Climate Variability and Irregular Migration to the European Union*

Fabien Cottier† and Idean Salehyan‡

Abstract

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.

*Earlier versions of this paper were presented at the Center for International Earth Science Information Network (CIESIN), Columbia University, June 25, 2019 and at the ISA Annual Convention, Toronto, March 27–30, 2019. We thank Cullen Hendrix, Simon Hug, Vally Koubi, Anouch Missirian, Ángel G. Muñoz, Daniel Naujoks, Wolfram Schlenker, Richard Seager, Alex de Sherbinin, Craig Spencer and Nina von Uexkull for helpful comments. Fabien Cottier gratefully acknowledges funding by the Swiss National Science Foundation through the R4D Programme (n° 400240_171175) and an Early Postdoc.Mobility scholarship (n° P2GEP1_184485), as well as by the National Science Foundation through an OIA award (nº 1934798).
† Lamont-Doherty Earth Observatory, Columbia University. Email: Fabien.Cottier@gmail.com. Corresponding author.
‡ Department of Political Science, University of North Texas. Email: Idean.Salehyan@unt.edu

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. 2012, 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. (2016*a, b*), 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 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 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

[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)

to work in more lucrative areas in order to receive remittances and diversify risk (Massey 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 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 (Marchiori et al. 2012, Backhaus et al. 2015, Cai et al. 2016, 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). Dustman 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 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 et al. 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

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).

[Figure 1 about here]

Figure 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). Figure 1 also reveals that migration patterns present high seasonality, with winter months consistently registering lower migration levels. Figure 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.

[Figure 2 about here]

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 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 Figure 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.

<u>Independent variable: Weather shocks</u>

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 precipitations are 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 Maurel 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 fit 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 in 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., Cattaneo and Peri 2016, Cai et al. 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 Maurel 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 Maurel 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.

Empirical specification

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

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

The unit of analysis is the country of origin–year-quarter, indexed by i, t and q, *respectively*. The dependent variable, *Migration*, is a log-transformed quarterly measure of migration levels. $Weather_{it}$ represents the SPEI variable. a_i is a vector of country of origin fixed effects. $Year_t$ and $quarter_q$ are vectors of year and quarter dummies. ε_{it} 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, 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 (Missirian and Schlenker 2017, Cattaneo and Peri 2016), 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 2015). 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 = -3.63, 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 to influence 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 about here]

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%, -7.9%]. 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. Figure 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, these 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 rejects the null of hypothesis that the lagged terms are jointly zero. Figure 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 ($CV\ rmse = \sqrt{\frac{1}{n}\sum_i^n mse_i}$) 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 error never outperform the null model. Overall, the evidence does not support Hypothesis H1, 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 who 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 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.

[Table 2 about here]

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, unusually 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 Figure 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 (χ^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-validation 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,

[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).

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).

[Table 3 about here]

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 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 Teynero 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 of 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 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 Balkans 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, Figures 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).

[Figure 3 about here]

[Figure 4 about here]

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 of 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 soil moisture (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, Bazzy 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 et 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. 2016*a, b*).

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.

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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	*Model 6*	*Model 7*	*Model 8*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*
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	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

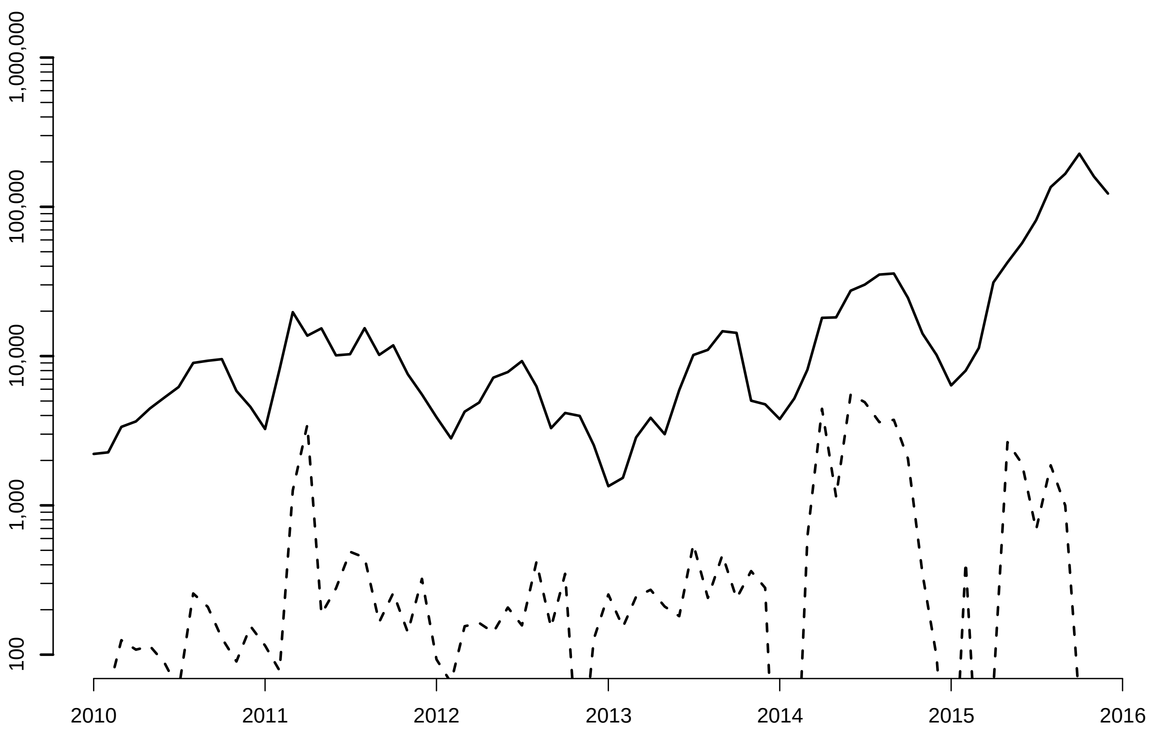

Figure 1: Monthly irregular migration flow to the EU (2010–2015)

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.

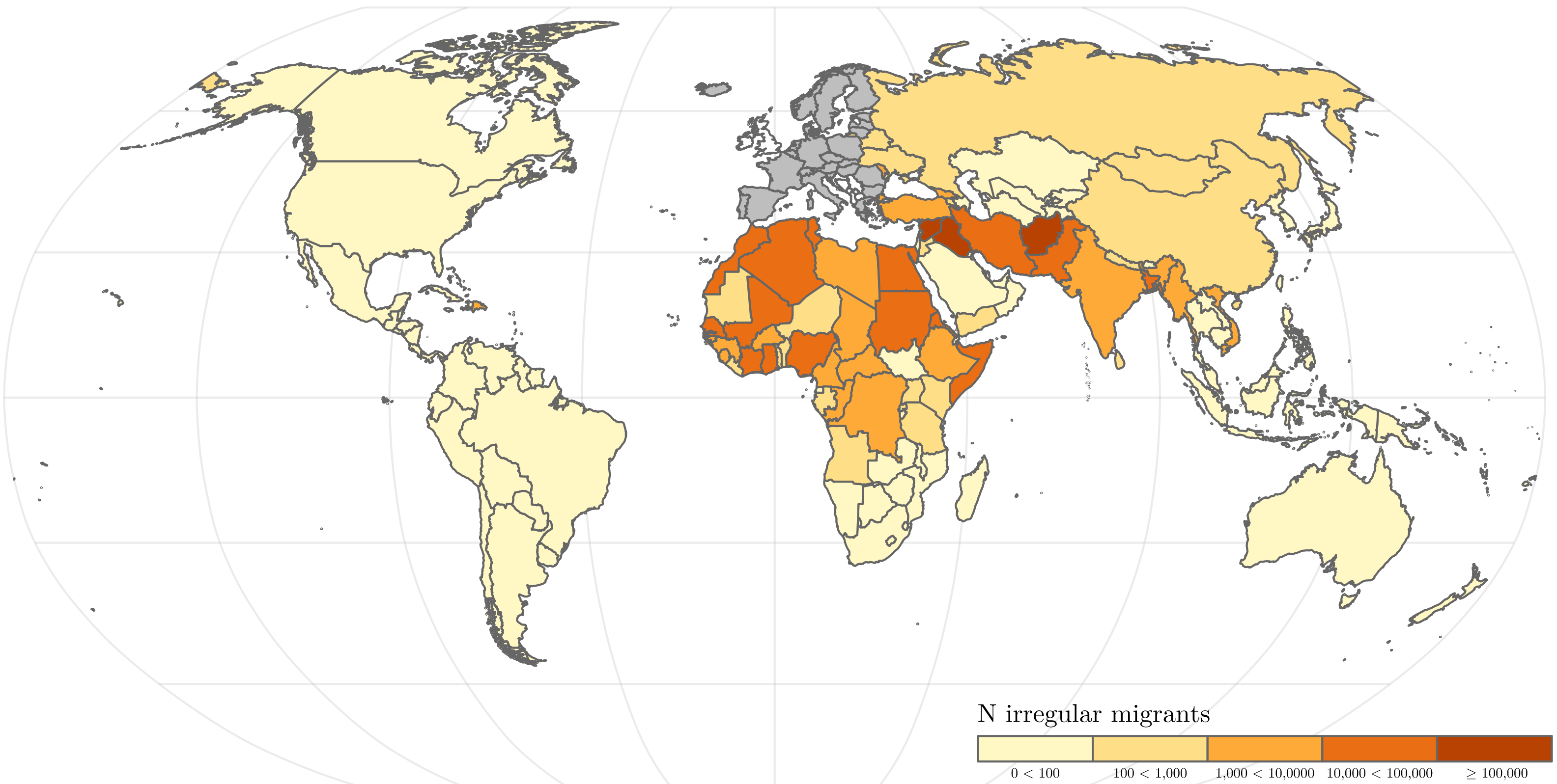

Figure 2: Number of irregular migrants (2010–2015)

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 the United Kingdom, which are not part of the Schengen area. The map uses a Robison projection.

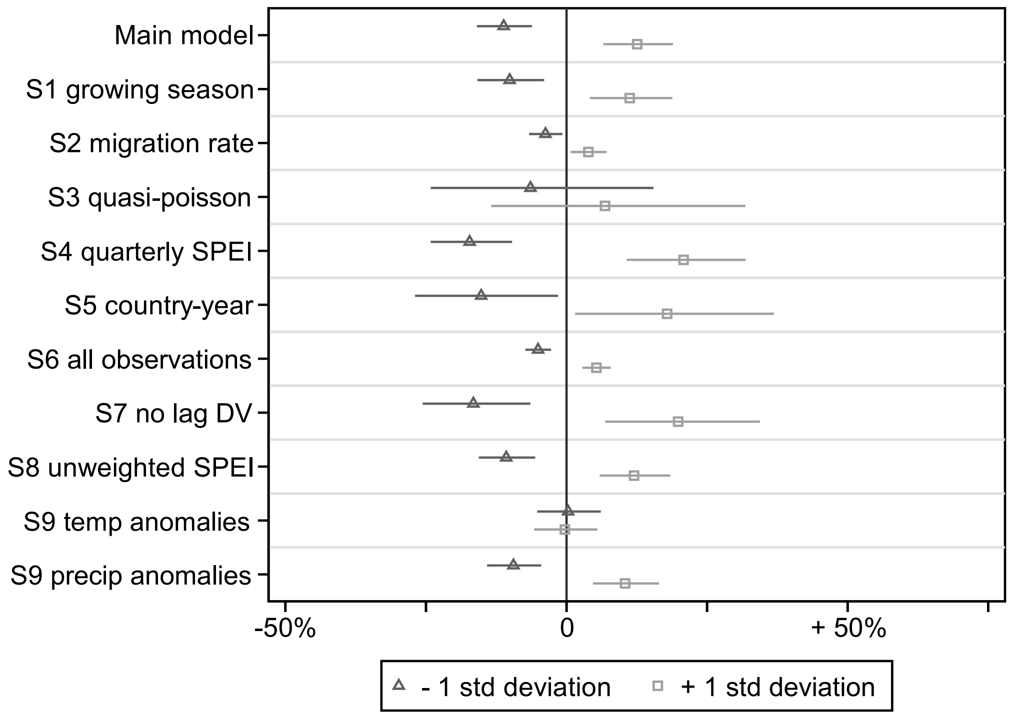

Figure 3: Results of the sensitivity analysis (Model 1)

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.

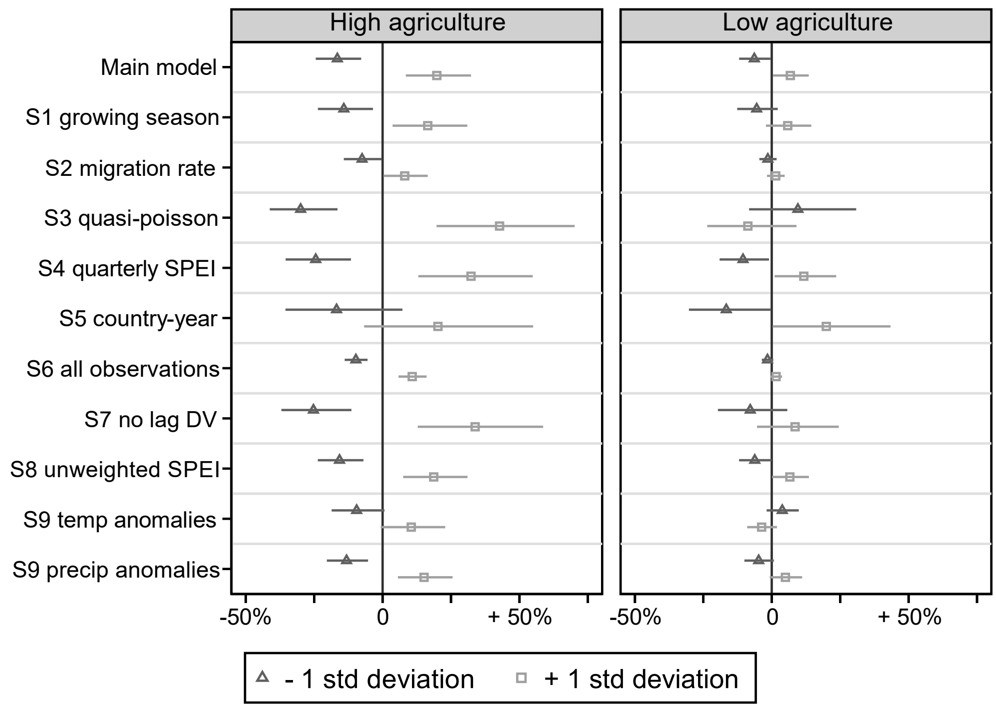

Figure 4: Results of the sensitivity analysis (Models 5–6)

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.

Climate Variability and Irregular Migration to the European Union

Appendix

Fabien Cottier† and Idean Salehyan‡

In the appendix, we first provide in Section A.1 additional information on the data on irregular migration flows provided by Frontex. Next in Section A.2, we present summary statistics based on Table 1 in the main text. Section A.3 presents the full results of Tables 2–3 in the main text. Finally, Section A.4 provides the results of the sensitivity analysis.

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† Lamont-Doherty Earth Observatory, Columbia University. Email: Fabien.Cottier@gmail.com. Corresponding author.
‡ Department of Political Science, University of North Texas. Email: Idean.Salehyan@unt.edu

A.1 Frontex data on irregular migration flows

The Frontex data is available in a monthly format, starting in 2009. The data measures the number of irregular migrants apprehended at EU external borders. The counts are disaggregated by country of origin and migration route (and further divided by land and sea borders where applicable). There are eight migration routes in total: *Western Africa, Western Mediterranean, Central Mediterranean*, *Eastern Mediterranean*, *Circular route from Albania to Greece*, *Western Balkans*, *Black Sea Route* and *Eastern Land Borders*, as well as a residual migration route, but it registers less than 50 irregular migrants over the whole period up to the end of 2017. Because of a risk of double counting migrants, which may have been apprehended a first time while transiting on the *Eastern Mediterranean* route before continuing the journey towards Western Europe through the Balkans, we exclude the two Balkan migration routes from the sample, as well as the residual migration route. As a consequence, we also remove Balkan countries from the sample. In section A.4 (Tables A.37–39), we show the results of models including data from these two routes. If anything, the results are in substance similar to those presented in the main text.

Figure A.1 plots the monthly rate of detection of irregular migrants for the eight largest sending countries in the sample (Syria, Afghanistan, Iraq, Eritrea, Nigeria, Pakistan, Somalia, Tunisia) between 2010 and 2015. As the data reveal, the so-called "2015 Migration Crisis" was driven by a steep increase in the detection of irregular migrants in just about three countries: Syria, Afghanistan and Iraq.

Finally, Table A.1 provides for each country in the sample the aggregate number of irregular migrants detected at the EU external borders over the period 2010–2015, corresponding to the timeframe of the empirical analysis (along with the number of migrants, for which the nationality is unknown). The table excludes data from the migration routes going through the Balkans.

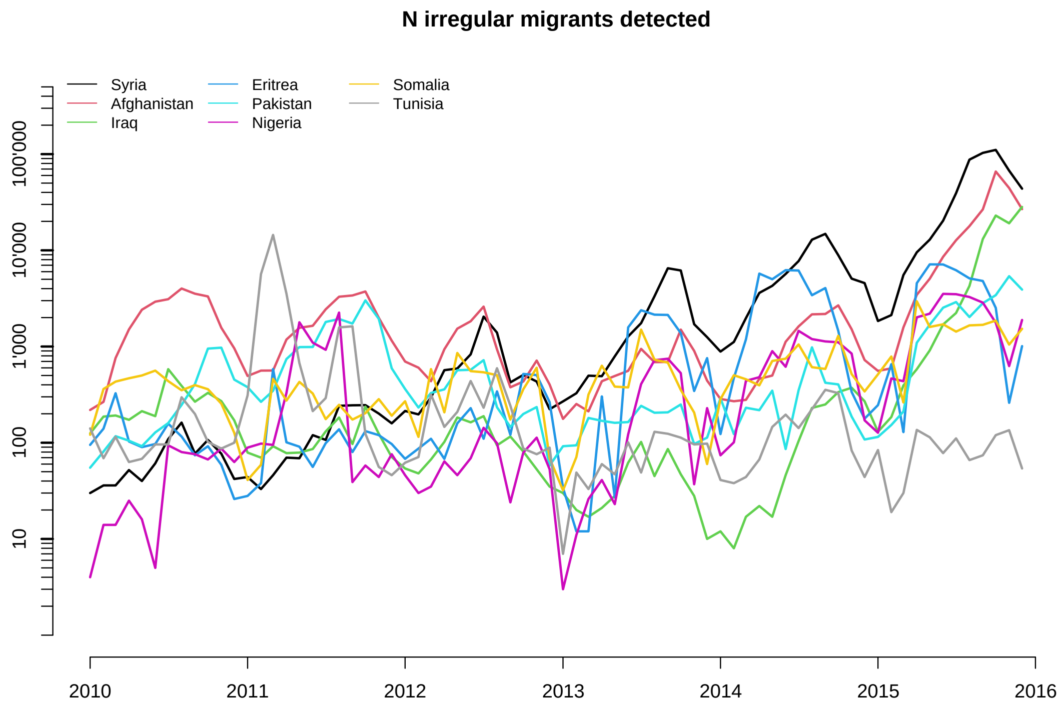

Figure A 1: Monthly number of irregular migrants for the 8 largest sending countries (2010–2015)

The plot is based on Frontex data on the detection of irregular migrants between border-crossing points aggregated across all migration routes, except 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.

