available at the monthly level and can be calculatedly for different timescales: from a 1- month timescale up to 48-month timescale. The climate literature has long recognized that droughts are multiscalar phenomena. Soil water content, river discharge and groundwater storage are important determinants of droughts. The degree to which a hydrological system depends on these components is crucial in determining the timescale at which drought occurs (Vicente-Serrano et al., 2010: 1697–8). We selected the 3-month SPEI as a compromise timescale between hydrological systems where immediate precipitation is an important determinant of droughts and hydrological systems, which have access to groundwater, and for which drought emerges at longer timescale. We note that the prior literature offers little guidance. Some studies have used the SPEI at very short timescales (1 month) (von Uexkull et al., 2016), while other focusing on arid or semi-arid countries have used longer timescale (12 months) (Mueller et al., 2014; Kubik and Mathilde, 2016).

The SPEI is obtained by first calculating a water balance index, subtracting potential evapotranspiration (PET) from the monthly total amount of precipitation. The index is then aggregated at the desired timescale. PET, which measures the amount of water lost from the soil to the atmosphere under hypothetical conditions, is calculated using the Penman–Monteith equation, which incorporates in addition to temperature, wind speeds, solar radiations and relative humidity (see Beguería et al., 2014). A three-parameter log-logistic distribution is then fitted to the water balance index in order to obtain a standardized drought indicator. The SPEI is an improvement over its precursor the SPI, which did not account for the effects of temperature, via evapotranspiration, and hence is unable to account for the increased duration and magnitude of droughts in recent times as a result of global warming (Vicente-Serrano et al., 2010: 1698–9). Negative SPEI values indicate water deficits, while positive values correspond to water surpluses relative to a "normal" water balance. The data are provided at monthly intervals in a raster format with a 0.5 degree resolution.

To measure deviations at the country-year level, we take the mean SPEI value per cell over the past 12-month ending with the current quarter and average across all cells in given country. Hence, for the first quarter of the year, we take the average over the first three months of the current year (January–March), as well as the nine last months of the previous year (April-December). In computing the value for a given country, we weight the SPEI data by population. Data on 2005 global population count is provided by the Gridded Population of the World (UN adjusted estimates) (v4.11) (CIESIN, 2018).

Using a meteorological drought index is in contrast to some previous studies that use the direct effects of temperature and precipitation on international migration (e.g., Cai et al., 2016; Cattaneo and Peri, 2016; Missirian and Schlenker, 2017). Droughts are complex phenomena characterized by both temperature and precipitation (McLeman, 2013: 144). In general, the SPEI is known to correlate with crop yields both at global (Vicente-Serrano et al., 2012) and local scales (e.g., Kubik and Mathilde, 2016; Peña-Gallardo et al., 2019). Prior research has successfully relied on drought indicators, including the SPEI, to measure the impact of weather shocks on migration (Mueller et al., 2014; Mastrorillo et al., 2016; Kubik and Mathilde, 2016). Of particular note, Missirian and Schlenker (2017) and Missirian (2019) use measures of temperature and precipitation levels to estimate migration to the EU, rather than deviations from normal. We prefer the SPEI, which is a standardized indicator of drought. Particularly in cross-national studies, it is important to consider long term averages and deviations from it, rather than direct indicators, as some regions naturally experience hotter/drier conditions and/or greater normal variability. In the Appendix, we present the results of an alternative specification of the models using temperature and precipitation anomalies.

3.3. Empirical specification

To examine the effect of weather shocks on irregular migration to the EU, we estimate the following equation:

$$Ln\ Migration_{itq} = \sum_{p=1}^{4} \theta_p\ Ln\ Migration_{itq-p} + \beta\ Weather_{itq} + \alpha_i + Year_t + Quarter_q + \varepsilon_{itq}$$

The unit of analysis is the country of origin–year–quarter, indexed by *i*, *t* and *q, respectively*. The dependent variable, ***Ln Migration***$_{itq}$, is a log-transformed quarterly measure of migration levels. ***Weather***$_{itq}$ represents the SPEI variable. α_i is a vector of country of origin fixed effects. ***Year***$_t$ and ***Quarter***$_q$ are vectors of year and quarter dummies. ε_{itq} are robust errors clustered by country. To account for temporal correlation in migration flows, we control for past levels of migration flows in the four prior quarters. Because the association between weather anomalies and migration may exhibit non-linearities, as well as delayed and temporal displacement effects (Carleton and Hsiang, 2016), we include in subsequent models a quadratic polynomial of the SPEI variable, as well as two lag variables (Year–1 and Year–2). In fact, available data suggest significant variation in the duration of travels to Europe. For instance, while many sub-Saharan migrants require up to two years or more to complete their trips, about half do so in less than 12 months (Crawley et al., 2016: 27, see also Ribot et al., 2020: 46).