Table A 1: Number of irregular migrants by sending country, excluding Balkan countries (2010–2015)

Nationality	N
Syria	610,072
Afghanistan	293,448
Iraq	101,633
Eritrea	90,764
Pakistan	54,489
Nigeria	42,324
Somalia	41,933
Tunisia	36,229
Iran	26,185
Bangladesh	25,248
Algeria	25,067
Morocco	23,770
Mali	22,565
Palestine	22,104
Gambia	21,415
Egypt	15,184
Sudan	14,752
Senegal	13,546
Ghana	11,254
Cote d'Ivoire	10,060
Guinea	9,406
Cameroon	5,772
Central African Republic	5,477
Congo, Rep	4,315
Ethiopia	4,266
Lebanon	2,661
Burkina Faso	2,491
Chad	2,345
Georgia	2,338
Libya	1,669
India	1,666
Guinea-Bissau	1,620
Turkey	1,504
Myanmar (Burma)	1,228
Congo, DRC	1,217
Vietnam	1,147
Moldova	1,117
Sierra Leone	1,110
Dominican Republic	1,083
Comoros	1,042
Togo	995
Sri Lanka	950

Nationality	N
Ukraine	795
Russia	744
Benin	700
Niger	664
Yemen	524
Mauritania	517
Nepal	502
Liberia	455
Uganda	404
China	400
Dominica	366
Rwanda	304
Gabon	254
Kenya	181
Armenia	160
Belarus	149
Jordan	145
Angola	139
Mongolia	112
Tanzania	111
Equatorial Guinea	84
Kuwait	79
Laos	61
Zimbabwe	58
Malawi	48
Uzbekistan	47
Burundi	43
Haiti	40
Zambia	37
South Africa	35
Philippines	33
North Korea	32
Cuba	29
Saudi Arabia	27
Western Sahara	26
Madagascar	25
Kazakhstan	19
Tajikistan	19
Mauritius	18
Colombia	16
Azerbaijan	15
Kyrgyzstan	15

Nationality	N
Israel	12
South Sudan	12
Jamaica	11
Turkmenistan	11
Ecuador	9
Indonesia	9
Djibouti	8
Malaysia	6
Bhutan	4
United States	4
Bolivia	3
Botswana	3
Brazil	3
Namibia	3
Oman	3
Panama	3
Peru	3
Cape Verde	2
Maldives	2
Mozambique	2
South Korea	2
Thailand	2
United Arab Emirates	2
Venezuela	2
Belize	1
Cambodia	1
Canada	1
Kiribati	1
Lesotho	1
Mexico	1
Papua New Guinea	1
Taiwan	1
Antigua & Barbuda	0
Argentina	0
Australia	0
Bahamas	0
Bahrain	0
Barbados	0
Brunei	0
Chile	0
Costa Rica	0
El Salvador	0
Eswatini	0
Fiji	0

Nationality	N
Grenada	0
Grenada	0
Guatemala	0
Guatemala	0
Guyana	0
Guyana	0
Honduras	0
Honduras	0
Japan	0
Japan	0
Marshall Islands	0
Marshall Islands	0
Micronesia	0
Micronesia	0
Palau	0
Singapore	0
Solomon Islands	0
St. Kitts & Nevis	0
St. Lucia	0
St. Vincent & Grenadines	0
Suriname	0
Timor-Leste	0
Tonga	0
Trinidad & Tobago	0
Tuvalu	0
Uruguay	0
Vanuatu	0
Nationality not specified	*49,344*
Total	1,615,366

A.2. Summary statistics

Table A.2 presents summary statistics of the main variables included in the empirical analysis, as well as a number of additional variables from the sensitivity analysis. The summary statistics are based on the sample of Table 1. Table A.3 then reports the correlation matrix between the population weighted SPEI variable and its two immediate lags and Figure A.2 shows a density plot of the SPEI variable, both based again on the sample for Table 1.

Table A 2: Summary statistics — Table 1 sample

	Obs	Mean	Std. deviation	Min	Max
N Migr	1536	1004.69	9407.456	0	229987
N Migr per 100K inhabitants (S2)	1520	6.061	55.763	0	1635.512
SPEI, pop weighted	1536	-0.036	0.389	-1.460	1.437
SPEI, pop weighted, growing season (S1)	1536	-0.045	0.426	-2.474	1.437
SPEI, pop weighted, quarterly (S4)	1536	-0.039	0.650	-2.918	2.054
SPEI, no weight (S7)	1536	-0.089	0.395	-1.593	1.433
Temp anomalies (S9)	1536	0.073	0.697	-2.699	2.215
Precip anomalies (S9)	1536	-0.069	0.932	-3.663	2.754

Table A 3: Correlation matrix SPEI — Table 1 sample

	SPEI (Y0)	*SPEI (Y-1)*	*SPEI (Y-2)*
SPEI (Y0)	1		
SPEI (Y-1)	0.229	1	
SPEI (Y-2)	0.289	0.265	1

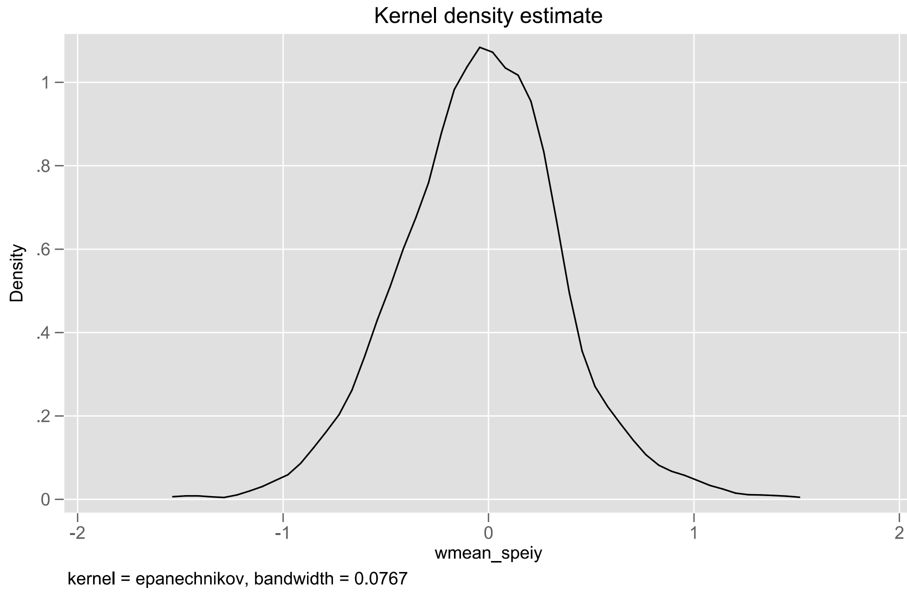

Figure A 2: Density plot SPEI — Table 1 sample

A.3 Additional analyses and complete results of Tables 2–3.

Tables A.4 and A.5 present the full results of Tables 2 and 3 in the main text, including additional specifications testing for an association between lag SPEI variables (Year-1 and Year-2) and irregular migration.

Table A 4: Full results — split sample models (Table 2, main models)

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.524**	0.564**	0.524**	0.564**	0.525**	0.562**	0.524**	0.561**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
N Migr, ln (Q-2)	-0.062	0.069+	-0.063	0.069+	-0.060	0.070+	-0.062	0.071+
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.137**	0.061	0.136**	0.061	0.140**	0.063	0.140**	0.064
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.008	0.050	0.008	0.050	0.012	0.052	0.012	0.053
	(0.03)	(0.06)	(0.03)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
SPEI (Y0)	0.464**	0.169*	0.467**	0.171*	0.429**	0.158+	0.421**	0.150+
	(0.12)	(0.08)	(0.12)	(0.07)	(0.13)	(0.08)	(0.14)	(0.08)
$SPEI^2$ (Y0)			0.067	0.045			0.086	0.030
			(0.11)	(0.11)			(0.13)	(0.11)
SPEI (Y-1)					-0.159	-0.076	-0.171	-0.074
					(0.16)	(0.08)	(0.16)	(0.09)
$SPEI^2$ (Y-1)							0.049	-0.012
							(0.23)	(0.10)
SPEI (Y-2)					-0.024	0.042	-0.041	0.038
					(0.09)	(0.15)	(0.09)	(0.15)
$SPEI^2$ (Y-2)							0.183	-0.128
							(0.18)	(0.20)
2nd quarter	0.861**	0.824**	0.861**	0.823**	0.860**	0.823**	0.861**	0.822**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
3rd quarter	0.796**	0.845**	0.796**	0.844**	0.791**	0.845**	0.792**	0.844**
	(0.09)	(0.11)	(0.09)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)
4th quarter	0.654**	0.501**	0.654**	0.502**	0.650**	0.503**	0.650**	0.500**
	(0.08)	(0.11)	(0.08)	(0.11)	(0.08)	(0.11)	(0.09)	(0.11)
Constant	0.719**	0.425*	0.714**	0.414+	0.672**	0.415*	0.647**	0.440*
	(0.13)	(0.20)	(0.14)	(0.20)	(0.13)	(0.20)	(0.14)	(0.21)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2025.083	1895.390	2026.869	1897.286	2027.236	1898.461	2031.841	1903.259
Joint F test (SPEI)	13.81**	4.85*	8.48**	3.17+	4.70**	2.54+	4.75**	1.65
CV rmse	1.478	1.112	1.487	1.115	1.438	1.098	1.463	1.104
N	768	768	768	768	768	768	768	768
N Countries	*32*	*32*	*32*	*32*	*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 A 5: Full results — split sample models (Table 3, main models)

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.532**	0.567**	0.527**	0.564**
	(0.05)	(0.05)	(0.05)	(0.05)
N Migr, ln (Q-2)	-0.060	0.069+	-0.063	0.078*
	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.131**	0.061	0.138**	0.063
	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.008	0.049	0.009	0.042
	(0.04)	(0.06)	(0.04)	(0.06)
Drought (Y0)	-0.312*	-0.063	-0.267+	-0.103
	(0.13)	(0.12)	(0.14)	(0.12)
Drought (Y-1)			0.230	-0.130
			(0.16)	(0.11)
Drought (Y-2)			0.068	-0.246
			(0.13)	(0.15)
Ex. rainfall (Y0)	0.375*	0.155*	0.366*	0.116*
	(0.14)	(0.07)	(0.14)	(0.05)
Ex. rainfall (Y-1)			-0.055	-0.110
			(0.13)	(0.10)
Ex. rainfall (Y-2)			0.134	-0.140
			(0.12)	(0.15)
2nd quarter	0.872**	0.825**	0.867**	0.824**
	(0.11)	(0.12)	(0.11)	(0.11)
3rd quarter	0.799**	0.836**	0.800**	0.846**
	(0.09)	(0.11)	(0.10)	(0.11)
4th quarter	0.653**	0.492**	0.655**	0.502**
	(0.08)	(0.11)	(0.09)	(0.11)
Constant	0.688**	0.405+	0.655**	0.516*
	(0.13)	(0.20)	(0.13)	(0.19)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	2030.101	1898.267	2034.026	1899.136
Joint F test (SPEI)	6.44**	2.91+	3.46**	1.84
CV rmse	1.460	1.102	1.470	1.111
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

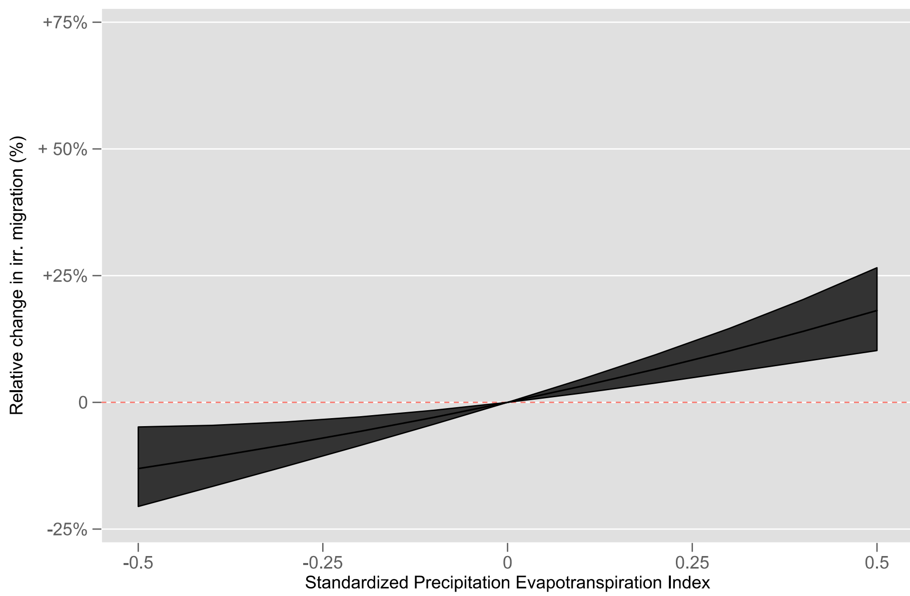

Figure A 3: Immediate effects of weather shocks on migration with 95% confidence interval (Model 2)

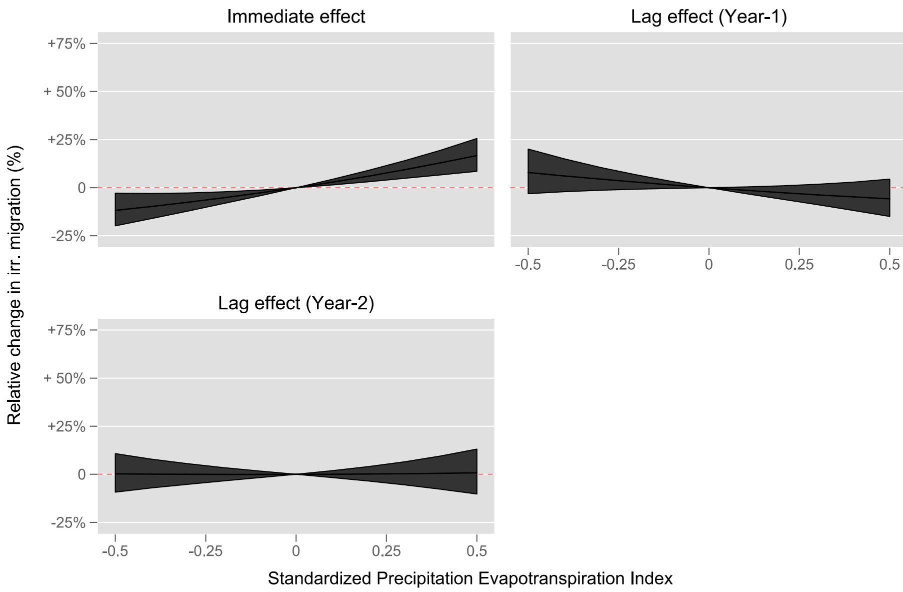

Figure A 4: Immediate and lag effects of weather shocks on migration with 95% confidence intervals (Model 4)

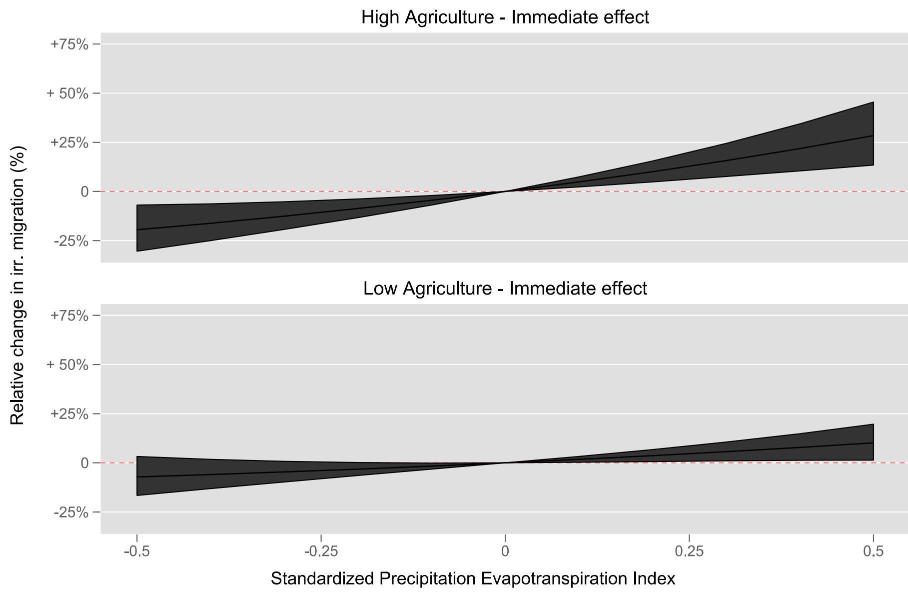

Figure A 5: Immediate effects of weather shocks on migration conditional on agriculture reliance with 95% confidence intervals (Models 7 and 8)

A.4 Sensitivity analysis

To assess the sensitivity of the findings presented in the main text to alternative specifications, we conducted thirteenth different sets of robustness checks. To do so, we reproduce each time the full results of the analysis (see Table 1 in the main text and Tables A.4–5 in Section A.3). In discussing the outcome of the sensitivity analysis, we mostly focus on the models with a single linear SPEI term (Models 1 and Models 5–6). Nonetheless, for reasons of consistency, we also replicate for each set of robustness checks the plots depicting the *immediate* effects of adverse weather shocks based on specifications including quadratic SPEI terms (see Figures A.3 and A.5). We discuss these plots in the text only when the results of models including quadratic terms markedly differ from linear models. As a word of caution, it is important to note from the outset that none of the models shown here indicate that including climate variables substantial improves the out-of-sample predictive ability, compared to a null model (see cross-validated root mean squared errors at the bottom of each table). Overall, this suggests —as we state in the paper— that it is very well possible that climatic variables may have no discernable effects on irregular migration towards the European Union.

First, we replace the primary SPEI indicator with a measure of soil moisture generated using information from the SPEI dataset during the growing season (S1). To do so, we draw on the PRIO-GRID (v 2.0), which provides information on the main crop harvested in a given area, along with information on the starting and ending months of the growing season (Tollefsen et al. 2012).[1] The data is provided at a raster resolution of 0.5 degree. To compute the *growing season* SPEI, we proceed similarly as for the main SPEI variable, but restrict the aggregation process of the underlying monthly SPEI cells to only the months corresponding to the growing season for the maincrop in each cell. The correlation between the SPEI and its *growing season* variant is high (ρ=0.89) over the period 2010-2015.[2] Tables A.6–7 present the results of this alternate specification (see also Figures A.6–7). In line with the models presented in the main text, the results suggest that droughts reduce irregular migration to the EU, in particular for country highly reliant on the agricultural sector for labor, and for large weather shocks. Regarding non-agrarian countries, the results are less clear-cut, but specifications

[1] The PRIO-GRID data on crop harvested area and the start and end dates of the growing season is provided by the MIRCA 2000 dataset (v 1.1.) (Portmann et al. 2010). The MIRCA 2000 dataset contains information on harvested area for 26 irrigated and rainfed crops and growing season across the globe at a 5 arc-minutes resolution.

[2] The intra-panel coefficients of correlation drop below 0.8 in only nine countries out of 64 in the sample for Model 1. Among these, Ethiopia is the only major outlier with a coefficient of correlation between the SPEI and SPEI growing season variables equal to 0.39.

including a quadratic SPEI term would suggest that wetter-than-usual conditions are associated with higher migration (See Figure A.7).

Second, we replicate the main analyses, but replace the dependent variable, measured in levels, by a rate variable, which measures the annual number of irregular migrants detected at EU external borders per 100,000 people in the country of origin (S2).[3] As for the primary dependent variable, this alternative operationalization of the dependent variable is added to the model log-transformed.[4] Tables A.9–11 and Figures A.8–9 in the Appendix present the results using this alternate specification.[5] In general, the conclusions obtained in the main set of models are not altered by this new specification, although the estimated effects appear smaller in comparison to the results reported in the main text. Weather shocks in non-agrarian countries are not associated with irregular migration. With regards to extreme events, we report tentative evidence consistent with the results of the main analysis (Table A.11).

Next, Tables A.12–14 and Figures A.10–11 replicate the main sets of models but replace the log-linearization of the model with a (fixed-effects) quasi-Poisson (S3) (Silva and Teynero 2006, 2011). We add this specification, because there may be concerns that the presence of zeroes in the dependent variable, which forces us to add unity before taking the natural logarithm, is susceptible to introduce bias in the estimates. In general, we note that the number of observations with zero migration is low in our data (about 7.6% for the sample of Table 1). Under this specification, the dependent variable is included directly in the estimated model, without taking logs. The results reported tend to mirror those reported in the main analysis when it comes to water surpluses but differ somewhat with regards to the effects of drought. Models including only a linear SPEI term are generally consistent with the effects of drought reported in the main text. However, after the inclusion of a quadratic term, we no longer find evidence that the incidence of a drought immediately decreases out-migration (Figure A.10), in particular for countries highly reliant on agriculture (Figure A.11).[6] Finally, the estimates of models for extreme weather events are generally not consistent with the results reported in prior models (Table A.14). Nonetheless, the estimates indicate that unusually high water surpluses in an agrarian country correlate with an increase in the level of migration detected at EU borders.

[3] The population data is provided by the World Development Indicators (World Bank 2019).
[4] We add unit prior to the log transformation.
[5] Under this specification, the sample is reduced to 1'520 observations, because of missing population data for specific years in Eritrea.
[6] Compared to models presented in the main text, the results of a χ^2 test supports adding a quadratic term to the equation estimated by a quasi-Poisson regression both for the sample pooling together agrarian and non-agrarian countries (Table 1 in the main text) and the sample of composed only of agrarian countries (Table 2 in the main text).

The next three sets of specifications examine the sensitivity to changes in the temporal resolution of the data and in the sample size. First, we replicate the main analysis, but use a SPEI measure based on the average 3-month SPEI in each quarter, instead of taking the average 3-month SPEI in the previous 12 months ending in the current quarter (S4) (Tables A.15–7, Figures A.12–13).[7] As expected, the data suggests that the dampening effect of a drought on irregular migration is initially close to zero and not statistically significant (for the contemporary quarterly measure), but then increases in magnitude in latter quarters and becomes significant (Table A.15). Depending on the set of countries considered, the effect peaks in the second quarter (3–5 months after the initial shock; non-agrarian countries) or the third quarter (6–8 months after the initial shock; agrarian countries) (see Table A.16). While it is difficult to speculate about the cause of this temporal discrepancy, we note that agrarian countries in the sample are located on average at a distance from the European Union twice as large in comparison to non-agrarian countries; thus requiring a longer journey.[8] To shed light on the aggregate *annual* effect and compared them to those obtained in the main text, we have linearly combined the coefficients by calendar year.[9] In general, the estimates for the *annualized* effects are of similar magnitude to those reported in the main text . For Model 1 (Table A.15), a severe drought (–0.75 *quarterly* SPEI) shock is predicted to dampen annual migration by about 20 %, while unusually wet conditions (+0.75 *quarterly* SPEI) would increase it by about 24%.[10] For the split sample analysis, the corresponding predicted annual impacts for shocks of similar magnitude are –28% and +38% for agrarian countries (Model 5, Table A.16) and –12% and +14% for non-agrarian countries (Model 6, Table A.16). As regards the estimates for models of extreme events, we find a similar immediate drought dampening effects, when linearly combining all the coefficients for the first year (Quarter 0 to Quarter –3), even though none of the quarterly coefficients are individually statistically significant (Table A.17). In substantive terms, a severe drought reduces the number of migrants

[7] Compared to the main models, this specification requires the inclusion of a large number of lag quarterly SPEI measures. For the models examining only the immediate impact (over the same year) of the SPEI variable on irregular migration, this involves one contemporary term (for the same quarter) and three lagged quarterly SPEI measures (three prior quarters). For the models examining the same association over the past two years, this requires the inclusion of no less than twelves quarterly SPEI measures (four for each year).

[8] The average distance from the EU for agrarian countries in the sample of Model 1 is 2,860 km (std. deviation: 1,567 km), respectively 1,645 km for non-agrarian countries (std. deviation: 1,612 km).

[9] We similarly depict the total annual effects of the SPEI using specifications with quadratic terms in Figures A.12–13.

[10] Careful readers will note that the magnitude of the SPEI shocks used to predict migration do not match the magnitude of the shocks reported in the main text (similarly, Figures A.12–13 differ with regards the SPEI scale). This is the result of the shorter temporal window at which the quarterly SPEI measure is aggregated compared to the main indicator (i.e., at intervals of three months, instead of twelve). Thus, the quarterly SPEI exhibits more variations. However, the magnitude of the SPEI events spans the same interval, i.e., approximately the range extending from the 10^{th} percentile to the 90^{th} percentile of the variable.

detected at EU external borders by about 38%, everything else being equal (Model 13).[11] Conversely, an excess level of rainfall increases the total annual level of migration by about 112 %. On the other hand, we find little evidence under this specification that large weather shocks affect irregular migration in non-agrarian countries.

Second, we aggregate the migration data to the annual level, dropping the quarterly resolution (S5). The sample is now reduced to 384 observations. In general, the results, presented in Tables A.18–20 and Figures A.14–15 are in line with the results reported in the main analysis when it comes to the pooled analysis, but differ for the analysis separating agrarian from non-agrarian countries. Although the point estimate of the SPEI variable for agrarian countries is of similar magnitude as the one for non-agrarian countries, we note that it is not statistically significant (see Models 5–6, Table A.19). By contrast, the results for extreme events are generally consistent with those reported in the main text (Table A.23).

Third, in Tables A.21–23 and Figures A.16–17, we report the results of models estimated using the complete sample of countries of origin in the Frontex dataset, irrespective of whether these countries sent a cumulative total of at least 100 migrants over the period 2009–2017 (S6). The new sample comprises 3,589 observations across 150 countries.[12] As a result, the median share of labor employed in the agricultural sector amounts to 31.6%, compared to 47.2% in the sample for the main set of models.[13] Under this specification, the estimates unambiguously indicate that the incidence of a drought results in an immediate decrease in the level of migration (Table A.21). This effect is driven primarily by countries which are highly dependent on the agricultural sector (Table A.22). Regarding extreme events, the results are similar to those reported in Table 3 (Table A.23).

Because controlling for past migration levels in the four prior quarter may have introduced bias in the results reported, we replicate in the next robustness check the main analysis but exclude the controls for the migration levels in the four prior quarters from the estimated equation (S7). The results, presented in Tables A.24–26 and Figures A.18–19, are in substance very similar to those reported in the main analysis, only of larger magnitude.[14]

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[11] This effect is significant at the 90% confidence interval in Model 13, but not in Model 15.

[12] Extending the sample to include all countries results in the share of quarterly observations registering zero migrant rising to 53.6%.

[13] In this regard, we note that the median value of labor employed in agriculture used to split the sample in the main text is high (47.2%). It results from the fact that countries, which have sent a cumulative total of at least 100 irregular migrants tend to be significantly more agrarian than those who did not.

[14] To ensure consistency between samples and enable the comparison of the results, we exclude observations for the year 2009 from the sample for this set of sensitivity analysis. The data for 2009 was previously excluded because of the inclusion

While population-weighting ensures that sparsely populated or deserted areas have less influence on the computation of the country-level SPEI measure compared to (rural) areas, where population levels are substantially higher, it also has the adverse consequence that urban areas are permitted to have a large influence. Given that we hypothesize that the effects of weather shocks are channeled through the agricultural sector, this represents a potential threat to our argument. In addition, it is possible that population may choose to strategically locate in areas more resilient to climate shocks (see Hsiang and Jina 2014: 15 fn 12). Hence, we assess the sensitivity of the empirical models to the operationalization rule of the SPEI, by generating an alternative measure taking a simple average of the annual SPEI across countries, instead of a population weighted measure (S8). We present the results in Tables A.27–29 and Figures A.20–21. In general, we find little evidence that the weighting scheme influence the findings of the main text reported in Tables 1–3. Episodes of drought correlate with a decrease in irregular migration to the European Union. This is not surprising given that the correlation coefficient between the population weighted SPEI and the simple average SPEI is about 0.89, reflecting spatial co-variance in weather patterns (based on the sample for Table 1 in the main text). The only noticeable difference is that the coefficient for extreme water surpluses in non-agrarian countries is no longer statistically significant (Table A.29).

Next, we replace the main independent variable, *SPEI*, with two variables measuring *annual* anomalies in temperature and precipitation (S9).[15] The results are presented in Table A.30–32 and Figures A.22–24. To do so, we use data provided by the Climate Research Unit (CRU TS series 3.25).[16] We generate the anomalies data in the same way as for the SPEI data. We first take the average precipitation/temperature over the current quarter and the previous nine months and then take a population-weighted average over the entire country. For each country, we subtract the long-term mean value from each quarterly temperature and precipitation realization and standardize over 1970-2016 period ($\frac{x_{itq}-\overline{x_{\iota q}}}{\sigma_{iq}}$).[17] To correct for trending in the variables measuring anomalies (i.e., due to climate change), we use the 10-year moving average for $\bar{x}$. Table A.30 reproduces Table 1. We find

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of lagged migration variables for the four prior quarters in the estimated equation. Replicating the models with the Frontex data for 2009 does not substantively alter the results.

[15] Similarly, as for the main analysis, we estimate this set of a model on a sample extending from 2010 to 2015 to facilitate comparisons, even though CRU 3.25 data extends until 2016. Extending the analysis to 2016, however, does not appreciatively alter the results.

[16] The SPEI is based on the temperature and precipitation data from the Climate Research Unit (TS series 3.25). It should be noted that the SPEI variable is highly correlated with precipitation anomalies (ρ= 0.74). By contrast, it is only weakly correlated with temperature anomalies (ρ = –0.10) (based on sample for Model 1, Table 1 in the main text).

[17] The data for the CRU TS 3.25 extends until 2016.

little evidence that temperature anomalies correlate generally with the detection of irregular migrants at the EU external borders. By contrast, and consistent with the results reported in the main text, we find that reduced levels of precipitation have a dampening effect on migration, and conversely for higher than usual levels of precipitation (see also Figures A.22). When it comes to the analyses carried out on sub-samples (Table A.31), precipitation deficits and surpluses are again associated with a decrease, respectively an increase, in migration in agrarian countries (see also Figure A.24). Regarding temperature anomalies, we find tentative evidence that higher temperature than usual is associated with more out-migration in countries highly reliant on the agricultural sector for labor (see also Figure A.23).[18] The analysis of extreme events suggests a similar picture. The coefficients for high temperature and high levels of rainfall are both statistically significant in agrarian countries, and tentatively so for lower levels of rainfall (see Table A.32).[19] In light of the results reported for the SPEI and precipitation anomalies, the result for temperature anomalies in agrarian countries can be considered a puzzle. While it is hard to speculate about what lies behind this correlation, it is possible that it may hint at a distinct pathway through which higher temperature could potentially influence migration rates, for instance through an amenity mechanism (Marchiori et al. 2012: 356), or through a separate effect of heat on crop yields (Schlenker and Roberts 2009).

The two next robustness checks examine the appropriateness of splitting the sample into groups of countries depending on their reliance on agriculture for labor. To do so, we first replicate the split samples analyses (only Tables A.4 and A.5), but this time we divide the sample between rich and poor countries (S10).[20] Tables A.33–34 present the results of this specification. Albeit hinting at possibly larger impact of weather shocks in poorer countries, the results of the analyses are very similar in the two samples: Drought exerts a dampening effect on migration in both samples, and conversely for periods of surpluses in the water balance (Table A.33, see also Figure A.25). When it comes to extreme events, the results are again very similar in both samples, except for the coefficient for severe droughts, which is only significant in the sample of poorer countries. Overall, we interpret these evidence as suggestive that if drought influences irregular migration to the European Union, this effect

[18] It should be noted that the SPEI variable is highly correlated with precipitation anomalies (ρ= 0.74). By contrast, it is only weakly correlated with temperature anomalies (ρ = –0.08). At face values, this may indicate that the effect of temperature on migration is distinct from the effect of drought and excess water balance.

[19] In a similar way as the models using the SPEI, we define extreme weather events as precipitation and temperature anomalies below or equal to the 10th percentile, respectively above or equal to the 90th percentiles.

[20] The median GDP per capita at purchase power parity value in the sample is 3,816 USD at constant 2011 USD. Countries below the median are classified as poor. In general, the correlation between the share of agriculture in total employment and GDP per capita is moderate (ρ = –0.55). The GDP data is provided by the World Development Indicators (World Bank 2019).

is probably rather channeled by its impact on agriculture, proxied here by the share of labor employed in this sector.

We next replicate again the analysis but split the sample into two alternate groups of countries, those located on the African continent, and those located elsewhere in the world (S11). We do so because there may be unobserved factors specific to African countries, which could both heighten the impact of drought on societies (e.g., recurrence of armed conflict), and facilitate migration (e.g., such as established migration routes, large diasporas in European countries). Compared to the sample of countries highly reliant on agriculture for labor (32 countries), the sample of Africa countries is made of 38 countries, of which 24 are classified as agrarian countries in Tables 2–3 of the main paper. The results of this set of models are presented in Tables A.35–A.36. In general, the results are very similar to those presented in Tables 2–3 of the main paper in both the size and statistical significance of the estimates (see also Figure A.26), despite the addition of 14 additional African countries and the removal of eight non-African countries highly reliant on agriculture for labor. If anything, the SPEI coefficient for agrarian countries is slightly larger than the same coefficient for the sample made exclusively of African countries (compare the results of Model 1, Table 2 in the main text with the results reported in Model 1, Table A.35). Overall, we believe that these results are indicative that the impact of weather shocks on irregular migration is probably primarily mediated through the impact of these shocks on the agricultural sector. Yet, as we note in the main text, we cannot rule out, based on the evidence presented here, that the results we report in the main text are driven by some other unobserved characteristics of the sample specific to the African continent.

Furthermore, there may be concerns that by excluding estimates from the Balkan migration routes, this may have influenced our results. Therefore, we replicate again the entire set of estimated models, but replace the dependent variable with an alternative operationalization, which includes as well the number of migrants from the previously excluded migration routes: The *Western Balkan Route*, the *Circular Route from Albania to Greece* and the residual "Other" migration route (S12). In effect, we now run the analysis on a slightly larger sample (N=1694). This is because, we compute the list of countries, which sent a cumulative toral of more than 100 migrants over the period 2009-2017, based on these new data. Compared to the original sample, the new sample is composed of 71 countries, including six Balkans countries: Albania, Bosnia and Herzegovina, Croatia, Kosovo, Macedonia and

Serbia.[21] The results, which are in general substantively similar, if less precisely estimated, to those reported in the main text, are presented in Tables A.37–39 and Figures A.27–28. Nevertheless, we remain wary of drawing any inference from these data, due to two major limitations a) the risk of double counting migrants (for a discussion, see Section 3.1 of the main text) and b) the large number of migrants for whom nationality is unspecified on the *Western Balkan Migration Route* in late 2015. Indeed, including this route in the data significantly increases the share of unspecified nationality, as border agencies in Hungary, and elsewhere, essentially stopped recording the nationality of migrants in late 2015 (the share of unspecified nationality of migrants reaches 50% in November 2015).

In a final set of models, we correct the estimates of standard errors to account for potential spatial correlation in the errors across panels (S13). To do so, we use the procedure developed by Hsiang (2010, see also Conley 1999, 2008) to adjust standard errors for spatial and serial correlation in OLS. Standard errors are adjusted for spatial correlation between countries whose population-weighted centroids lie within 1,000 kilometers of each others (together with lag length of 2 for serial autocorrelation).[22] The results of these specifications are presented in Tables A.40–42 and Figures A.39–30. In general, adjusting for spatial autocorrelation in the errors does not affect the conclusion of the empirical analysis.[23,24]

[21] Croatia is only part of the sample until the end of the second quarter of 2013. After its admission to the European Union on July 1st 2013, it is removed from the sample. In addition to the Balkan countries, Cuba is now also part of the sample, as it has sent a cumulative total of more than 100 migrants across all migration routes over the period 2009–2017.
[22] The lag of order 2 was chosen based on existing practices in the literature. In effect, it is based on the fourth root of the total number of periods ($24^{1/4}$) (see Greene 2018: 999). In line with the weighting scheme of the gridded SPEI data, we compute population-weighted centroids of countries, instead of area-weighted centroids.
[23] We have considered different distance cutoffs (from 100 km to 2,000 km), but these do not appear to have much effect on the estimated standard errors.
[24] We do not show cross-validated RMSE in Tables A.40–42, since these are by definition identical to those shown in Tables 1–3 in the main text and Tables A.4–5 in the appendix.

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Table A 6: Main Models — SPEI growing season

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Q-1)	0.552**	0.549**	0.549**	0.546**
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-2)	-0.004	-0.005	-0.002	-0.003
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-3)	0.109**	0.110**	0.113**	0.113**
	(0.03)	(0.03)	(0.03)	(0.03)
N Migr, ln (Q-4)	0.027	0.029	0.031	0.032
	(0.03)	(0.03)	(0.03)	(0.03)
SPEI (Y0)	0.250**	0.285**	0.225**	0.260**
	(0.08)	(0.06)	(0.08)	(0.07)
$SPEI^2$ (Y0)		0.150**		0.147**
		(0.05)		(0.05)
SPEI (Y-1)			-0.165*	-0.163*
			(0.08)	(0.08)
$SPEI^2$ (Y-1)				-0.010
				(0.09)
SPEI (Y-2)			0.014	0.021
			(0.08)	(0.07)
$SPEI^2$ (Y-2)				-0.006
				(0.11)
2nd quarter	0.841**	0.840**	0.839**	0.837**
	(0.08)	(0.08)	(0.08)	(0.08)
3rd quarter	0.817**	0.817**	0.813**	0.813**
	(0.07)	(0.07)	(0.07)	(0.07)
4th quarter	0.579**	0.580**	0.576**	0.577**
	(0.07)	(0.07)	(0.07)	(0.07)
Constant	0.556**	0.534**	0.531**	0.512**
	(0.12)	(0.12)	(0.12)	(0.12)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	3922.409	3919.558	3919.829	3921.046
Joint F test (SPEI)	10.41**	13.83**	7.21**	7.33**
CV rmse	1.250	1.259	1.230	1.238
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 A 7: Split sample models — SPEI growing season

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.527**	0.568**	0.524**	0.561**	0.526**	0.564**	0.523**	0.557**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
N Migr, ln (Q-2)	-0.059	0.072+	-0.060	0.069+	-0.056	0.073+	-0.057	0.071+
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.142**	0.062	0.142**	0.064	0.146**	0.065	0.146**	0.068
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.007	0.049	0.008	0.053	0.012	0.051	0.013	0.056
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
SPEI (Y0)	0.359*	0.133	0.404**	0.162+	0.328*	0.117	0.368**	0.144
	(0.13)	(0.09)	(0.10)	(0.08)	(0.14)	(0.10)	(0.10)	(0.09)
$SPEI^2$ (Y0)			0.142**	0.222			0.143**	0.196
			(0.04)	(0.15)			(0.04)	(0.13)
SPEI (Y-1)					-0.186	-0.104	-0.183	-0.119
					(0.14)	(0.09)	(0.12)	(0.09)
$SPEI^2$ (Y-1)							0.038	-0.082
							(0.12)	(0.10)
SPEI (Y-2)					-0.041	0.078	-0.054	0.062
					(0.06)	(0.13)	(0.06)	(0.13)
$SPEI^2$ (Y-2)							0.170	-0.142
							(0.12)	(0.15)
2nd quarter	0.861**	0.826**	0.863**	0.820**	0.858**	0.824**	0.867**	0.815**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.11)
3rd quarter	0.795**	0.846**	0.798**	0.842**	0.786**	0.847**	0.795**	0.839**
	(0.09)	(0.11)	(0.09)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)
4th quarter	0.656**	0.501**	0.655**	0.505**	0.647**	0.504**	0.649**	0.500**
	(0.08)	(0.11)	(0.08)	(0.11)	(0.09)	(0.11)	(0.09)	(0.11)
Constant	0.691**	0.405+	0.673**	0.371+	0.647**	0.400+	0.596**	0.428+
	(0.13)	(0.21)	(0.14)	(0.21)	(0.12)	(0.21)	(0.14)	(0.22)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2026.853	1896.570	2025.681	1896.103	2027.083	1898.258	2029.109	1899.586
Joint F test (SPEI)	7.09*	2.18	14.54**	2.82+	6.14**	2.44+	6.51**	4.54**
CV rmse	1.435	1.100	1.446	1.110	1.390	1.084	1.413	1.096
N	768	768	768	768	768	768	768	768
N Countries	*32*	*32*	*32*	*32*	*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 A 8: Large Weather Shocks — SPEI growing season

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.524**	0.569**	0.524**	0.565**
	(0.05)	(0.05)	(0.05)	(0.05)
N Migr, ln (Q-2)	-0.057	0.073+	-0.053	0.078*
	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.137**	0.061	0.144**	0.063
	(0.03)	(0.05)	(0.03)	(0.05)
N Migr, ln (Q-4)	0.004	0.050	0.009	0.050
	(0.04)	(0.06)	(0.04)	(0.06)
Drought (Y0)	-0.317*	-0.115	-0.281+	-0.133+
	(0.14)	(0.08)	(0.15)	(0.08)
Drought (Y-1)			0.146	-0.015
			(0.20)	(0.12)
Drought (Y-2)			0.171	-0.304+
			(0.14)	(0.16)
Ex. rainfall (Y0)	0.439**	0.067	0.397**	0.029
	(0.12)	(0.09)	(0.12)	(0.10)
Ex. rainfall (Y-1)			-0.207	-0.098
			(0.13)	(0.11)
Ex. rainfall (Y-2)			0.005	-0.113
			(0.11)	(0.17)
2nd quarter	0.867**	0.826**	0.863**	0.814**
	(0.11)	(0.12)	(0.11)	(0.11)
3rd quarter	0.805**	0.843**	0.806**	0.839**
	(0.10)	(0.11)	(0.10)	(0.11)
4th quarter	0.649**	0.496**	0.652**	0.496**
	(0.08)	(0.11)	(0.09)	(0.11)
Constant	0.670**	0.401+	0.623**	0.501*
	(0.12)	(0.20)	(0.13)	(0.23)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	2024.214	1899.332	2026.706	1899.338
Joint F test (SPEI)	10.20**	1.23	5.94**	1.87
CV rmse	1.453	1.081	1.403	1.089
AIC	2024.214	1899.332	2026.706	1899.338
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

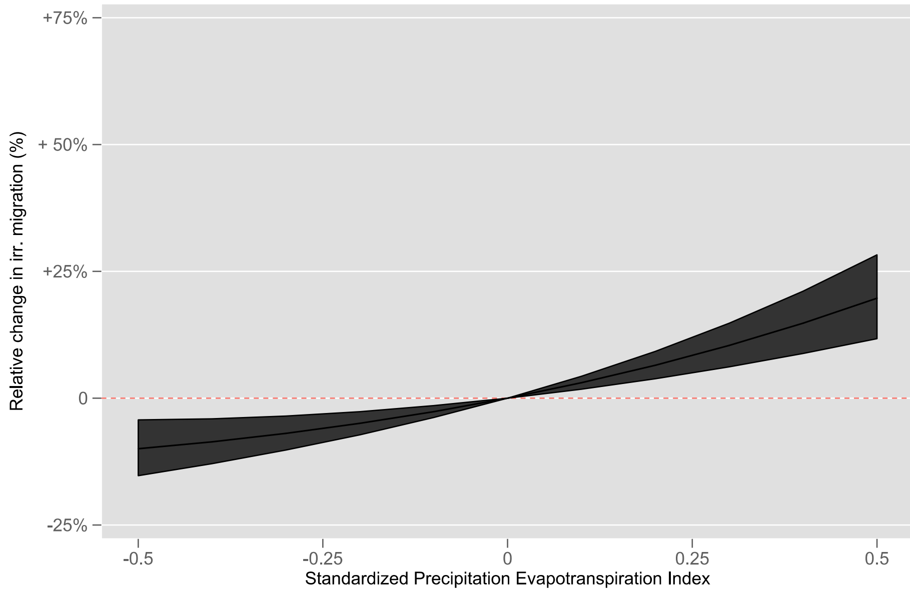

Figure A 6: SPEI growing season — Immediate effects of weather shocks on migration with 95% confidence interval (Model 2, Table A.6).