Following recent studies (Cattaneo and Peri, 2016; Missirian and Schlenker, 2017), we do not include control variables (e.g., GDP per capita; conflict fatalities), as we are interested in measuring the total effect of weather variability on unauthorized migration. Weather is exogenous to social processes such as economic production or armed conflict, and so, omitted variable bias should not be a concern. Rather, factors such as economic growth may be conceived of as mediators through which weather may affect migration, and inclusion of these variables directly would lead to biased estimates (Dell et al., 2012; Hsiang and Burke, 2014; O'Loughlin et al., 2014; Salehyan and Hendrix, 2014). While a full mediation analysis is beyond the scope of this paper, we leave the question of such effects for future research.

Because we include lags of the dependent variable in the estimated equation, we have examined the stationarity of the dependent variable using the Levin-Lin-Chu panel unit-root test with panel-specific means terms and cross-sectional means removed (Levin et al., 2002). The number of lags in the panel ADF regressions is selected based on the AIC, from a maximum of 8 lags determined using the Schwert criterion (1989). The results lead us to reject the null of hypothesis of unit root (adjusted $T = -3.64$, p-value < 0.001).

The sample for the main set of analyses comprises 1,536 country-year-quarter observations extending over the period 2010–2015. To prevent countries from which few migrants originate from influencing the results, we restrict the sample to countries, which have sent a cumulative total of at least 100 irregular migrants to the European Union over the entire period for which we have access to Frontex data (2009–2017). By systematically controlling for past migration flows and restricting the sample to only major source countries, we take a conservative approach. We exclude also estimates of irregular migration flows for Palestine and Western Sahara, as it is likely that a substantial number of migrants from these two regions may have originated from the broader Middle East and North Africa, instead of the territory encompassed by the present borders of Israel/Palestine and Morocco. In total, the sample is made of 64 countries, comprising 38 countries located on the African continent, 20 in Asia, 4 in Eastern Europe and 2 in the Americas.

4. Results

Table 1 presents the results of the primary set of empirical analyses. Model 1 is a baseline country-year fixed-effects specification with quarter dummies and a single, contemporaneous SPEI term. As shown by the positive coefficient, wetter than normal conditions in a given country increase the number of irregular migrants detected. By contrast, the results suggest that adverse shocks, such as a drought, may potentially reduce migration. In substantive terms, we note that the effect of a severe drought (SPEI –0.5) on irregular migration is moderate, resulting in a decrease of about 14% in the number of migrants detected [95% CI: −20.0%, −7.8%]. Conversely, a large positive weather shock increases migration by about 16% [95% CI: + 8.5%, +25.0%]. The predictions (on the log scale) are exponentiated to obtain a measure of relative change in migration levels.

Next, Model 2 replicates Model 1, but includes a quadratic term for weather shocks, to account for the possibility that the association with irregular migration is nonlinear. In general, the result of the quadratic specification suggest that the association is very close to linear, with droughts causing a decrease in migration, while water surpluses are associated with more migration. In fact, the AIC suggests that Models 1 and 2 are essentially indistinguishable (Burnham and Anderson, 2004; Raftery, 1995). Results of a F-test (not shown) leads to the same conclusion. Fig. A.3 in the Appendix depicts the relative change in the size of irregular migration flows for various levels of weather shocks, based on the more flexible specification of Model 2. In general, the results of the first two models are suggestive of a "migration as investment" narrative, whereby positive shocks immediately increase the disposable income of individuals and households and help them overcome financial barriers to emigrate.

Models 3 and 4 replicate the previous analyses adding lags for the SPEI values in the two previous years. In general, neither model reveals evidence for lagged or temporal displacement effects of water deficits or surpluses on migration. The results of a F-test (not shown) carried out on the lagged SPEI variables of both models 3 and 4 fails to reject the null of hypothesis that the lagged terms are jointly zero. Fig. A.4 in the Appendix depicts the relative change in irregular migration as a result of weather shocks at various timescales (Year 0 to Year-2), based on the estimates of the more flexible Model 4.