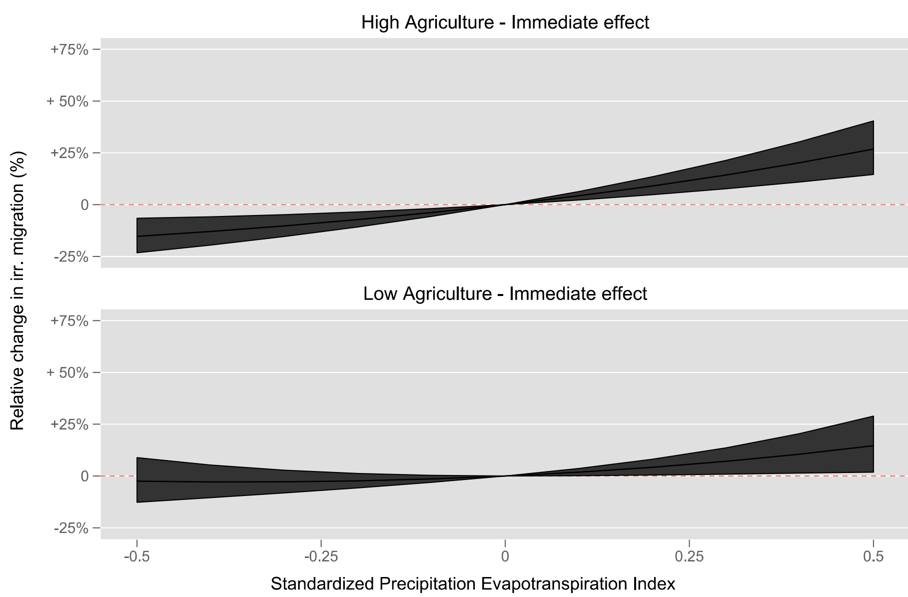

Figure A 7: SPEI growing season — Immediate effects of weather shocks on migration conditional on agriculture reliance with 95% confidence interval (Model 7 and 8, Table A.7)

Table A 9: Main Models — N Migrants per 100,000 inhabitants

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Q-1)	0.764**	0.760**	0.760**	0.753**
	(0.06)	(0.06)	(0.06)	(0.06)
N Migr, ln (Q-2)	-0.172*	-0.174*	-0.170*	-0.169*
	(0.07)	(0.07)	(0.07)	(0.07)
N Migr, ln (Q-3)	0.125	0.124	0.130	0.128
	(0.09)	(0.09)	(0.09)	(0.09)
N Migr, ln (Q-4)	0.083	0.085	0.089	0.097
	(0.06)	(0.06)	(0.06)	(0.06)
SPEI (Y0)	0.098*	0.101**	0.088*	0.097*
	(0.04)	(0.04)	(0.04)	(0.04)
$SPEI^2$ (Y0)		0.063		0.051
		(0.05)		(0.04)
SPEI (Y-1)			-0.067	-0.066
			(0.05)	(0.05)
$SPEI^2$ (Y-1)				-0.109
				(0.11)
SPEI (Y-2)			0.069	0.076
			(0.05)	(0.05)
$SPEI^2$ (Y-2)				-0.045
				(0.06)
2^{nd} quarter	0.251**	0.250**	0.251**	0.248**
	(0.04)	(0.04)	(0.04)	(0.04)
3^{rd} quarter	0.182**	0.182**	0.183**	0.180**
	(0.03)	(0.03)	(0.03)	(0.03)
4^{th} quarter	0.088*	0.089*	0.090*	0.088*
	(0.04)	(0.04)	(0.04)	(0.04)
Constant	-0.012	-0.022	-0.019	-0.001
	(0.05)	(0.05)	(0.05)	(0.05)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	1583.519	1583.804	1577.943	1576.171
Joint F test (SPEI)	6.15*	4.16*	2.42+	2.36*
CV rmse	0.363	0.369	0.365	0.363
N	1520	1520	1520	1520
N Countries	*64*	*64*	*64*	*64*

Std. errors clustered by country. CV rmse null model: 0.353
+ p<0.10, * p<0.05, ** p<0.01

Table A 10: Split sample models — N Migrants per 100,000 inhabitants

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.691**	0.821**	0.673**	0.820**	0.690**	0.813**	0.664**	0.810**
	(0.05)	(0.11)	(0.05)	(0.11)	(0.05)	(0.11)	(0.06)	(0.11)
N Migr, ln (Q-2)	-0.204**	-0.140	-0.211**	-0.140	-0.199**	-0.137	-0.203**	-0.135
	(0.05)	(0.14)	(0.05)	(0.14)	(0.05)	(0.14)	(0.05)	(0.14)
N Migr, ln (Q-3)	0.169**	0.042	0.163**	0.042	0.175**	0.042	0.170**	0.041
	(0.03)	(0.19)	(0.03)	(0.19)	(0.03)	(0.19)	(0.03)	(0.19)
N Migr, ln (Q-4)	0.000	0.192	0.003	0.192	0.008	0.195	0.029	0.197
	(0.02)	(0.12)	(0.02)	(0.12)	(0.02)	(0.12)	(0.04)	(0.12)
SPEI (Y0)	0.200*	0.037	0.214*	0.038	0.176*	0.039	0.208*	0.033
	(0.09)	(0.04)	(0.09)	(0.04)	(0.08)	(0.04)	(0.10)	(0.04)
SPEI² (Y0)			0.192*	0.014			0.170*	0.008
			(0.09)	(0.05)			(0.08)	(0.05)
SPEI (Y-1)					-0.102	-0.014	-0.097	-0.013
					(0.09)	(0.04)	(0.08)	(0.04)
SPEI² (Y-1)							-0.186	-0.008
							(0.20)	(0.05)
SPEI (Y-2)					0.020	0.085	0.022	0.082
					(0.05)	(0.06)	(0.06)	(0.06)
SPEI² (Y-2)							0.052	-0.092
							(0.08)	(0.08)
2nd quarter	0.267**	0.239**	0.266**	0.239**	0.266**	0.239**	0.262**	0.239**
	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)
3rd quarter	0.180**	0.179**	0.181**	0.178**	0.178**	0.180**	0.178**	0.180**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
4th quarter	0.130*	0.045	0.129*	0.045	0.128*	0.049	0.131*	0.046
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Constant	0.047	-0.056	0.031	-0.059	0.029	-0.051	0.024	-0.026
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)	(0.06)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	865.432	682.388	860.543	684.342	865.618	682.112	857.818	685.320
Joint F test (SPEI)	4.50*	0.84	3.04+	0.68	1.58	1.19	2.86*	1.19
CV rmse	0.445	0.333	0.466	0.333	0.434	0.336	0.454	0.338
N	752	768	752	768	752	768	752	768
N Countries	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*

Std errors clustered by country. CV rmse null models: 0.415 (agrarian sample) and 0.329 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

Table A 11: Large weather shocks — N Migrants per 100,000 inhabitants

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.693**	0.822**	0.687**	0.811**
	(0.05)	(0.11)	(0.05)	(0.10)
N Migr, ln (Q-2)	-0.200**	-0.141	-0.205**	-0.132
	(0.05)	(0.14)	(0.05)	(0.14)
N Migr, ln (Q-3)	0.166**	0.042	0.175**	0.040
	(0.03)	(0.19)	(0.03)	(0.18)
N Migr, ln (Q-4)	0.001	0.192	0.010	0.190
	(0.02)	(0.12)	(0.02)	(0.12)
Drought (Y0)	-0.092+	0.010	-0.082+	-0.013
	(0.05)	(0.06)	(0.04)	(0.06)
Drought (Y-1)			0.035	-0.069
			(0.05)	(0.06)
Drought (Y-2)			0.017	-0.192*
			(0.08)	(0.08)
Ex. rainfall (Y0)	0.214+	0.043	0.209+	0.031
	(0.12)	(0.03)	(0.11)	(0.03)
Ex. rainfall (Y-1)			-0.122	0.002
			(0.08)	(0.04)
Ex. rainfall (Y-2)			0.075	-0.039
			(0.08)	(0.06)
2nd quarter	0.271**	0.240**	0.266**	0.239**
	(0.06)	(0.04)	(0.06)	(0.04)
3rd quarter	0.183**	0.177**	0.180**	0.178**
	(0.04)	(0.04)	(0.04)	(0.04)
4th quarter	0.131*	0.042	0.131*	0.047
	(0.05)	(0.05)	(0.05)	(0.05)
Constant	0.028	-0.064	0.019	-0.005
	(0.05)	(0.06)	(0.05)	(0.06)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	866.861	684.375	868.433	679.970
Joint F test (SPEI)	2.12	1.34	1.80	1.39
CV rmse	0.445	0.332	0.443	0.342
N	752	768	752	768
N Countries	*32*	*32*	*32*	*32*

Std errors clustered by country. CV rmse null models: 0.415 (agrarian sample) and 0.329 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

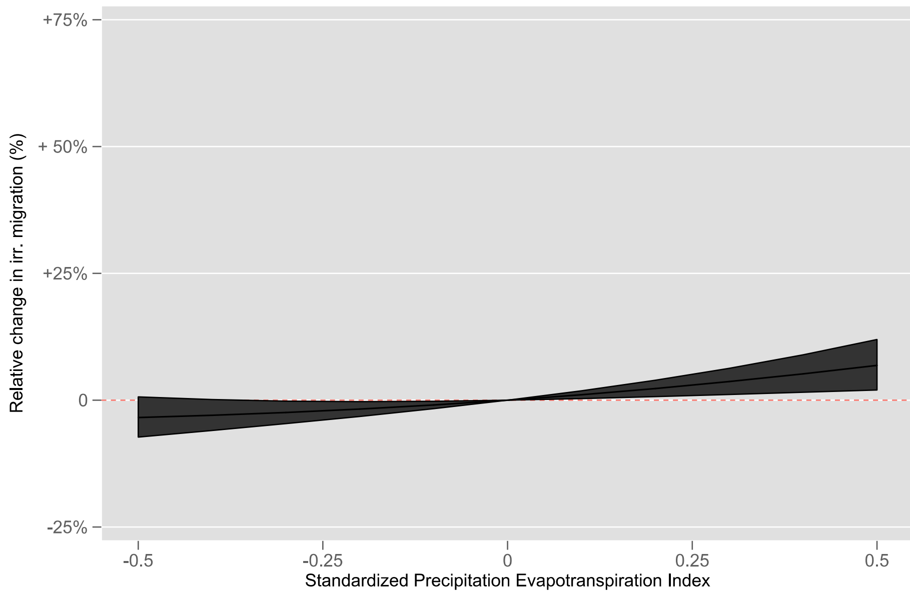

Figure A 8: Number of migrants per 100,000 inhabitants — Immediate effects of weather shocks on migration (Model 2, Table A.9)

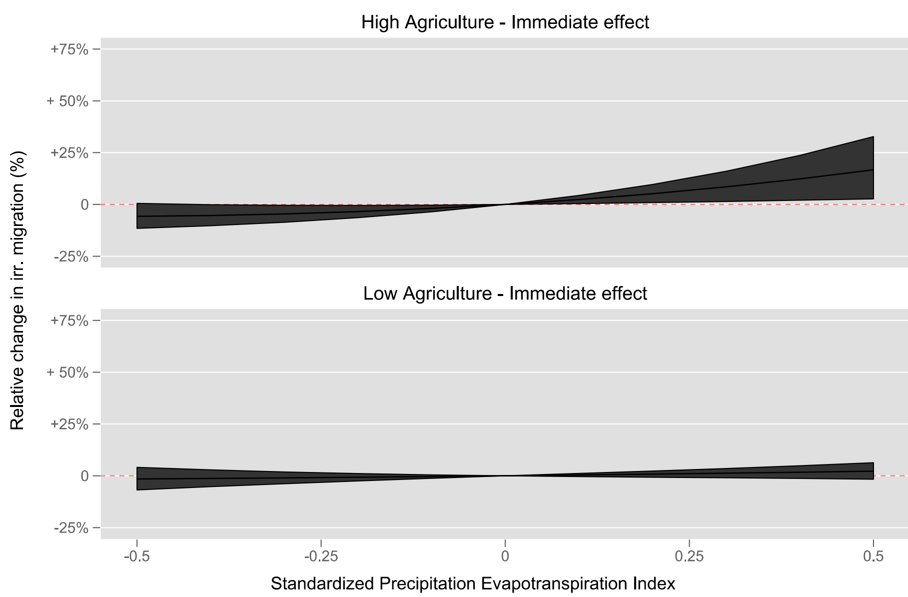

Figure A 9: Number of migrants per 100,000 inhabitants — Immediate effects of weather shocks on migration conditional on agri. reliance (Models 7 and 8, Table A.11)

Table A 12: Main models — Quasi-Poisson

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Q-1)	0.630**	0.610**	0.642**	0.596**
	(0.09)	(0.09)	(0.10)	(0.10)
N Migr, ln (Q-2)	-0.081	-0.099	-0.087	-0.104
	(0.10)	(0.09)	(0.10)	(0.09)
N Migr, ln (Q-3)	0.126	0.110	0.110	0.100
	(0.18)	(0.18)	(0.17)	(0.17)
N Migr, ln (Q-4)	0.093	0.156	0.101	0.158
	(0.14)	(0.15)	(0.14)	(0.15)
SPEI (Y0)	0.170	0.264	0.018	0.242
	(0.28)	(0.20)	(0.26)	(0.24)
$SPEI^2$ (Y0)		0.875*		0.740+
		(0.43)		(0.41)
SPEI (Y-1)			-0.283	-0.453+
			(0.22)	(0.24)
$SPEI^2$ (Y-1)				-0.467+
				(0.27)
SPEI (Y-2)			0.362+	0.188
			(0.19)	(0.21)
$SPEI^2$ (Y-2)				-0.443
				(0.36)
2^{nd} quarter	1.134**	1.018**	1.135**	1.016**
	(0.31)	(0.32)	(0.33)	(0.34)
3^{rd} quarter	1.072**	0.945*	1.042**	0.935*
	(0.40)	(0.41)	(0.40)	(0.42)
4^{th} quarter	0.739*	0.663+	0.775*	0.675+
	(0.35)	(0.34)	(0.34)	(0.36)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Joint chi2 test (SPEI)	0.38	4.50	12.28**	46.17**
CV rmse	6164.208	6198.004	6207.225	6146.084
N	1536	1536	1536	1536
N Countries	*64*	*64*	*64*	*64*

Heteroskedasticity robust std. errors. CV rmse null model: 5845.168
+ p<0.10, * p<0.05, ** p<0.01

Table A 13: Split sample models — Quasi-Poisson

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.744**	0.628**	0.630**	0.618**	0.686**	0.606**	0.602**	0.592**
	(0.17)	(0.11)	(0.11)	(0.11)	(0.13)	(0.11)	(0.10)	(0.12)
N Migr, ln (Q-2)	-0.352**	-0.031	-0.294**	-0.044	-0.312**	-0.018	-0.257**	-0.037
	(0.12)	(0.05)	(0.08)	(0.05)	(0.09)	(0.04)	(0.07)	(0.05)
N Migr, ln (Q-3)	0.436*	-0.040	0.366**	-0.045	0.363**	-0.053	0.302**	-0.073
	(0.18)	(0.14)	(0.13)	(0.15)	(0.10)	(0.14)	(0.08)	(0.12)
N Migr, ln (Q-4)	-0.152*	0.244	-0.056*	0.278	-0.102+	0.246	-0.022	0.289
	(0.06)	(0.21)	(0.02)	(0.23)	(0.06)	(0.21)	(0.05)	(0.23)
SPEI (Y0)	0.914**	-0.234	0.770**	-0.099	0.811**	-0.262	0.679**	0.065
	(0.23)	(0.23)	(0.21)	(0.21)	(0.18)	(0.24)	(0.21)	(0.24)
$SPEI^2$ (Y0)			1.770**	0.539			1.764**	0.242
			(0.42)	(0.62)			(0.49)	(0.55)
SPEI (Y-1)					-0.813*	0.099	-0.670**	0.042
					(0.35)	(0.19)	(0.21)	(0.20)
$SPEI^2$ (Y-1)							0.429	-0.098
							(0.66)	(0.46)
SPEI (Y-2)					-0.037	0.469*	-0.151	0.309
					(0.17)	(0.24)	(0.19)	(0.24)
$SPEI^2$ (Y-2)							0.842**	-0.999*
							(0.30)	(0.47)
2nd quart.	1.521**	0.902+	1.407**	0.822	1.513**	0.916	1.442**	0.832
	(0.21)	(0.53)	(0.17)	(0.56)	(0.18)	(0.56)	(0.16)	(0.61)
3rd quart.	0.768**	1.038+	0.747**	0.972	0.810**	1.028	0.816**	0.977
	(0.17)	(0.63)	(0.14)	(0.66)	(0.19)	(0.66)	(0.17)	(0.70)
4th quart.	1.170**	0.410	0.943**	0.402	1.126**	0.507	0.916**	0.410
	(0.32)	(0.46)	(0.24)	(0.46)	(0.29)	(0.48)	(0.24)	(0.54)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Joint chi2 test (SPEI)	15.74**	1.01	78.16**	1.32	205.81**	4.63	203.00**	51.37**
CV rmse	6151.055	6130.395	6228.762	6162.172	6186.825	6204.672	6227.337	6165.344
N	768	768	768	768	768	768	768	768
N Country	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*

Heteroskedasticity robust std. errors. CV rmse null models: 5930.408 (agrarian sample) and 5818.323 (non-agrarian sample).

+ p<0.10, * p<0.05, ** p<0.01

Table A 14: Large weather shocks — Quasi-Poisson

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.656**	0.635**	0.580**	0.541**
	(0.12)	(0.11)	(0.12)	(0.10)
N Migr, ln (Q-2)	-0.252**	-0.050	-0.197**	-0.019
	(0.09)	(0.05)	(0.07)	(0.08)
N Migr, ln (Q-3)	0.324**	-0.048	0.289**	-0.022
	(0.12)	(0.14)	(0.07)	(0.11)
N Migr, ln (Q-4)	-0.071	0.258	-0.025	0.265
	(0.05)	(0.22)	(0.08)	(0.19)
Drought (Y0)	0.277	0.308	0.283	0.130
	(0.32)	(0.27)	(0.28)	(0.15)
Drought (Y-1)			0.587*	-0.542**
			(0.27)	(0.20)
Drought (Y-2)			0.141	-1.085**
			(0.11)	(0.28)
Ex. rainfall (Y0)	0.823**	-0.380*	0.741**	-0.078
	(0.16)	(0.17)	(0.13)	(0.25)
Ex. rainfall (Y-1)			-0.228	0.014
			(0.36)	(0.23)
Ex. rainfall (Y-2)			0.321**	-0.318
			(0.12)	(0.37)
2nd quarter	1.436**	0.889	1.382**	0.779
	(0.17)	(0.55)	(0.10)	(0.50)
3rd quarter	0.665**	1.056+	0.682**	0.769
	(0.13)	(0.64)	(0.14)	(0.71)
4th quarter	0.954**	0.434	0.966**	0.274
	(0.23)	(0.46)	(0.21)	(0.54)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Joint chi2 test (SPEI)	25.74**	5.57+	164.15**	83.48**
CV rmse	6178.990	6119.864	6240.213	6162.154
N	768	768	768	768
N Countries	*32*	*32*	*32*	*32*

Heteroskedasticity robust std. errors. CV rmse null models: 5930.408 (agrarian sample) and 5818.323 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

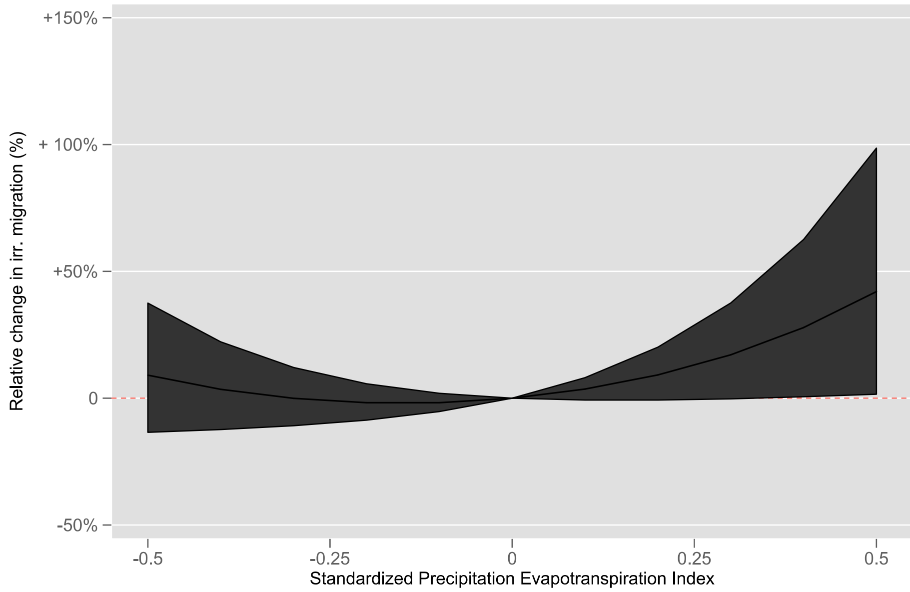

Figure A 10: Quasi-Poisson — Immediate effects of weather shocks on migration (Model 2, Table A.12)

Note the wider scale of the y axis.