To better assess the extent to which the inclusion of the SPEI variable improves on the predictive ability of the model and to guard against overfitting (Cranmer and Desmarais, 2017), we carried 5-fold out-of-sample cross-validations with the Stata crossfold package (Daniels 2012). For each model, we report the root of the average mean square errors ($CVrmse = \sqrt{\frac{1}{n}\sum_i^n mse_i}$) and compare it to the same metric for a null modeling without the SPEI variables. The results suggest that care should be taken when drawing conclusions about the association between weather shocks and irregular migration as the estimated average cross-validated errors never outperform the null model. Overall, the evidence does not support Hypothesis H1, which posits that migration increases as a result of drought conditions. To the contrary, they provide tentative support for hypothesis H2, which predicts that droughts have a dampening effect on migration.

We note that the number of unauthorized migrants detected in the previous quarter correlates with future detections. The presence of temporal correlation is likely indicative of two distinct dynamics. First, such an effect is probably related to the establishment of migrant and smuggling networks, which facilitate future movement. Second, the presence of temporal correlation could also reflect stronger monitoring by border agencies, following a period of increasing migration flows along a given route. Interestingly, we find weaker, but significant, evidence for a temporal correlation with the level of migration two quarters earlier. While it is hard to speculate on the reason for such a correlation, it could reflect differences in the speed of adjustments of migrant networks and monitoring by border agencies to an increase in unauthorized migration. Finally, there are strong seasonal patterns in the data. The number of irregular migrants detected in the second (April-June) and third (July-September) quarters are more than twice as high as in the first quarter (January-March). In the fourth quarter (October-December), the numbers are still about 75% percent higher.

Could the association between weather shocks and irregular migration be stronger in countries which exhibit higher labor dependency on the agricultural sector? Countries more reliant on agriculture are widely held to be more exposed to the adverse consequences of climate change (Marchiori et al., 2012). Thus, Table 2 presents the results of the analyses, when we re-estimate Models 1–2, but split the sample into two equal groups of observations: those whose 2010 share of labor employed in the agricultural sector is above the median, and those for which it is below or equal to the median (47.2%) (World Bank, 2019). We refer to these two groups as "agrarian" and "non-agrarian" countries. We also note that 47% of labor employed in agriculture is a high threshold value. It results from the fact that countries which have sent a cumulative total of at least 100 irregular migrants tend to be more agrarian than those that did not. In the Appendix, we show the results of specifications, which include all the countries irrespective of the number of irregular migrants and use the global median share of agricultural labor instead (31.6%).

Essentially, we are testing for a conditional effect to ascertain if different sets of countries in our sample respond differently to climatic variations. We note, however, that parsing the sample into agrarian and non-agrarian countries assumes that any differences primarily occur through the agricultural production channel. While we believe there are

Table 1
Main Models.

	Model 1	Model 2	Model 3	Model 4
N Migr, ln (Q-1)	0.549**	0.548**	0.548**	0.547**
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-2)	−0.006	−0.007	−0.005	−0.006
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-3)	0.106**	0.106**	0.109**	0.109**
	(0.03)	(0.03)	(0.03)	(0.03)
N Migr, ln (Q-4)	0.028	0.029	0.032	0.032
	(0.03)	(0.03)	(0.03)	(0.03)
SPEI (Y0)	0.304**	0.306**	0.279**	0.280**
	(0.07)	(0.07)	(0.07)	(0.07)
$SPEI^2$ (Y0)		0.053		0.060
		(0.08)		(0.09)
SPEI (Y-1)			−0.136	−0.135
			(0.09)	(0.09)
$SPEI^2$ (Y-1)				0.034
				(0.12)
SPEI (Y-2)			0.003	0.005
			(0.09)	(0.09)
$SPEI^2$ (Y-2)				0.020
				(0.13)
2nd quarter	0.840**	0.839**	0.838**	0.838**
	(0.08)	(0.08)	(0.08)	(0.08)
3rd quarter	0.815**	0.815**	0.813**	0.813**
	(0.07)	(0.07)	(0.07)	(0.07)
4th quarter	0.578**	0.577**	0.577**	0.577**
	(0.07)	(0.07)	(0.07)	(0.07)
Constant	0.581**	0.573**	0.553**	0.536**
	(0.11)	(0.12)	(0.11)	(0.12)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	3919.706	3921.428	3920.362	3925.957
Joint F test (SPEI)	18.52**	12.06**	6.90**	4.73**
CV rmse	1.279	1.285	1.260	1.267
N	1536	1536	1536	1536
N Countries	*64*	*64*	*64*	*64*

Std. errors clustered by country. CV rmse null model: 1.232.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 2
Split sample models.