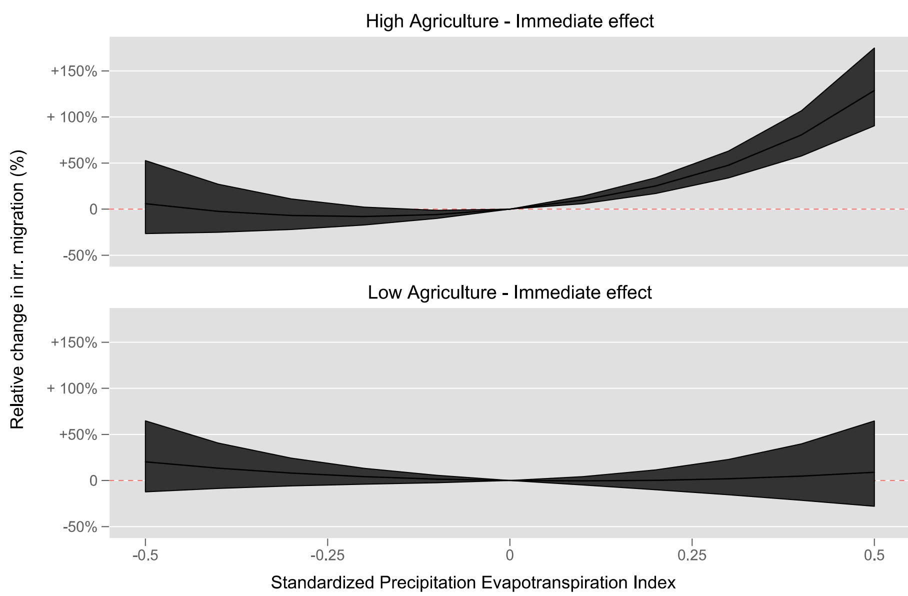

Figure A 11: Quasi-Poisson — Immediate effects of weather shocks on migration conditional on agriculture reliance (Models 7 and 8, Table A.13)

Note the wider scale of the y axis.

Table A 15: Main models — Quarterly SPEI Measure

	Model 1	*Model 2*	*Model 3*	*Model 4*
SPEI (Q0)	0.007	0.005	0.004	0.002
	(0.04)	(0.04)	(0.04)	(0.04)
$SPEI^2$ (Q0)		0.021		0.031
		(0.04)		(0.04)
SPEI (Q-1)	0.113*	0.115*	0.105*	0.109*
	(0.04)	(0.05)	(0.04)	(0.04)
$SPEI^2$ (Q-1)		0.017		0.015
		(0.05)		(0.05)
SPEI (Q-2)	0.082+	0.086*	0.074+	0.073+
	(0.04)	(0.04)	(0.04)	(0.04)
$SPEI^2$ (Q-2)		0.054		0.060+
		(0.03)		(0.03)
SPEI (Q-3)	0.090*	0.093*	0.080*	0.081*
	(0.04)	(0.04)	(0.03)	(0.04)
$SPEI^2$ (Q-3)		0.025		0.036
		(0.03)		(0.03)
SPEI (Q-4)			-0.009	-0.004
			(0.04)	(0.04)
$SPEI^2$ (Q-4)				0.005
				(0.04)
SPEI (Q-5)			-0.047	-0.040
			(0.04)	(0.04)
$SPEI^2$ (Q-5)				0.056+
				(0.03)
SPEI (Q-6)			-0.047	-0.050
			(0.04)	(0.04)
$SPEI^2$ (Q-6)				0.050
				(0.03)
SPEI (Q-7)			-0.031	-0.028
			(0.05)	(0.04)
$SPEI^2$ (Q-7)				-0.020
				(0.04)
SPEI (Q-8)			0.032	0.040
			(0.04)	(0.04)
$SPEI^2$ (Q-8)				0.035
				(0.04)
SPEI (Q-9)			-0.045	-0.046
			(0.04)	(0.04)
$SPEI^2$ (Q-9)				0.015
				(0.04)
SPEI (Q-10)			-0.007	-0.001
			(0.04)	(0.04)
$SPEI^2$ (Q-10)				-0.034
				(0.04)
SPEI (Q-11)			0.040	0.043
			(0.04)	(0.04)
$SPEI^2$ (Q-11)				0.024
				(0.03)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	3921.665	3926.612	3930.546	3945.066
Joint F test (SPEI)	5.77**	4.34**	2.45*	3.15**
CV rmse	1.281	1.292	1.262	1.291
N	1536	1536	1536	1536
N Countries	64	*64*	*64*	*64*

Std. errors clustered by country. CV rmse null model: 1.232
Constant, lag migration variables and quarterly dummies omitted from the table.
+ p<0.10, * p<0.05, ** p<0.01

Table A 16: Split sample models — Quarterly SPEI Measure

	Model 5 *High Agr.*	*Model 6* *Low Agr.*	*Model 7* *High Agr.*	*Model 8* *Low Agri*	*Model 9* *High Agr.*	*Model 10* *Low Agr.*	*Model 11* *High Agr.*	Model 12 Low Agr.
SPEI (Q0)	0.041	-0.010	0.036	-0.010	0.045	-0.009	0.050	-0.017
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
SPEI² (Q0)			0.013	0.030			0.015	0.030
			(0.05)	(0.06)			(0.05)	(0.06)
SPEI (Q-1)	0.101+	0.121+	0.105+	0.121+	0.087	0.110	0.083	0.122+
	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.05)	(0.07)
SPEI² (Q-1)			0.003	0.024			0.013	0.013
			(0.08)	(0.06)			(0.07)	(0.06)
SPEI (Q-2)	0.191*	-0.021	0.194**	-0.018	0.183*	-0.023	0.172*	-0.029
	(0.07)	(0.05)	(0.07)	(0.05)	(0.08)	(0.05)	(0.08)	(0.05)
SPEI² (Q-2)			0.100**	0.010			0.086*	0.022
			(0.03)	(0.05)			(0.03)	(0.06)
SPEI (Q-3)	0.098+	0.081	0.100+	0.088+	0.084+	0.079	0.094*	0.087+
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
SPEI² (Q-3)			-0.006	0.065			-0.001	0.070
			(0.04)	(0.05)			(0.04)	(0.05)
SPEI (Q-4)					-0.009	0.005	0.011	-0.000
					(0.07)	(0.06)	(0.07)	(0.06)
SPEI² (Q-4)							0.075	-0.050
							(0.06)	(0.05)
SPEI (Q-5)					-0.103	0.004	-0.095	0.017
					(0.07)	(0.04)	(0.07)	(0.04)
SPEI² (Q-5)							0.035	0.086*
							(0.05)	(0.04)
SPEI (Q-6)					0.058	-0.115*	0.046	-0.121*
					(0.07)	(0.05)	(0.06)	(0.04)
SPEI² (Q-6)							0.100*	-0.005
							(0.04)	(0.05)
SPEI (Q-7)					-0.108	0.027	-0.091	0.021
					(0.08)	(0.06)	(0.07)	(0.05)
SPEI² (Q-7)							-0.020	-0.016
							(0.06)	(0.06)
SPEI (Q-8)					0.042	0.049	0.043	0.056
					(0.05)	(0.06)	(0.05)	(0.06)
SPEI² (Q-8)							0.071	0.001
							(0.06)	(0.06)
SPEI (Q-9)					-0.059	-0.033	-0.058	-0.041
					(0.06)	(0.06)	(0.05)	(0.07)
SPEI² (Q-9)							0.029	-0.003
							(0.07)	(0.05)
SPEI (Q-10)					0.005	-0.019	0.028	-0.016
					(0.05)	(0.06)	(0.06)	(0.06)
SPEI² (Q-10)							-0.073	-0.021
							(0.07)	(0.05)
SPEI (Q-11)					0.026	0.053	0.040	0.060
					(0.06)	(0.05)	(0.07)	(0.05)
SPEI² (Q-11)							-0.016	0.064
							(0.06)	(0.05)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2027.486	1897.196	2032.062	1903.397	2037.005	1904.636	2039.557	1911.250
Joint F test (SPEI)	5.14**	1.82	3.44**	1.53	2.43*	2.88**	6.50**	3.96**
CV rmse	1.467	1.127	1.487	1.128	1.442	1.109	1.511	1.131
N	768	768	768	768	768	768	768	768
N Countries	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*

Std. errors clustered by country. CV rmse null models: 1.377 (agrarian sample) and 1.092 (non-agrarian sample).
Constant, lag migration variables and quarterly dummies omitted from the table.
+ p<0.10, * p<0.05, ** p<0.01

Table A 17: Large Weather Shocks— Quarterly SPEI Measure

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
Drought (Q0)	-0.100	-0.033	-0.068	-0.017
	(0.11)	(0.13)	(0.12)	(0.13)
Drought (Q-1)	-0.172	-0.136	-0.151	-0.140
	(0.12)	(0.11)	(0.13)	(0.12)
Drought (Q-2)	-0.071	-0.100	-0.055	-0.071
	(0.13)	(0.09)	(0.13)	(0.10)
Drought (Q-3)	-0.132	0.013	-0.120	0.022
	(0.12)	(0.10)	(0.12)	(0.11)
Drought (Q-4)			0.210	-0.062
			(0.20)	(0.13)
Drought (Q-5)			0.075	0.076
			(0.12)	(0.10)
Drought (Q-6)			0.157	0.205+
			(0.12)	(0.11)
Drought (Q-7)			0.082	-0.052
			(0.12)	(0.13)
Drought (Q-8)			0.094	0.020
			(0.11)	(0.12)
Drought (Q-9)			0.102	0.031
			(0.18)	(0.10)
Drought (Q-10)			0.067	0.014
			(0.21)	(0.11)
Drought (Q-11)			-0.014	0.172
			(0.12)	(0.10)
Ex. rainfall (Q0)	0.193*	0.063	0.167+	0.070
	(0.09)	(0.11)	(0.10)	(0.10)
Ex. rainfall (Q-1)	0.017	0.012	0.006	0.013
	(0.16)	(0.11)	(0.16)	(0.11)
Ex. rainfall (Q-2)	0.484**	-0.120	0.431**	-0.128
	(0.14)	(0.10)	(0.15)	(0.10)
Ex. rainfall (Q-3)	0.057	0.151	0.043	0.152
	(0.13)	(0.09)	(0.13)	(0.10)
Ex. rainfall (Q-4)			-0.093	-0.069
			(0.14)	(0.11)
Ex. rainfall (Q-5)			-0.165	0.106
			(0.12)	(0.10)
Ex. rainfall (Q-6)			0.021	-0.172+
			(0.12)	(0.09)
Ex. rainfall (Q-7)			-0.157	0.103
			(0.14)	(0.10)
Ex. rainfall (Q-8)			0.043	0.000
			(0.13)	(0.12)
Ex. rainfall (Q-9)			-0.018	-0.086
			(0.13)	(0.08)
Ex. rainfall (Q-10)			-0.083	-0.059
			(0.11)	(0.11)
Ex. rainfall (Q-11)			0.031	0.189
			(0.11)	(0.12)
Cntr FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
AIC	2034.614	1905.372	2046.404	1909.082
Joint F test (SPEI)	4.30**	1.29	2.66**	6.88**
CV rmse	1.490	1.105	1.460	1.116
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). Constant, lag migration variables and quarterly dummies omitted from the table.
+ p<0.10, * p<0.05, ** p<0.01

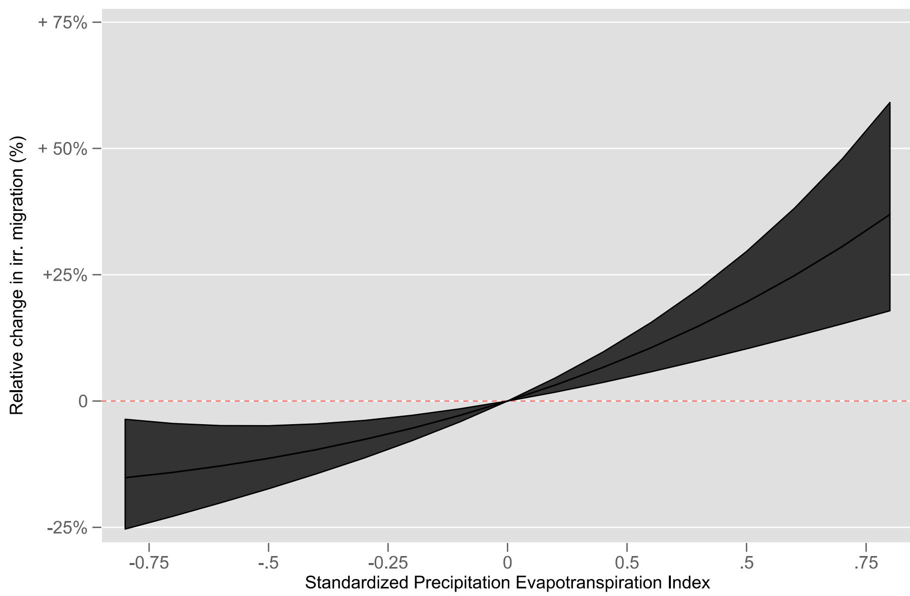

Figure A 12: Quarterly SPEI measure — Immediate effects of weather shocks on migration (Model 2, Table A.15)

Quarterly coefficients have been linearly combined to produce annual estimates.

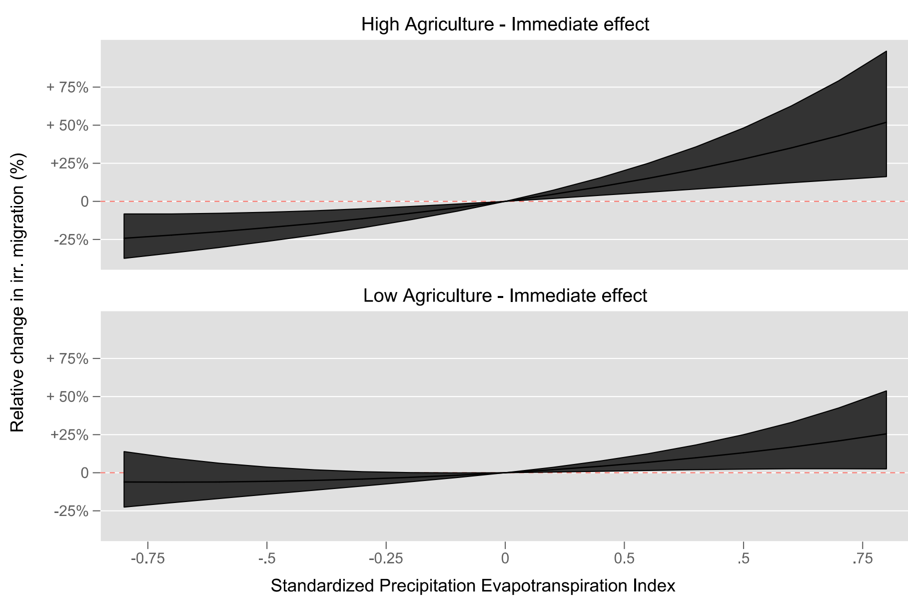

Figure A 13: Quarterly SPEI measure — Immediate effects of weather shocks on migration conditional on agri. reliance (Models 7 and 8, Table A.16)

Quarterly coefficients have been linearly combined to produce annual estimates.

Table A 18: Main models — Country-year analysis

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Y-1)	0.326**	0.327**	0.316**	0.311**
	(0.06)	(0.06)	(0.06)	(0.06)
SPEI (Y0)	0.423*	0.442*	0.439*	0.472*
	(0.19)	(0.18)	(0.19)	(0.18)
$SPEI^2$ (Y0)		0.300		0.336
		(0.29)		(0.31)
SPEI (Y-1)			0.200	0.199
			(0.16)	(0.15)
$SPEI^2$ (Y-1)				0.235
				(0.21)
SPEI (Y-2)			-0.116	-0.076
			(0.17)	(0.16)
$SPEI^2$ (Y-2)				0.230
				(0.21)
Constant	3.204**	3.130**	3.267**	3.149**
	(0.31)	(0.32)	(0.30)	(0.31)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	1013.888	1013.928	1015.272	1018.026
Joint F test (SPEI)	4.85*	3.87*	2.77*	2.52*
CV rmse	2.897	2.907	2.954	3.012
N	384	384	384	384
N Countries	*64*	*64*	*64*	*64*

Std. errors clustered by country. CV rmse null model: 2.826
+ p<0.10, * p<0.05, ** p<0.01

Table A 19: Split sample models — Country-year analysis

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Y-1)	0.258**	0.415**	0.258**	0.420**	0.239**	0.406**	0.238**	0.416**
	(0.07)	(0.11)	(0.07)	(0.11)	(0.07)	(0.11)	(0.07)	(0.11)
SPEI (Y0)	0.473	0.467*	0.474	0.461*	0.531	0.468*	0.488	0.514*
	(0.32)	(0.23)	(0.35)	(0.22)	(0.34)	(0.23)	(0.36)	(0.24)
$SPEI^2$ (Y0)			0.002	0.672			0.118	0.624
			(0.48)	(0.45)			(0.51)	(0.49)
SPEI (Y-1)					0.277	0.142	0.294	0.166
					(0.25)	(0.23)	(0.22)	(0.22)
$SPEI^2$ (Y-1)							0.541*	-0.311
							(0.26)	(0.37)
SPEI (Y-2)					-0.024	-0.177	-0.034	-0.099
					(0.27)	(0.21)	(0.25)	(0.22)
$SPEI^2$ (Y-2)							0.102	0.284
							(0.30)	(0.36)
Constant	3.442**	2.837**	3.442**	2.592**	3.573**	2.867**	3.496**	2.599**
	(0.31)	(0.57)	(0.31)	(0.58)	(0.33)	(0.57)	(0.35)	(0.57)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	524.996	493.404	526.996	491.726	527.439	496.005	530.270	496.728
Joint F test (SPEI)	2.19	4.30*	1.25	7.25**	0.95	2.79+	3.73**	2.87*
CV rmse	3.214	2.627	3.151	2.615	3.234	2.587	3.312	2.647
N	192	192	192	192	192	192	192	192
N Countries	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*

Std. errors clustered by country. CV rmse null models: 2.956 (agrarian sample) and 2.588 (non-agrarian sample).