	Model 5 *High Agr.*	Model 6 *Low Agr.*	Model 7 *High Agr.*	Model 8 *Low Agr.*
SPEI (Y0)	0.464**	0.169*	0.467**	0.171*
	(0.12)	(0.08)	(0.12)	(0.07)
$SPEI^2$ (Y0)			0.067	0.045
			(0.11)	(0.11)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Lag migration variables	Yes	Yes	Yes	Yes
AIC	2025.083	1895.390	2026.869	1897.286
Joint F test (SPEI)	13.81**	4.85*	8.48**	3.17+
CV rmse	1.478	1.112	1.487	1.115
N	768	768	768	768
N Countries	*32*	*32*	*32*	*32*

Std. errors clustered by country. CV rmse null models: 1.377 (agrarian sample) and 1.092 (non-agrarian sample).
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 3
Large Weather Shocks.

	Model 9 *High Agr.*	Model 10 *Low Agr.*
Drought (Y0)	−0.312*	−0.063
	(0.13)	(0.12)
Ex. rainfall (Y0)	0.375*	0.155*
	(0.14)	(0.07)
Cntr FE	Yes	Yes
Year FE	Yes	Yes
Quarter dummies	Yes	Yes
Lag migration variables	Yes	Yes
AIC	2030.101	1898.267
Joint F test (SPEI)	6.44**	2.91+
CV rmse	1.460	1.102
N	768	768
N Countries	*32*	*32*

Std. errors clustered by country. CV rmse null models: 1.377 (agrarian sample) and 1.092 (non-agrarian sample).
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

good theoretical reasons to make this assumption, this set of countries could also exhibit other common characteristics such as poverty and geographic region. In the Appendix, we divide the sample by GDP per capita as well as Africa/non-Africa and note that there is considerable overlap between these categories. Ultimately, it is beyond the scope of this paper to ascertain if agricultural dependence is the primary channel through which results diverge and we leave this issue for future research.

In total, the sample of agriculturally reliant countries contains 32 countries, which are disproportionally located in Africa (24) (all of which located in Sub-Saharan Africa, except Sudan). The rest is made of countries located in Asia (7), and in the Americas (1). By contrast, the sample of countries less reliant on agriculture is made of 32 countries, 14 in Africa, 13 in Asia, 4 in Eastern Europe, and 1 in the Americas. Because Models 3–4 did not reveal any evidence for a delayed impact of the SPEI on migration, we do not replicate the analysis for these two models. Interest readers may consult the Appendix, which displays the full results of the split sample analysis including for specifications with lagged SPEI variables.

The results of Table 2 indicate that the drought effects reported earlier are primarily driven by agrarian countries. The estimates of Model 5 suggest that a drought in an agrarian country reduces the number of migrants by about 21% on average [95% CI: –30.2%, –10.0%] (–0.5 SPEI). Conversely, wet conditions in the same country would on average increase migration by about 26% [95% CI: +11.0%, +43.3%] (+0.5 SPEI). By contrast, Model 6 suggests that the effects of weather shocks of similar amplitudes in non-agrarian countries are more than twice as small, resulting for instance in a decrease in the number of irregular migration by about 8% ([95% CI: –15.0%, –0.6%] for a severe drought. As before, the results of the quadratic specification suggest that the association between the SPEI and irregular migration is close to linear (see also Fig. A.5 in the Appendix, which depicts the relative change in the level of observed irregular migration based on the specifications of Models 7–8).