+ p<0.10, * p<0.05, ** p<0.01

Table A 20: Large weather shocks — Country-year analysis

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Y-1)	0.240**	0.419**	0.222**	0.418**
	(0.07)	(0.11)	(0.07)	(0.10)
Drought (Y0)	-0.745*	0.225	-0.658+	0.185
	(0.27)	(0.40)	(0.35)	(0.41)
Drought (Y-1)			0.266	-0.678
			(0.35)	(0.44)
Drought (Y-2)			0.270	-0.172
			(0.33)	(0.34)
Ex. rainfall (Y0)	0.520	0.333*	0.651	0.436*
	(0.42)	(0.15)	(0.44)	(0.20)
Ex. rainfall (Y-1)			0.595+	0.079
			(0.31)	(0.23)
Ex. rainfall (Y-2)			0.245	0.111
			(0.32)	(0.34)
Constant	3.513**	2.708**	3.528**	2.786**
	(0.30)	(0.59)	(0.31)	(0.54)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	520.972	498.607	523.614	501.194
Joint F test (SPEI)	4.46*	2.41	2.57*	1.25
CV rmse	3.279	2.596	3.366	2.658
N	192	192	192	192
N Countries	*32*	*32*	*32*	*32*

Std. errors clustered by country: 2.956 (agrarian sample) and 2.588 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

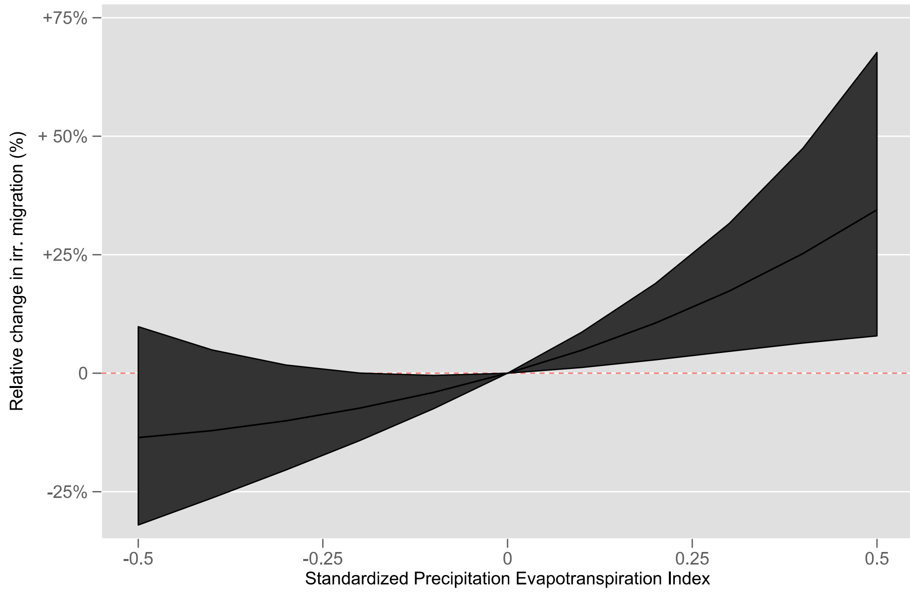

Figure A 14: Country-year analysis — Immediate effects of weather shocks on migration (Model 2, Table A.18)

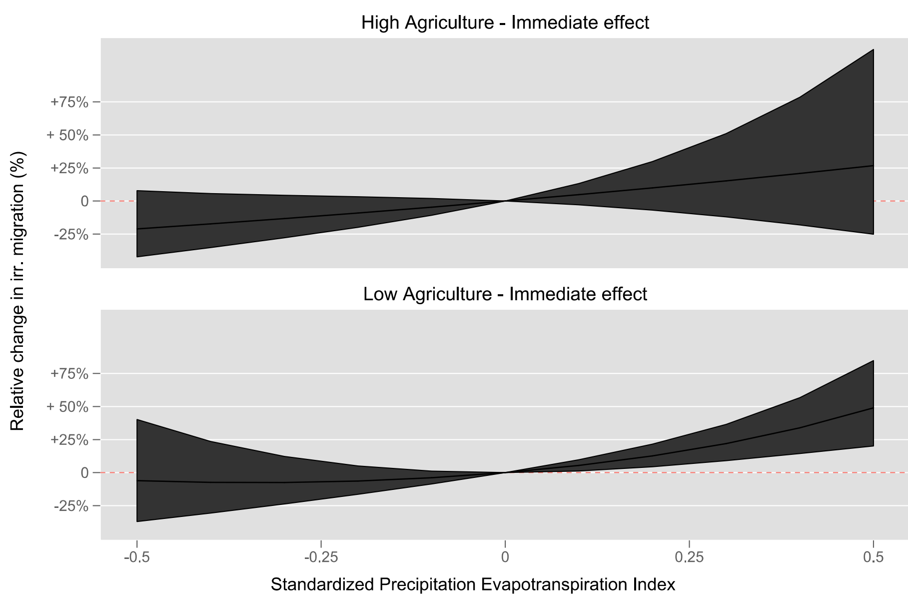

Figure A 15: Country-year analysis — Immediate effects of weather shocks on migration conditional on agriculture reliance (Models 7and 8, Table A.19)

Table A 21: Main models — All observations

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Q-1)	0.541**	0.541**	0.541**	0.540**
	(0.03)	(0.03)	(0.03)	(0.03)
N Migr, ln (Q-2)	0.005	0.005	0.006	0.006
	(0.03)	(0.03)	(0.03)	(0.03)
N Migr, ln (Q-3)	0.091**	0.091**	0.092**	0.093**
	(0.03)	(0.03)	(0.03)	(0.03)
N Migr, ln (Q-4)	0.049+	0.049+	0.050+	0.050+
	(0.03)	(0.03)	(0.03)	(0.03)
SPEI (Y0)	0.121**	0.121**	0.122**	0.119**
	(0.03)	(0.03)	(0.03)	(0.03)
$SPEI^2$ (Y0)		0.007		0.009
		(0.04)		(0.04)
SPEI (Y-1)			-0.033	-0.038
			(0.04)	(0.04)
$SPEI^2$ (Y-1)				0.052
				(0.05)
SPEI (Y-2)			0.045	0.046
			(0.04)	(0.04)
$SPEI^2$ (Y-2)				0.020
				(0.04)
2nd quarter	0.371**	0.371**	0.371**	0.372**
	(0.05)	(0.05)	(0.05)	(0.05)
3rd quarter	0.394**	0.394**	0.394**	0.396**
	(0.04)	(0.04)	(0.04)	(0.04)
4th quarter	0.251**	0.251**	0.251**	0.253**
	(0.04)	(0.04)	(0.04)	(0.04)
Constant	0.249**	0.248**	0.244**	0.228**
	(0.06)	(0.06)	(0.06)	(0.06)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	7235.570	7237.543	7234.799	7239.146
Joint F test (SPEI)	18.22**	9.55**	6.73**	5.05**
CV rmse	0.996	0.996	0.996	0.996
N	3589	3589	3588	3588
N Countries	*150*	*150*	*150*	*150*

Std. errors clustered by country. CV rmse null model: 0.987
+ p<0.10, * p<0.05, ** p<0.01

Table A 22: Split sample models — All observations

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.537**	0.529**	0.537**	0.528**	0.536**	0.528**	0.536**	0.527**
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
N Migr, ln (Q-2)	-0.028	0.060	-0.028	0.061	-0.027	0.061	-0.027	0.062
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-3)	0.118**	0.050	0.118**	0.051	0.120**	0.050	0.120**	0.052
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)
N Migr, ln (Q-4)	0.018	0.119+	0.018	0.120+	0.020	0.118+	0.020	0.120*
	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)
SPEI (Y0)	0.240**	0.037	0.241**	0.031	0.232**	0.042+	0.231**	0.034
	(0.05)	(0.02)	(0.05)	(0.03)	(0.05)	(0.02)	(0.05)	(0.03)
SPEI² (Y0)			-0.004	0.048			0.009	0.047
			(0.06)	(0.05)			(0.06)	(0.05)
SPEI (Y-1)					-0.075	0.024	-0.080	0.028
					(0.07)	(0.03)	(0.07)	(0.04)
SPEI² (Y-1)							0.032	0.032
							(0.09)	(0.05)
SPEI (Y-2)					0.062	0.034	0.051	0.043
					(0.05)	(0.05)	(0.05)	(0.05)
SPEI² (Y-2)							0.071	-0.053
							(0.07)	(0.06)
2nd quarter	0.492**	0.236**	0.492**	0.237**	0.491**	0.237**	0.491**	0.237**
	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)
3rd quarter	0.470**	0.302**	0.470**	0.304**	0.469**	0.303**	0.470**	0.304**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
4th quarter	0.366**	0.134**	0.366**	0.136**	0.365**	0.134**	0.364**	0.136**
	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)
Constant	0.348**	0.140	0.348**	0.128	0.333**	0.143	0.320**	0.139
	(0.08)	(0.11)	(0.08)	(0.11)	(0.08)	(0.11)	(0.09)	(0.10)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	4263.442	2785.507	4265.439	2786.586	4262.948	2788.435	4267.828	2791.587
Joint F test (SPEI)	19.54**	2.17	9.73**	2.73+	7.21**	1.12	4.50**	1.85
CV rmse	1.088	0.916	1.089	0.911	1.079	0.911	1.085	0.918
N	1920	1656	1920	1656	1920	1656	1920	1656
N Countries	*80*	*69*	*80*	*69*	*80*	*69*	*80*	*69*

Std. errors clustered by country. CV rmse null models: 1.059 (agrarian sample) and 0.893 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

Table A 23: Large weather shocks — All observations

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.540**	0.528**	0.538**	0.526**
	(0.04)	(0.06)	(0.04)	(0.06)
N Migr, ln (Q-2)	-0.026	0.062	-0.027	0.065
	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-3)	0.114**	0.050	0.116**	0.049
	(0.03)	(0.05)	(0.03)	(0.05)
N Migr, ln (Q-4)	0.019	0.120+	0.021	0.120+
	(0.03)	(0.06)	(0.03)	(0.06)
Drought (Y0)	-0.193**	0.016	-0.182**	0.003
	(0.06)	(0.05)	(0.07)	(0.05)
Drought (Y-1)			0.092	-0.049
			(0.08)	(0.06)
Drought (Y-2)			0.025	-0.078
			(0.07)	(0.06)
Ex. rainfall (Y0)	0.194**	0.082*	0.204**	0.086*
	(0.06)	(0.03)	(0.06)	(0.03)
Ex. rainfall (Y-1)			-0.022	0.006
			(0.05)	(0.03)
Ex. rainfall (Y-2)			0.129*	0.018
			(0.06)	(0.08)
2nd quarter	0.492**	0.237**	0.494**	0.234**
	(0.07)	(0.06)	(0.07)	(0.06)
3rd quarter	0.467**	0.304**	0.468**	0.301**
	(0.06)	(0.06)	(0.06)	(0.06)
4th quarter	0.357**	0.135**	0.356**	0.131**
	(0.06)	(0.04)	(0.06)	(0.04)
Constant	0.348**	0.124	0.326**	0.147
	(0.08)	(0.11)	(0.08)	(0.10)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	4269.053	2785.909	4270.445	2790.463
Joint F test (SPEI)	9.20**	2.84+	4.28**	1.29
CV rmse	1.080	0.915	1.083	0.909
N	1920	1656	1920	1656
N Countries	*80*	*69*	*80*	*69*

Std. errors clustered by country. CV rmse null models: 1.059 (agrarian sample) and 0.893 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

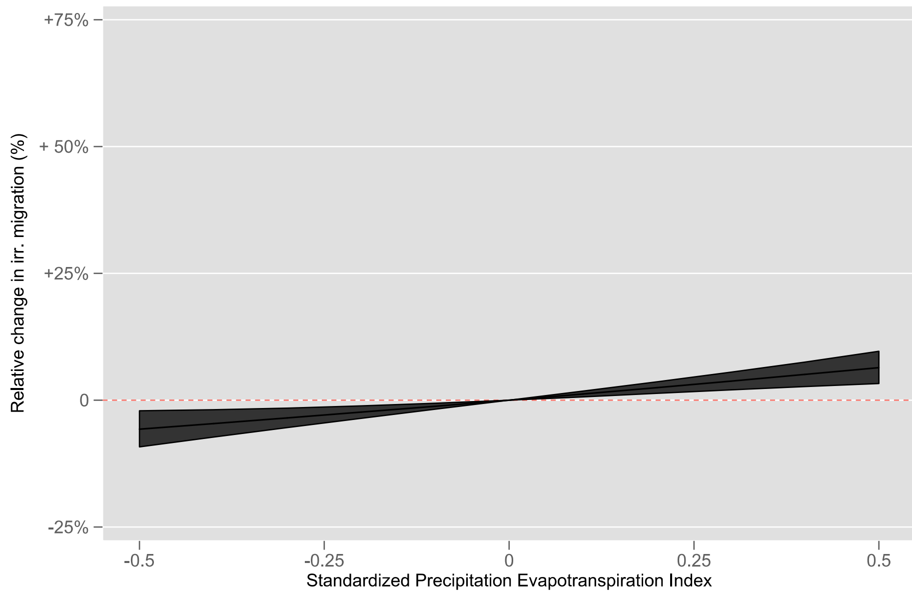

Figure A 16: All observations — Immediate and lag effects of weather shocks on migration (Model 2, Table A.21).

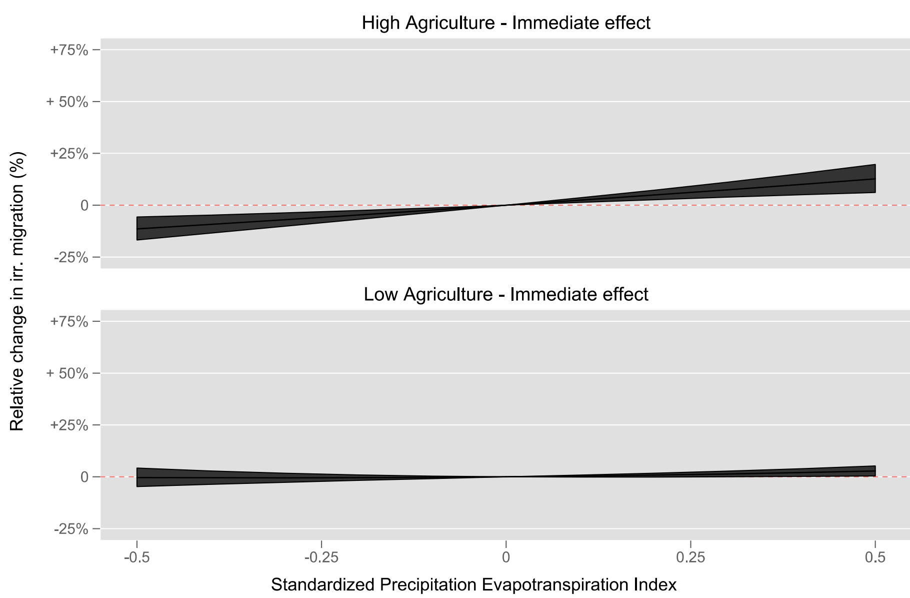

Figure A 17: All observations — Immediate and lag effects of weather shocks on migration conditional on agriculture reliance (Models 7 and 8, Table A.22)

Table A 24: Main models — No lagged migration variables

	Model 1	*Model 2*	*Model 3*	*Model 4*
SPEI (Y0)	0.570**	0.577**	0.565**	0.566**
	(0.16)	(0.15)	(0.17)	(0.16)
$SPEI^2$ (Y0)		0.214		0.261
		(0.21)		(0.21)
SPEI (Y-1)			0.015	0.007
			(0.17)	(0.17)
$SPEI^2$ (Y-1)				0.200
				(0.20)
SPEI (Y-2)			-0.119	-0.113
			(0.17)	(0.17)
$SPEI^2$ (Y-2)				0.242
				(0.18)
2nd quarter	0.648**	0.648**	0.648**	0.650**
	(0.06)	(0.06)	(0.06)	(0.06)
3rd quarter	0.962**	0.962**	0.960**	0.965**
	(0.08)	(0.08)	(0.08)	(0.08)
4th quarter	0.837**	0.835**	0.834**	0.838**
	(0.06)	(0.06)	(0.06)	(0.06)
Constant	2.534**	2.496**	2.533**	2.407**
	(0.16)	(0.16)	(0.16)	(0.18)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	4626.032	4625.177	4628.150	4626.165
Joint F test (SPEI)	13.22**	7.36**	5.49**	5.21**
CV rmse	3.142	3.150	3.136	3.160
N	1536	1536	1536	1536
N Countries	64	64	64	64

Std. errors clustered by country. CV rmse null models: 3.133.
+ p<0.10, * p<0.05, ** p<0.01

Table A 25: Split sample models — No lagged migration variables

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
SPEI (Y0)	0.816**	0.361*	0.824**	0.364*	0.838**	0.337+	0.821**	0.330+
	(0.26)	(0.16)	(0.24)	(0.16)	(0.26)	(0.18)	(0.26)	(0.18)
$SPEI^2$ (Y0)			0.303	0.060			0.365	0.063
			(0.27)	(0.24)			(0.26)	(0.27)
SPEI (Y-1)					0.138	-0.095	0.114	-0.087
					(0.26)	(0.24)	(0.25)	(0.25)
$SPEI^2$ (Y-1)							0.106	0.134
							(0.30)	(0.30)
SPEI (Y-2)					-0.054	-0.163	-0.073	-0.166
					(0.20)	(0.28)	(0.19)	(0.29)
$SPEI^2$ (Y-2)							0.376	-0.040
							(0.26)	(0.25)
2^{nd} quarter	0.681**	0.616**	0.683**	0.615**	0.680**	0.616**	0.687**	0.616**
	(0.10)	(0.08)	(0.10)	(0.08)	(0.10)	(0.08)	(0.10)	(0.08)
3^{rd} quarter	0.970**	0.952**	0.971**	0.951**	0.970**	0.949**	0.977**	0.952**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
4^{th} quarter	0.871**	0.798**	0.866**	0.798**	0.872**	0.793**	0.866**	0.797**
	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.11)
Constant	2.339**	2.740**	2.298**	2.726**	2.357**	2.727**	2.253**	2.694**
	(0.23)	(0.22)	(0.23)	(0.22)	(0.24)	(0.21)	(0.23)	(0.29)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2315.487	2301.331	2314.504	2303.223	2318.078	2303.435	2317.434	2308.642
Joint F test (SPEI)	9.99**	5.00*	6.09**	3.50*	3.58*	3.34*	8.74**	2.27+
CV rmse	3.155	3.145	3.170	3.143	3.163	3.123	3.210	3.130
N	768	768	768	768	768	768	768	768
N Countries	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*

Std. errors clustered by country. CV rmse null models: 3.109 (agrarian sample) and 3.141 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

Table A 26: Large weather shocks — No lagged migration variables

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
Drought (Y0)	-0.521*	-0.166	-0.465*	-0.209
	(0.19)	(0.23)	(0.21)	(0.24)
Drought (Y-1)			0.329	-0.179
			(0.28)	(0.19)
Drought (Y-2)			0.470**	-0.207
			(0.16)	(0.33)
Ex. rainfall (Y0)	0.646*	0.246*	0.636*	0.214*
	(0.28)	(0.11)	(0.27)	(0.10)
Ex. rainfall (Y-1)			0.120	-0.032
			(0.20)	(0.21)
Ex. rainfall (Y-2)			0.251	-0.198
			(0.23)	(0.19)
2nd quarter	0.689**	0.613**	0.695**	0.608**
	(0.09)	(0.08)	(0.10)	(0.08)
3rd quarter	0.975**	0.936**	0.988**	0.932**
	(0.11)	(0.11)	(0.11)	(0.11)
4th quarter	0.878**	0.784**	0.874**	0.785**
	(0.06)	(0.10)	(0.07)	(0.10)
Constant	2.300**	2.734**	2.237**	2.841**
	(0.23)	(0.22)	(0.22)	(0.26)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	2326.293	2307.797	2322.717	2311.097
Joint F test (SPEI)	5.43**	3.59*	3.74**	2.10+
CV rmse	3.149	3.136	3.191	3.137
N	768	768	768	768
N Countries	*32*	*32*	*32*	*32*

Std. errors clustered by country. CV rmse null models: 3.109 (agrarian sample) and 3.141 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

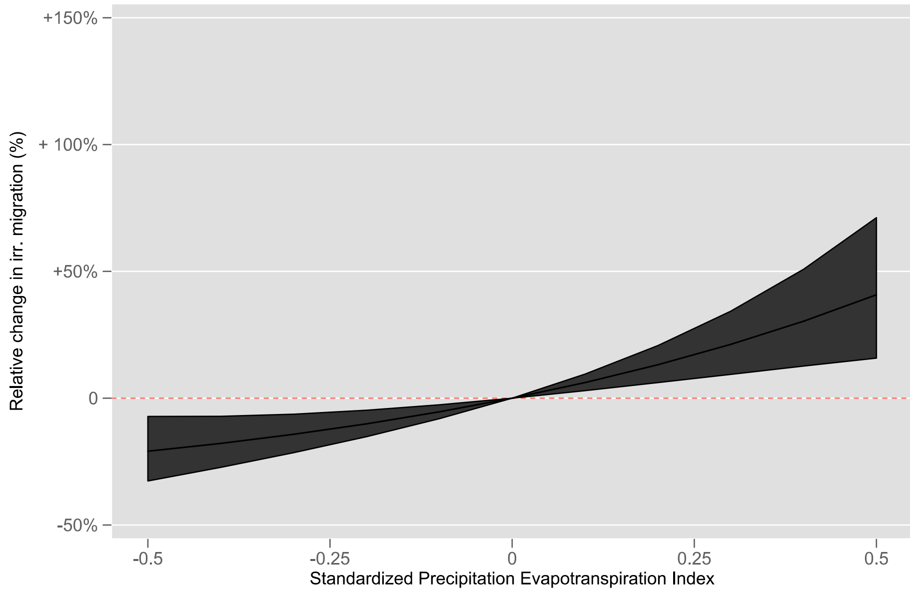

Figure A 18: No lagged migration variables — Immediate effects of weather shocks on migration (Model 2, Table A.24)

Note the wider scale of the y axis.

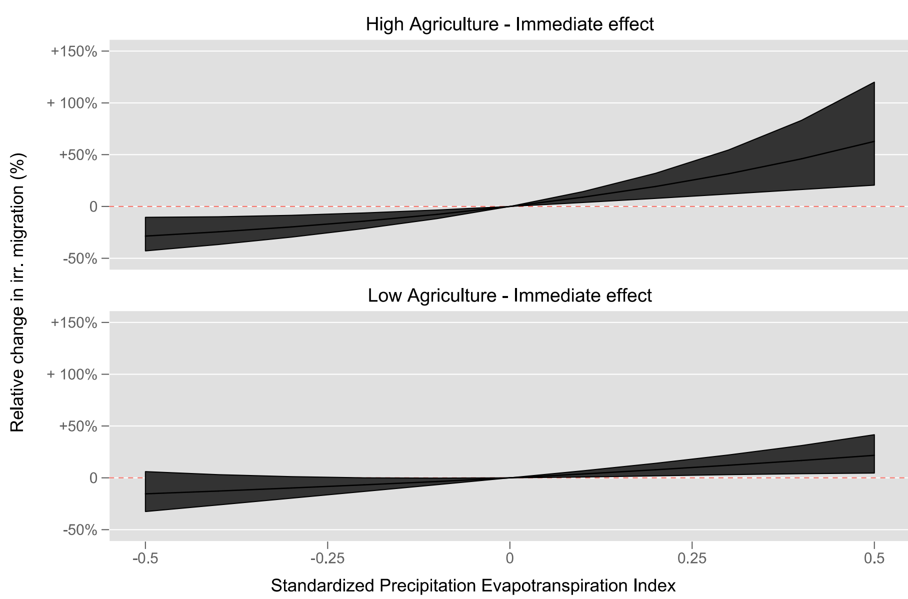

Figure A 19: No lagged migration variables — Immediate effects of weather shocks on migration conditional on agriculture reliance (Models 7 and 8, Table A.25)

Note the wider scale of the y axis.