To assess whether the difference between the coefficients for the SPEI are statistically significant, we re-estimated Models 5 and 6 in a seemingly unrelated regression. The results of a χ^2 test suggests that the two coefficients are effectively distinct ($\chi^2 = 4.19$, p-value = 0.041). Nevertheless, this result should be approached cautiously, since the test assumes that the two estimates are statistically independent.[2] Moreover, cross-validations indicate that the predictive performance of these models does not improve compared the null models of each sample.

All in all, the empirical analysis provides evidence in support of Hypothesis 3 with the results showing a stronger association between the SPEI and migration in agrarian countries. In this regard, our results diverge from previous findings, which have suggested that agrarian countries face an increased risk of migration as a result of higher temperatures (Marchiori et al., 2012; Cai et al., 2016). In general, our results do not support the view that dry weather conditions cause more people to migrate internationally. To the contrary, drought can potentially dampen migration from agriculturally reliant countries, presumably by heightening existing financial barriers (Bazzi, 2017).

Could it be that particularly severe droughts might still induce people to leave at higher than usual rates? To examine this question, we replicate the previous split sample analyses, but replace the previous specifications with dummies for severe weather shocks. We operationalize severe weather shocks as weather anomalies with SPEI values equal to or below the 10th percentile (severe drought), or equal to or above the 90th percentile (excess rainfall) of the distribution. We present the results of these models in Table 3. We again find no evidence that particularly severe droughts force people to leave their country. In fact, a severe drought in an agriculturally-dependent country of origin results in an immediate decrease in the number of unauthorized migrants by about 27% on average [95% CI: –43.8%, –4.8%]. The same model provides evidence that periods of unusually heavy rainfall increase the number of irregular migrants by about 45% on average [95% CI: +8.5%, +94.8%], suggesting that natural disasters associated with these events could influence migration rates. Although anecdotal, we note that our data capture the devastating floods that occurred in Ivory Coast in 2010 as wells the 2013 Afghanistan/Pakistan floods lending credence to the claim that extreme values of the SPEI are related to flood damage (IFRC, 2010; Reuters, 2013). While we do not find that drought influences migration in non-agrarian countries, excess levels of rainfall increase migration by about 17% on average [95% CI: +1.4%, +34.3%] (Model 10).

While we have presented empirical evidence that drought may depress irregular migration from agrarian countries, there may be concerns that our findings may be driven by the operationalization of the dependent and independent variables, the choice of estimator and the criteria used for inclusion in the sample. To assess the sensitivity of the findings to alternative specifications, we conduct a number of robustness checks (for the full results, see the Appendix).

First, while our theoretical argument assume agriculture to be the primary channel linking weather shocks to migration, the operationalization of the SPEI does not specifically consider the crop-growing season. Hence, we replace the main SPEI variable with an alternate measure

[2] Alternatively, we have also re-estimated this model using an interaction term between the agrarian dummy and the SPEI variable. While suggestive, the results call for caution when it comes to the moderating influence of agriculture reliance for labor (interaction term = 0.227, s.e. = 0.131, p-value=0.088).

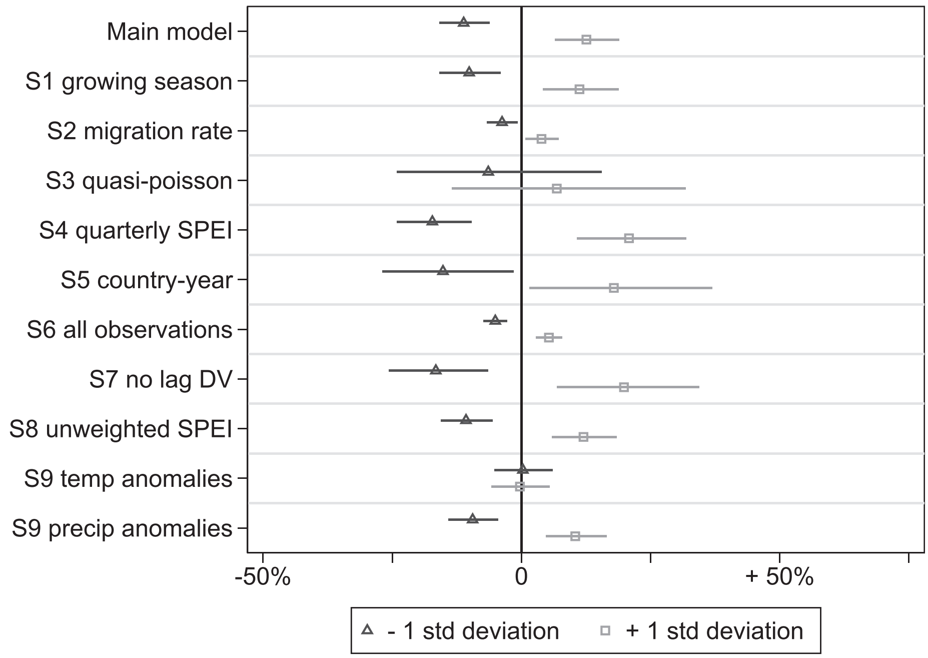

Fig. 3. Results of the sensitivity analysis (Model 1). The plot depicts for each set of robustness checks the predicted change in average irregular migration for an increase/decrease of one standard deviation change on the SPEI scale (S1–S8), respectively for temperature and precipitation anomalies (S9) (based on the estimates of Model 1). The bars depict the 95% confidence interval.

generated using only SPEI monthly values during the crop-growing season (S1). Second, we re-estimate the models using a rate variable (the number of migrants per 100,000 inhabitants) to address concerns that our results may be driven by primarily large countries (S2). Third, we assess the sensitivity of our results to an alternate estimator, a quasi-Poisson (Silva and Tenreyro, 2006; 2011) (S3). This is because about 7.6% of the observations in the sample record zero migration. Thus, adding unity before taking lags risks introducing bias in the estimated coefficient.

In the fourth and fifth rounds, we examine whether the temporal resolution at which the SPEI variable is operationalized may have influenced our results. To do so, we first replicate the analysis using a SPEI measure computed at the quarterly level (instead of a 12-month measure) (S4). We then replicate again the analysis this time

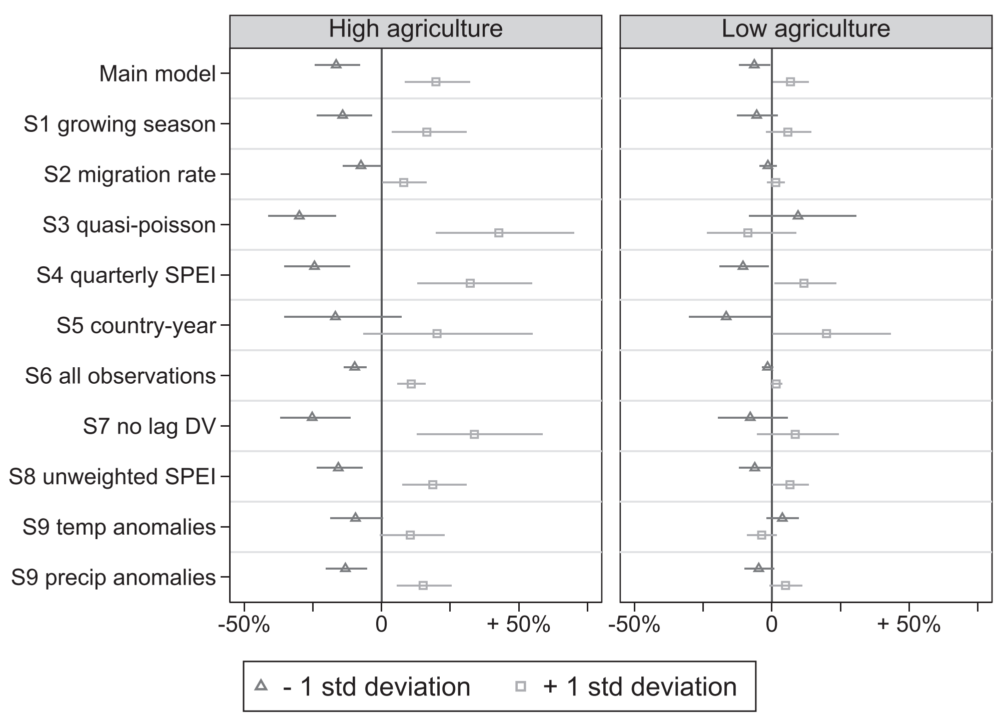

Fig. 4. Results of the sensitivity analysis (Models 5–6). The plot depicts for each set of robustness checks the predicted change in average irregular migration for an increase/decrease of one standard deviation change on the SPEI scale (S1–S8), respectively for temperature and precipitation anomalies (S9), disaggregated by agrarian versus non-agrarian countries (based on the estimates of Models 5–6). The bars depict the 95% confidence interval.