Table A 27: Main models — No population weighting

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Q-1)	0.550**	0.550**	0.548**	0.548**
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-2)	-0.006	-0.006	-0.005	-0.004
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-3)	0.105**	0.105**	0.108**	0.108**
	(0.03)	(0.03)	(0.03)	(0.03)
N Migr, ln (Q-4)	0.027	0.027	0.030	0.031
	(0.03)	(0.03)	(0.03)	(0.03)
SPEI (Y0)	0.287**	0.283**	0.264**	0.254**
	(0.07)	(0.07)	(0.07)	(0.08)
$SPEI^2$ (Y0)		-0.026		-0.045
		(0.08)		(0.09)
SPEI (Y-1)			-0.120	-0.115
			(0.08)	(0.08)
$SPEI^2$ (Y-1)				0.026
				(0.11)
SPEI (Y-2)			0.005	-0.010
			(0.08)	(0.09)
$SPEI^2$ (Y-2)				-0.105
				(0.12)
2^{nd} quarter	0.840**	0.840**	0.838**	0.838**
	(0.08)	(0.08)	(0.08)	(0.08)
3^{rd} quarter	0.815**	0.815**	0.814**	0.813**
	(0.07)	(0.07)	(0.07)	(0.07)
4^{th} quarter	0.576**	0.576**	0.576**	0.573**
	(0.07)	(0.07)	(0.07)	(0.07)
Constant	0.610**	0.615**	0.575**	0.598**
	(0.11)	(0.11)	(0.11)	(0.11)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	3921.743	3923.672	3922.991	3927.438
Joint F test (SPEI)	16.35**	8.10**	6.42**	3.56**
CV rmse	1.294	1.289	1.269	1.258
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 A 28: Split sample models — No population weighting

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.526**	0.564**	0.525**	0.565**	0.526**	0.562**	0.524**	0.560**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
N Migr, ln (Q-2)	-0.064	0.070+	-0.064	0.070+	-0.062	0.072+	-0.064	0.074+
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.134**	0.061	0.134**	0.060	0.138**	0.063	0.137**	0.059
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.05)
N Migr, ln (Q-4)	0.007	0.049	0.006	0.047	0.011	0.051	0.009	0.048
	(0.03)	(0.06)	(0.03)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
SPEI (Y0)	0.434**	0.162*	0.443**	0.142+	0.403**	0.152+	0.397**	0.101
	(0.12)	(0.08)	(0.12)	(0.08)	(0.13)	(0.08)	(0.13)	(0.09)
$SPEI^2$ (Y0)			0.064	-0.115			0.090	-0.200+
			(0.11)	(0.11)			(0.12)	(0.11)
SPEI (Y-1)					-0.130	-0.069	-0.126	-0.098
					(0.15)	(0.08)	(0.15)	(0.09)
$SPEI^2$ (Y-1)							0.130	-0.088
							(0.22)	(0.11)
SPEI (Y-2)					-0.024	0.048	-0.022	-0.032
					(0.09)	(0.14)	(0.09)	(0.16)
$SPEI^2$ (Y-2)							0.115	-0.286
							(0.13)	(0.20)
2nd quarter	0.861**	0.824**	0.861**	0.827**	0.859**	0.824**	0.859**	0.829**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)
3rd quarter	0.794**	0.845**	0.794**	0.847**	0.789**	0.847**	0.789**	0.847**
	(0.09)	(0.11)	(0.09)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)
4th quarter	0.651**	0.501**	0.651**	0.500**	0.648**	0.504**	0.647**	0.488**
	(0.08)	(0.11)	(0.08)	(0.11)	(0.08)	(0.11)	(0.09)	(0.11)
Constant	0.768**	0.438*	0.762**	0.473*	0.717**	0.426*	0.687**	0.593**
	(0.13)	(0.20)	(0.13)	(0.20)	(0.13)	(0.20)	(0.14)	(0.20)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2026.752	1895.765	2028.532	1897.116	2029.474	1898.858	2034.095	1898.517
Joint F test (SPEI)	12.50**	4.28*	7.26**	2.04	4.52**	2.68+	4.39**	1.65
CV rmse	1.503	1.124	1.514	1.122	1.460	1.106	1.503	1.113
N	768	768	768	768	768	768	768	768
N Countries	*32*	*32*	*32*	*32*	*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 A 29: Large weather shocks — No population weighting

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.531**	0.564**	0.526**	0.563**
	(0.05)	(0.05)	(0.05)	(0.05)
N Migr, ln (Q-2)	-0.056	0.073+	-0.056	0.074+
	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.127**	0.060	0.129**	0.053
	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.011	0.047	0.013	0.040
	(0.04)	(0.06)	(0.04)	(0.06)
Drought (Y0)	-0.394**	-0.142	-0.356**	-0.180+
	(0.12)	(0.10)	(0.12)	(0.10)
Drought (Y-1)			0.180	-0.174*
			(0.12)	(0.08)
Drought (Y-2)			0.101	-0.191
			(0.08)	(0.12)
Ex. rainfall (Y0)	0.282*	0.023	0.278*	-0.010
	(0.12)	(0.09)	(0.13)	(0.08)
Ex. rainfall (Y-1)			0.010	-0.075
			(0.11)	(0.12)
Ex. rainfall (Y-2)			0.078	-0.128
			(0.14)	(0.16)
2nd quarter	0.881**	0.823**	0.874**	0.819**
	(0.11)	(0.11)	(0.11)	(0.11)
3rd quarter	0.808**	0.842**	0.809**	0.840**
	(0.09)	(0.11)	(0.10)	(0.10)
4th quarter	0.659**	0.491**	0.656**	0.474**
	(0.08)	(0.11)	(0.09)	(0.11)
Constant	0.704**	0.455*	0.672**	0.602**
	(0.12)	(0.20)	(0.13)	(0.19)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	2029.799	1898.926	2035.554	1900.328
Joint F test (SPEI)	7.99**	1.00	3.75**	1.42
CV rmse	1.457	1.109	1.466	1.145
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

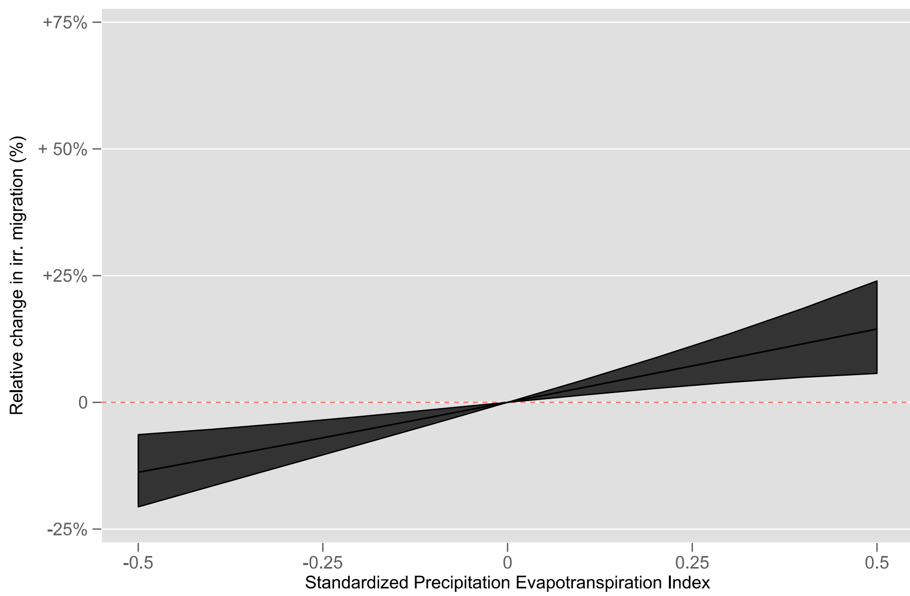

Figure A 20: No population weighting — Immediate effects of weather shocks on migration (Model 2, Table A.27)

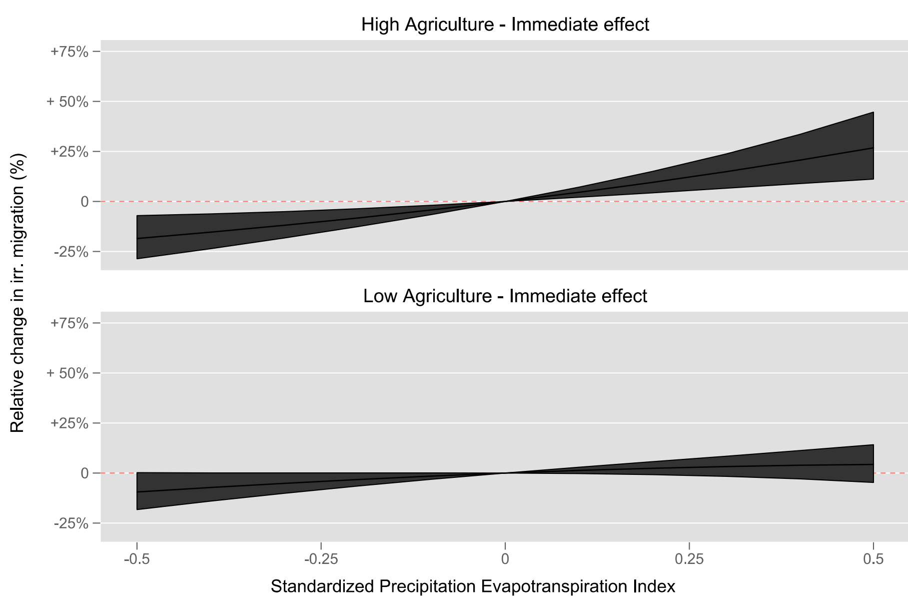

Figure A 21: No population weighting — Immediate effects of weather shocks on migration conditional on agriculture reliance (Models 7 and 8, Table A.28)

Table A 30: Main models — Temperature and precipitation anomalies

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Q-1)	0.554**	0.552**	0.549**	0.542**
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-2)	-0.005	-0.005	-0.003	-0.002
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-3)	0.108**	0.108**	0.111**	0.112**
	(0.03)	(0.03)	(0.03)	(0.03)
N Migr, ln (Q-4)	0.029	0.030	0.035	0.033
	(0.03)	(0.03)	(0.03)	(0.03)
Temp (Y0)	-0.004	-0.009	0.002	-0.012
	(0.04)	(0.04)	(0.04)	(0.04)
$Temp^2$ (Y0)		0.051		0.034
		(0.04)		(0.04)
Temp (Y-1)			0.030	0.018
			(0.04)	(0.03)
$Temp^2$ (Y-1)				-0.064+
				(0.03)
Temp (Y-2)			-0.071	-0.086+
			(0.05)	(0.05)
$Temp^2$ (Y-2)				-0.102**
				(0.04)
Precip (Y0)	0.106**	0.108**	0.096**	0.103**
	(0.03)	(0.03)	(0.03)	(0.03)
$Precip^2$ (Y0)		0.009		0.016
		(0.02)		(0.02)
Precip (Y-1)			-0.058+	-0.055
			(0.03)	(0.03)
$Precip^2$ (Y-1)				0.000
				(0.02)
Precip (Y-2)			-0.039	-0.040
			(0.03)	(0.03)
$Precip^2$ (Y-2)				0.005
				(0.02)
2nd quarter	0.843**	0.841**	0.834**	0.835**
	(0.08)	(0.08)	(0.08)	(0.08)
3rd quarter	0.816**	0.816**	0.803**	0.808**
	(0.07)	(0.07)	(0.07)	(0.07)
4th quarter	0.576**	0.575**	0.567**	0.571**
	(0.07)	(0.07)	(0.07)	(0.07)
Constant	0.530**	0.476**	0.497**	0.533**
	(0.11)	(0.12)	(0.12)	(0.14)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	3924.485	3926.075	3923.301	3921.905
Joint F test (Weather)	7.98**	4.58**	4.50**	3.47**
CV rmse	1.229	1.234	1.223	1.239
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 A 31: Split sample models — Temperature and precipitation anomalies

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.526**	0.565**	0.525**	0.559**	0.516**	0.562**	0.515**	0.543**
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
N Migr, ln (Q-2)	-0.060	0.069+	-0.060	0.067+	-0.056	0.070+	-0.054	0.066+
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.137**	0.062	0.138**	0.060	0.139**	0.065	0.139**	0.067
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.012	0.048	0.012	0.051	0.025	0.051	0.024	0.049
	(0.04)	(0.06)	(0.04)	(0.06)	(0.03)	(0.06)	(0.04)	(0.06)
Temp (Y0)	0.143+	-0.054	0.146+	-0.071	0.174*	-0.049	0.163+	-0.082+
	(0.07)	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)
Temp² (Y0)			0.036	0.071			0.035	0.041
			(0.04)	(0.06)			(0.03)	(0.06)
Temp (Y-1)					0.066	0.027	0.075	-0.005
					(0.08)	(0.06)	(0.07)	(0.05)
Temp² (Y-1)							-0.042	-0.081+
							(0.06)	(0.04)
Temp (Y-2)					-0.140+	-0.034	-0.144+	-0.061
					(0.08)	(0.07)	(0.08)	(0.06)
Temp² (Y-2)							-0.032	-0.170**
							(0.05)	(0.05)
Precip (Y0)	0.151**	0.052+	0.152**	0.055+	0.122*	0.049	0.122*	0.060
	(0.05)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)
Precip² (Y0)			0.009	0.004			0.012	0.018
			(0.02)	(0.03)			(0.02)	(0.03)
Precip (Y-1)					-0.070	-0.043	-0.068	-0.044
					(0.06)	(0.04)	(0.06)	(0.04)
Precip ² (Y-1)							-0.004	0.003
							(0.03)	(0.03)
Precip (Y-2)					-0.069*	0.003	-0.076*	0.007
					(0.03)	(0.05)	(0.04)	(0.05)
Precip² (Y-2)							0.004	0.003
							(0.03)	(0.03)
2nd quarter	0.861**	0.825**	0.859**	0.826**	0.840**	0.822**	0.843**	0.800**
	(0.11)	(0.12)	(0.11)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)
3rd quarter	0.794**	0.846**	0.792**	0.848**	0.763**	0.843**	0.769**	0.826**
	(0.09)	(0.11)	(0.09)	(0.11)	(0.09)	(0.11)	(0.10)	(0.11)
4th quarter	0.649**	0.504**	0.647**	0.506**	0.625**	0.503**	0.629**	0.496**
	(0.08)	(0.11)	(0.08)	(0.11)	(0.08)	(0.11)	(0.08)	(0.11)
Constant	0.524**	0.461*	0.478**	0.404*	0.434**	0.436+	0.428*	0.566*
	(0.14)	(0.20)	(0.14)	(0.20)	(0.13)	(0.22)	(0.17)	(0.27)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2026.909	1897.177	2030.213	1899.195	2025.219	1902.841	2035.264	1899.833
Joint F test (Weather)	5.82**	2.76+	3.46*	1.70	6.60**	1.92	3.98**	3.01**
CV rmse	1.428	1.108	1.431	1.119	1.417	1.086	1.432	1.156
N	768	768	768	768	768	768	768	768
N Countries	*32*	*32*	*32*	*32*	*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 A 32: Large weather shocks — Temperature and precipitation anomalies

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.522**	0.562**	0.514**	0.547**
	(0.05)	(0.06)	(0.05)	(0.05)
N Migr, ln (Q-2)	-0.055	0.071+	-0.051	0.065+
	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.130**	0.063	0.131**	0.069
	(0.03)	(0.05)	(0.03)	(0.05)
N Migr, ln (Q-4)	0.013	0.051	0.021	0.049
	(0.04)	(0.06)	(0.04)	(0.06)
Hi temp (Y0)	0.242+	0.086	0.264+	0.018
	(0.13)	(0.11)	(0.13)	(0.10)
Hi temp (Y-1)			0.073	-0.164
			(0.14)	(0.10)
Hi temp (Y-2)			-0.121	-0.207*
			(0.12)	(0.08)
Lo temp (Y0)	-0.126	0.181	-0.137	0.110
	(0.13)	(0.16)	(0.13)	(0.14)
Lo temp (Y-1)			-0.084	-0.374**
			(0.14)	(0.10)
Lo temp (Y-2)			0.093	-0.309*
			(0.12)	(0.12)
Hi precip (Y0)	0.349**	0.055	0.293*	0.082
	(0.10)	(0.10)	(0.11)	(0.10)
Hi precip (Y-1)			-0.179	0.003
			(0.11)	(0.14)
Hi precip (Y-2)			-0.134	0.053
			(0.09)	(0.12)
Lo precip (Y0)	-0.262+	-0.024	-0.239	0.015
	(0.14)	(0.08)	(0.15)	(0.08)
Lo precip (Y-1)			0.075	-0.025
			(0.13)	(0.07)
Lo precip (Y-2)			0.179	-0.091
			(0.11)	(0.13)
2nd quarter	0.864**	0.829**	0.843**	0.790**
	(0.11)	(0.11)	(0.12)	(0.11)
3rd quarter	0.809**	0.846**	0.782**	0.815**
	(0.10)	(0.11)	(0.10)	(0.11)
4th quarter	0.652**	0.504**	0.636**	0.475**
	(0.08)	(0.11)	(0.08)	(0.11)
Constant	0.555**	0.368+	0.547**	0.548*
	(0.14)	(0.21)	(0.15)	(0.26)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	2030.788	1901.935	2039.350	1898.095
Joint F test (Weather)	3.65*	0.50	1.74	2.82**
CV rmse	1.437	1.096	1.429	1.133
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

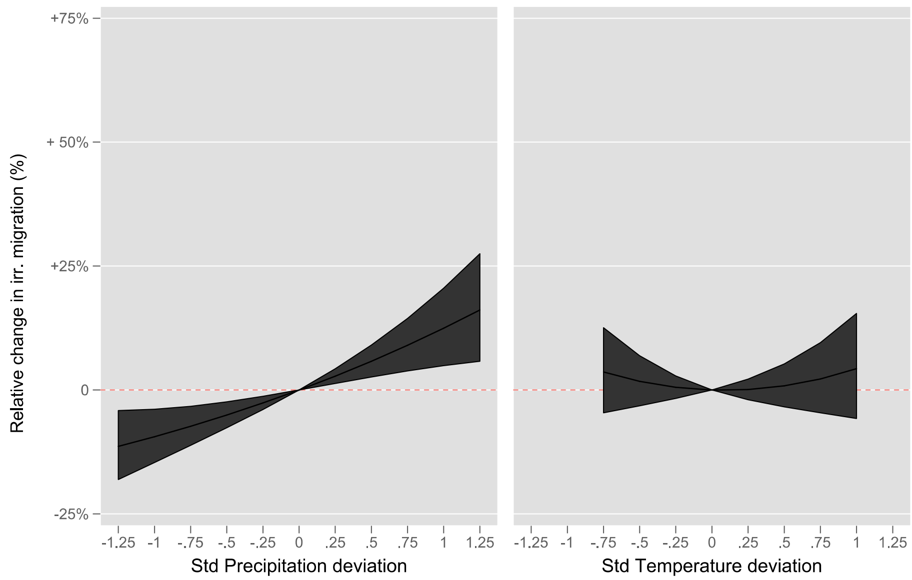

Figure A 22: Temperature and precipitation anomalies — Immediate effects of weather shocks on migration (Model 2, Table A.30)

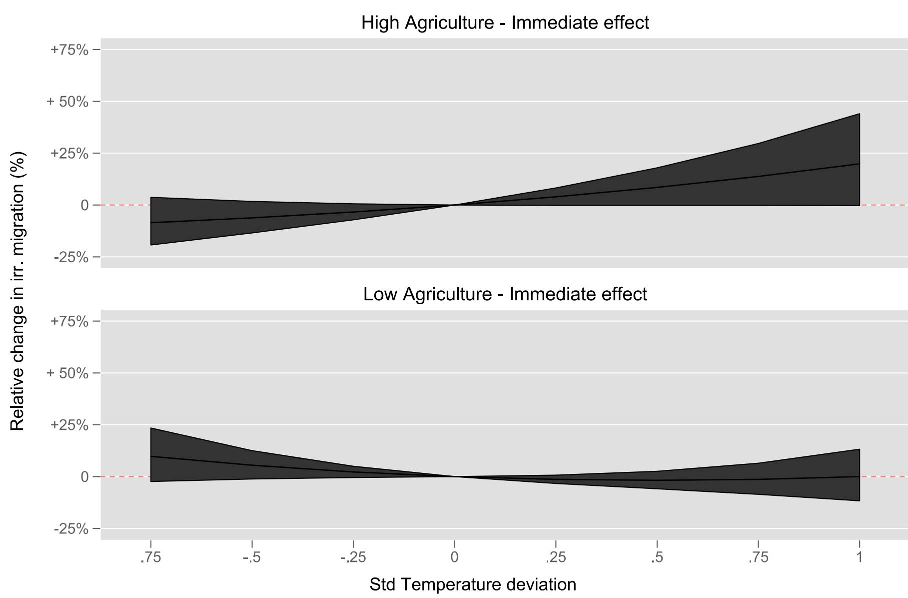

Figure A 23: Temperature anomalies — Immediate effects of weather shocks on migration conditional on agriculture reliance (Models 7 and 8, Table A.31)