aggregating the migration flows to the annual level (S5). Sixth, we extend the sample to include all sending countries in the analysis, and not just those countries that sent a cumulative total of at least 100 migrants over the period 2009–2017, to address concerns that the findings may be influenced by selection bias (S6). Seventh, endogeneity is a concern inasmuch as it is possible that the inclusion of lagged dependent variables may have affected the estimated SPEI parameters. To address, this concern we replicate the analysis, but remove the lagged migration variables (S7). Eighth, by weighting the SPEI by population, the results could potentially be driven by the effects of shocks in urban areas, instead of rural areas. Thus, we replace the population-weighted SPEI measure by a simple average of the SPEI across the territory of a state (S8). Ninth, we examine whether alternative measures of weather shocks show similar patterns. To do so, we replace the SPEI indicator with measures of precipitation and temperature anomalies from the long-term norm (1970–2016) (S9).

Next, we evaluate how the results are affected, when using GDP per capita (S10) or geographical location (African continent) (S11) to split the sample rather than agricultural dependence. Finally, in the last two rounds, we replace the dependent variable with an alternative version, which includes migration flows from the Balkan migration routes (S12), and use an estimator, which adjust standard errors for spatial correlation (Hsiang 2010) (S13). To better convey the results of the sensitivity analysis, Figs. 3–4 summarize the results of the nine first rounds by displaying the predicted change in migration caused by an increase/decrease of one standard deviation from zero on the SPEI scale based on the specifications of Model 1 and Models 5–6 (for the results of the last four robustness checks, see the Appendix).

In general, the results of the sensitivity analysis add confidence to our conclusion that the incidence of drought does not raise the level of irregular migration detected at EU external borders. If anything, the results provide additional support for the opposite association, particularly in agrarian countries: drought dampens the level of observed irregular migration. Therefore, we conclude that while drought may either decrease, or have no effect on international migration to the EU, it does not *increase* it. Finally, the sensitivity analysis provides additional evidence that wetter-than-usual conditions in countries reliant on agriculture may possibly raise the level of irregular migration, and to a lesser extent for countries less reliant on agriculture. Interestingly, while the results for precipitation anomalies reflect those of the SPEI, we note that our results tentatively suggest that higher than normal temperature in agrarian countries could increase emigration. In the Appendix, we provide a discussion of the results of the sensitivity analysis.

5. Conclusion

In this paper, we have examined the association between weather variability and irregular migration to the EU over the period 2010–2015. To do so, we have relied on Frontex data on unauthorized migration flows and a measure of water balance, the SPEI, which is explicitly designed to capture departures from normal weather conditions. These new data sources add to the debate about climate and migration by providing different metrics to assess the relationship. Overall, we can draw several conclusions. First, in line with others (Findley, 1994; Bohra-Mishra and Massey, 2011; Bazzi, 2017; Riosmena et al., 2018), we find no evidence that drought is associated with *more* emigration. If anything, the incidence of a drought tentatively reduces the immediate level of observed migration in countries, which are predominantly reliant on the agriculture sector.

Second, our findings also provide support for a perspective which sees international migration as an investment. Adverse weather conditions may increase financial barriers to migration, particularly in poor and agriculturally-reliant countries (see also Cattaneo and Peri, 2016). By contrast, wetter-than-usual conditions are likely to lead to higher migration by increasing resources and income available to households. Finally, our findings agree with recent studies, which suggest that sudden onset weather events, i.e., heavy rainfall, may be more strongly associated with migration, than gradual climate change processes, such as rising temperature and droughts (Koubi et al., 2016a; 2016b).

Clearly, more research is warranted into the relationship between weather shocks, climate change, and migration. By using data on apprehensions, we provide additional empirical evidence to the debate. Border apprehensions are not a perfect indicator of emigration rates, but it offers advantages over other measures, such as legal migration or asylum applications. We believe that the accumulation of evidence from alternative data choices, units of analysis, and estimation techniques, will provide a more complete picture regarding the effect of climatic variables on migration.

CRediT authorship contribution statement

Fabien Cottier: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing - original draft, Writing - review & editing. **Idean Salehyan:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2021.102275.

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