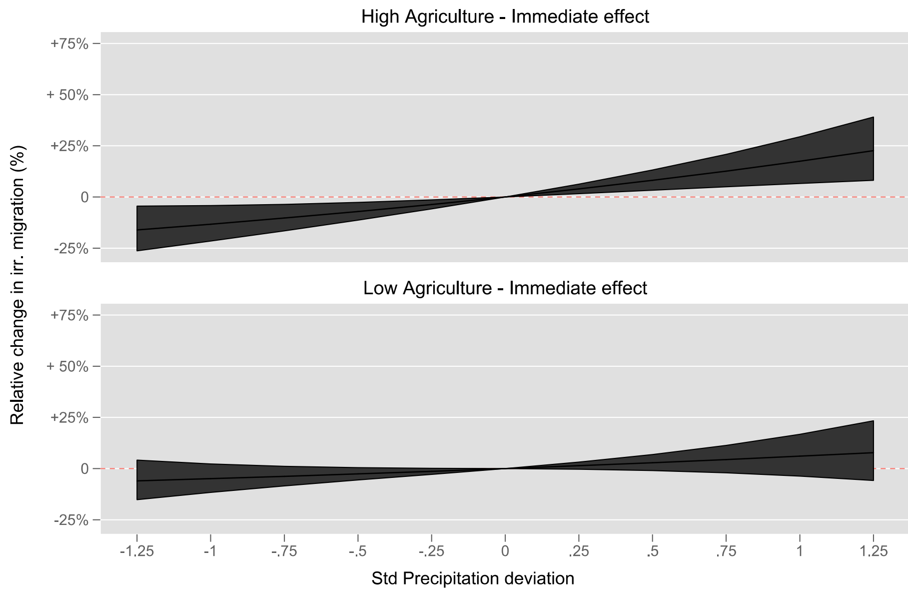

Figure A 24: Precipitation anomalies — Immediate effects of weather shocks on migration conditional on agriculture reliance (Models 7 and 8 Table A.31)

Table A 33: Split sample models — Poorer and richer countries

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	Poor	*Rich*	*Poor*	*Rich*	*Poor*	*Rich*	*Poor*	*Rich*
N Migr, ln (Q-1)	0.503**	0.557**	0.503**	0.556**	0.504**	0.555**	0.505**	0.554**
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
N Migr, ln (Q-2)	-0.055	0.041	-0.055	0.041	-0.052	0.043	-0.053	0.045
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.116**	0.086	0.116**	0.086	0.120**	0.088	0.118**	0.087
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.014	0.051	0.014	0.052	0.016	0.055	0.018	0.058
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
SPEI (Y0)	0.359**	0.244**	0.350**	0.242**	0.303*	0.236**	0.304*	0.248*
	(0.12)	(0.09)	(0.12)	(0.08)	(0.14)	(0.08)	(0.14)	(0.10)
$SPEI^2$ (Y0)			-0.053	0.054			0.014	0.024
			(0.15)	(0.10)			(0.18)	(0.10)
SPEI (Y-1)					-0.209	-0.072	-0.176	-0.056
					(0.18)	(0.09)	(0.17)	(0.08)
$SPEI^2$ (Y-1)							0.269	-0.182
							(0.18)	(0.15)
SPEI (Y-2)					-0.018	0.050	-0.012	0.062
					(0.09)	(0.13)	(0.10)	(0.13)
$SPEI^2$ (Y-2)							0.203	-0.088
							(0.25)	(0.16)
2nd quarter	0.982**	0.688**	0.981**	0.687**	0.981**	0.687**	0.984**	0.685**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
3rd quarter	0.850**	0.792**	0.850**	0.791**	0.846**	0.791**	0.842**	0.784**
	(0.08)	(0.12)	(0.08)	(0.12)	(0.08)	(0.12)	(0.09)	(0.12)
4th quarter	0.655**	0.532**	0.656**	0.533**	0.651**	0.534**	0.641**	0.523**
	(0.09)	(0.11)	(0.09)	(0.11)	(0.09)	(0.10)	(0.09)	(0.11)
Constant	0.688**	0.526*	0.695**	0.516*	0.640**	0.509*	0.595**	0.561*
	(0.13)	(0.24)	(0.13)	(0.24)	(0.12)	(0.23)	(0.14)	(0.24)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	1920.966	1984.096	1922.877	1985.906	1922.177	1987.004	1925.569	1990.199
Joint F test (SPEI)	8.34**	8.11**	4.34*	5.40**	3.11*	2.72+	4.10**	1.80
CV rmse	1.587	1.117	1.584	1.113	1.542	1.099	1.582	1.093
N	744	792	744	792	744	792	744	792
N Countries	*31*	*33*	*31*	*33*	*31*	*33*	*31*	*33*

Std. errors clustered by country. CV rmse null models: 1.538 (Poor sample) and 1.061 (Rich sample).
+ p<0.10, * p<0.05, ** p<0.01

Table A 34: Large weather shocks — Poorer and richer countries

	Model 13	*Model 14*	*Model 15*	*Model 16*
	Poor	*Rich*	*Poor*	*Rich*
N Migr, ln (Q-1)	0.507**	0.561**	0.504**	0.562**
	(0.05)	(0.06)	(0.05)	(0.06)
N Migr, ln (Q-2)	-0.055	0.042	-0.053	0.053
	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.108**	0.089+	0.112**	0.088+
	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.014	0.051	0.014	0.047
	(0.04)	(0.06)	(0.04)	(0.05)
Drought (Y0)	-0.329+	-0.110	-0.299+	-0.145
	(0.16)	(0.11)	(0.17)	(0.11)
Drought (Y-1)			0.192	-0.119
			(0.17)	(0.11)
Drought (Y-2)			0.026	-0.228
			(0.12)	(0.16)
Ex. rainfall (Y0)	0.225*	0.228*	0.210+	0.210*
	(0.11)	(0.09)	(0.11)	(0.09)
Ex. rainfall (Y-1)			-0.088	-0.112
			(0.16)	(0.10)
Ex. rainfall (Y-2)			0.062	-0.067
			(0.14)	(0.14)
2nd quarter	0.992**	0.687**	0.985**	0.684**
	(0.11)	(0.11)	(0.11)	(0.11)
3rd quarter	0.848**	0.783**	0.847**	0.784**
	(0.08)	(0.12)	(0.08)	(0.12)
4th quarter	0.652**	0.524**	0.649**	0.522**
	(0.09)	(0.11)	(0.09)	(0.11)
Constant	0.703**	0.481+	0.676**	0.551*
	(0.14)	(0.24)	(0.14)	(0.22)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	1923.592	1987.214	1929.100	1989.597
Joint F test (SPEI)	4.69*	3.91*	2.07+	1.65
CV rmse	1.594	1.093	1.581	1.086
N	744	792	744	792
N Countries	*31*	*33*	*31*	*33*

Std. errors clustered by country. CV rmse null models: 1.538 (Poor sample) and 1.061 (Rich sample).
+ p<0.10, * p<0.05, ** p<0.01

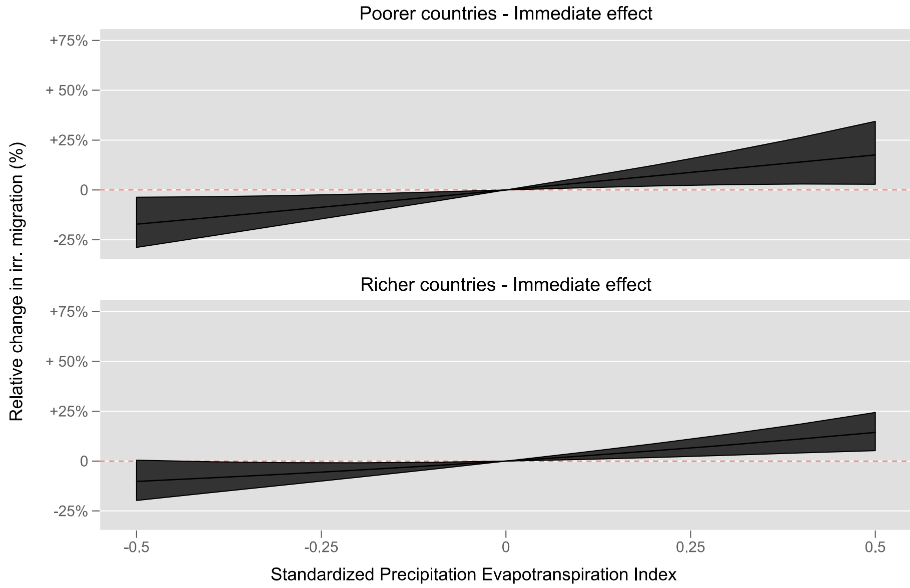

Figure A 25: Poorer and richer countries — Immediate effects of weather shocks on migration (Models 7 and 8, Table A.33)

Table A 35: Split sample models — Africa vs Non-Africa samples

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	Africa	Not Afr.	Africa	Not Afr.	Africa	Not Afr.	Africa	Not Afr.
N Migr, ln (Q-1)	0.480**	0.578**	0.479**	0.574**	0.480**	0.576**	0.479**	0.571**
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
N Migr, ln (Q-2)	-0.038	0.036	-0.037	0.035	-0.036	0.038	-0.037	0.039
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
N Migr, ln (Q-3)	0.092*	0.122**	0.091*	0.121**	0.094*	0.126**	0.093*	0.124**
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-4)	0.032	0.052	0.033	0.055	0.034	0.053	0.036	0.059
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
SPEI (Y0)	0.415**	0.201+	0.397**	0.197+	0.384**	0.200+	0.373**	0.207+
	(0.09)	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)
$SPEI^2$ (Y0)			-0.109	0.100			-0.090	0.100
			(0.16)	(0.09)			(0.17)	(0.09)
SPEI (Y-1)					-0.100	-0.059	-0.088	-0.055
					(0.13)	(0.11)	(0.13)	(0.11)
$SPEI^2$ (Y-1)							0.168	-0.096
							(0.17)	(0.17)
SPEI (Y-2)					-0.088	0.123	-0.090	0.132
					(0.10)	(0.13)	(0.10)	(0.13)
$SPEI^2$ (Y-2)							0.039	-0.012
							(0.15)	(0.17)
2nd quarter	0.884**	0.730**	0.884**	0.726**	0.884**	0.729**	0.883**	0.723**
	(0.09)	(0.13)	(0.09)	(0.13)	(0.09)	(0.13)	(0.09)	(0.13)
3rd quarter	0.902**	0.689**	0.902**	0.686**	0.898**	0.690**	0.898**	0.685**
	(0.08)	(0.13)	(0.08)	(0.13)	(0.08)	(0.13)	(0.08)	(0.13)
4th quarter	0.613**	0.567**	0.614**	0.566**	0.609**	0.570**	0.609**	0.566**
	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)
Constant	0.749**	0.381	0.765**	0.366	0.738**	0.375	0.722**	0.375
	(0.12)	(0.27)	(0.12)	(0.28)	(0.12)	(0.25)	(0.14)	(0.25)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2335.103	1551.783	2336.753	1553.095	2337.999	1553.417	2342.702	1557.851
Joint F test (SPEI)	20.97**	3.99+	10.60**	3.76*	8.77**	1.71	5.75**	1.74
CV rmse	1.640	0.994	1.633	0.991	1.614	0.980	1.619	0.984
N	912	624	912	624	912	624	912	624
N Countries	*38*	*26*	*38*	*26*	*38*	*26*	*38*	*26*

Std errors clustered by country. CV rmse null models: 1.565 (Africa sample) and 0.96 (non-Africa sample).
+ $p<0.10$, * $p<0.05$, ** $p<0.01$

Table A 36: Large weather shocks — Africa vs Non-Africa samples

	Model 13 Africa	*Model 14* Not Afr.	*Model 15* Africa	*Model 16* Not Afr.
N Migr, ln (Q-1)	0.485**	0.582**	0.481**	0.576**
	(0.05)	(0.06)	(0.05)	(0.06)
N Migr, ln (Q-2)	-0.036	0.037	-0.037	0.049
	(0.04)	(0.06)	(0.04)	(0.06)
N Migr, ln (Q-3)	0.089*	0.122**	0.089*	0.121**
	(0.04)	(0.03)	(0.04)	(0.03)
N Migr, ln (Q-4)	0.031	0.051	0.034	0.049
	(0.04)	(0.05)	(0.04)	(0.05)
Drought (Y0)	-0.275+	-0.091	-0.255+	-0.116
	(0.14)	(0.12)	(0.14)	(0.12)
Drought (Y-1)			0.167	-0.137
			(0.13)	(0.11)
Drought (Y-2)			0.154	-0.363*
			(0.11)	(0.16)
Ex. rainfall (Y0)	0.261**	0.189+	0.262**	0.208+
	(0.09)	(0.10)	(0.09)	(0.10)
Ex. rainfall (Y-1)			0.035	-0.123
			(0.14)	(0.08)
Ex. rainfall (Y-2)			-0.116	0.074
			(0.13)	(0.15)
2nd quarter	0.889**	0.732**	0.891**	0.735**
	(0.09)	(0.13)	(0.09)	(0.13)
3rd quarter	0.901**	0.678**	0.901**	0.686**
	(0.08)	(0.13)	(0.08)	(0.12)
4th quarter	0.613**	0.554**	0.610**	0.560**
	(0.09)	(0.10)	(0.10)	(0.10)
Constant	0.740**	0.349	0.730**	0.428+
	(0.12)	(0.27)	(0.13)	(0.23)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	2341.538	1554.578	2345.575	1552.597
Joint F test (SPEI)	6.70**	1.97	3.09*	2.06
CV rmse	1.623	0.982	1.629	0.996
N	912	624	912	624
N Countries	*38*	*26*	*38*	*26*

Std. errors clustered by country. CV rmse null models: 1.56 (Africa sample) and 0.96 (non-Africa sample).
+ p<0.10, * p<0.05, ** p<0.01

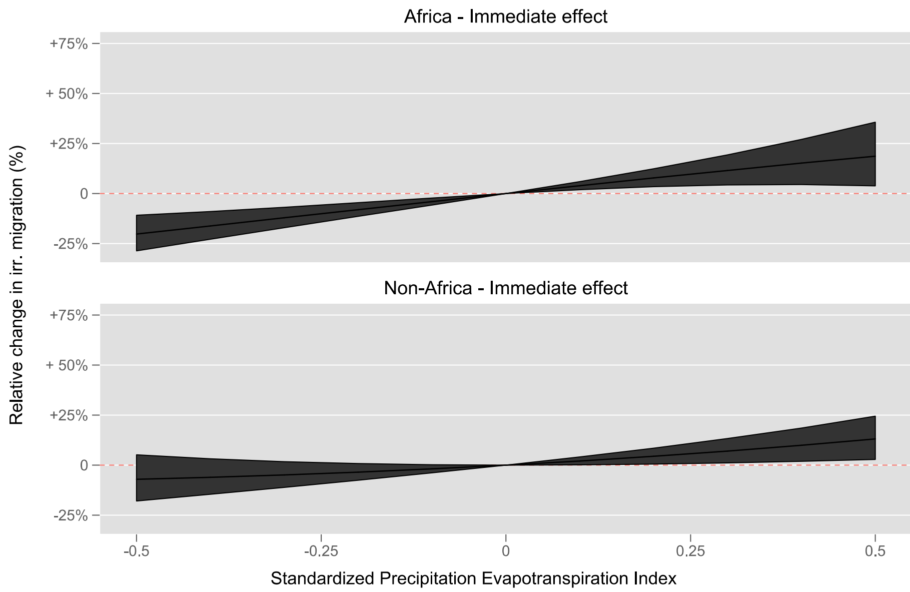

Figure A 26: Africa vs non-Africa sample — Immediate effects of weather shocks on migration (Models 7 and 8, Table A.35)

Table A 37: Main Models — Adding excluded migration routes

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Q-1)	0.583**	0.580**	0.580**	0.577**
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-2)	-0.053	-0.053	-0.051	-0.053
	(0.04)	(0.04)	(0.04)	(0.04)
N Migr, ln (Q-3)	0.108**	0.108**	0.113**	0.112**
	(0.03)	(0.03)	(0.03)	(0.03)
N Migr, ln (Q-4)	0.033	0.034	0.040	0.040
	(0.03)	(0.03)	(0.03)	(0.03)
SPEI (Y0)	0.169**	0.167**	0.138+	0.142*
	(0.06)	(0.06)	(0.07)	(0.07)
$SPEI^2$ (Y0)		0.133*		0.162*
		(0.06)		(0.06)
SPEI (Y-1)			-0.173*	-0.173*
			(0.08)	(0.08)
$SPEI^2$ (Y-1)				0.073
				(0.10)
SPEI (Y-2)			0.016	0.015
			(0.07)	(0.07)
$SPEI^2$ (Y-2)				0.099
				(0.11)
2nd quarter	0.766**	0.766**	0.763**	0.766**
	(0.07)	(0.07)	(0.07)	(0.07)
3rd quarter	0.666**	0.667**	0.664**	0.669**
	(0.07)	(0.07)	(0.07)	(0.07)
4th quarter	0.442**	0.442**	0.443**	0.444**
	(0.07)	(0.07)	(0.07)	(0.07)
Constant	0.702**	0.679**	0.667**	0.615**
	(0.11)	(0.11)	(0.11)	(0.11)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	4182.796	4182.323	4179.152	4180.719
Joint F test (SPEI)	7.08**	6.73**	4.88**	4.03**
CV rmse	1.283	1.287	1.255	1.276
N	1694	1694	1694	1694
N Countries	*71*	*71*	*71*	*71*

Std errors clustered by country. CV rmse null model: 1.243

+ p<0.10, * p<0.05, ** p<0.01

Table A 38: Split sample models — Adding excluded migration routes

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.569**	0.591**	0.563**	0.591**	0.566**	0.589**	0.558**	0.588**
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
N Migr, ln (Q-2)	-0.101+	0.016	-0.101+	0.015	-0.098+	0.016	-0.100+	0.016
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.143**	0.057	0.143**	0.057	0.151**	0.058	0.151**	0.059
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.005	0.067	0.007	0.068	0.015	0.070	0.016	0.071
	(0.03)	(0.06)	(0.03)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
SPEI (Y0)	0.275*	0.080	0.280*	0.078	0.224+	0.068	0.233+	0.066
	(0.12)	(0.06)	(0.11)	(0.07)	(0.13)	(0.07)	(0.12)	(0.07)
$SPEI^2$ (Y0)			0.232**	0.043			0.266**	0.065
			(0.08)	(0.08)			(0.09)	(0.08)
SPEI (Y-1)					-0.259+	-0.081	-0.269*	-0.084
					(0.13)	(0.08)	(0.13)	(0.08)
$SPEI^2$ (Y-1)							0.029	0.086
							(0.18)	(0.09)
SPEI (Y-2)					0.009	0.033	0.001	0.031
					(0.07)	(0.13)	(0.07)	(0.13)
$SPEI^2$ (Y-2)							0.248	-0.004
							(0.16)	(0.16)
2nd quarter	0.797**	0.740**	0.801**	0.740**	0.792**	0.739**	0.801**	0.740**
	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)
3rd quarter	0.649**	0.693**	0.658**	0.692**	0.643**	0.693**	0.660**	0.694**
	(0.09)	(0.10)	(0.09)	(0.10)	(0.09)	(0.10)	(0.10)	(0.11)
4th quarter	0.501**	0.381**	0.504**	0.380**	0.500**	0.383**	0.505**	0.383**
	(0.08)	(0.11)	(0.08)	(0.10)	(0.08)	(0.10)	(0.08)	(0.11)
Constant	0.798**	0.581**	0.775**	0.569*	0.732**	0.568*	0.682**	0.534*
	(0.11)	(0.21)	(0.12)	(0.21)	(0.10)	(0.21)	(0.12)	(0.21)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2248.876	1939.282	2247.407	1941.140	2245.463	1942.068	2244.986	1947.295
Joint F test (SPEI)	5.43*	1.55	6.07**	1.17	3.37*	1.65	5.03**	1.26
CV rmse	1.434	1.141	1.459	1.137	1.377	1.122	1.438	1.129
N	888	806	888	806	888	806	888	806
N Countries	*37*	*34*	*37*	*34*	*37*	*34*	*37*	*34*

Std errors clustered by country. CV rmse null models: 1.358 (agrarian sample) and 1.124 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

Table A 39: Large Weather Shocks — Adding excluded migration routes

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.573**	0.592**	0.562**	0.591**
	(0.05)	(0.06)	(0.05)	(0.06)
N Migr, ln (Q-2)	-0.100+	0.015	-0.103*	0.016
	(0.05)	(0.04)	(0.05)	(0.04)
N Migr, ln (Q-3)	0.144**	0.057	0.155**	0.059
	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.006	0.069	0.011	0.065
	(0.03)	(0.06)	(0.03)	(0.06)
Drought (Y0)	-0.122	0.025	-0.071	0.019
	(0.10)	(0.10)	(0.10)	(0.11)
Drought (Y-1)			0.334*	0.006
			(0.13)	(0.11)
Drought (Y-2)			0.097	-0.151
			(0.10)	(0.14)
Ex. rainfall (Y0)	0.272+	0.076	0.283+	0.044
	(0.15)	(0.05)	(0.15)	(0.05)
Ex. rainfall (Y-1)			-0.173	-0.027
			(0.13)	(0.08)
Ex. rainfall (Y-2)			0.261**	-0.121
			(0.09)	(0.16)
2nd quarter	0.802**	0.741**	0.800**	0.739**
	(0.10)	(0.11)	(0.10)	(0.11)
3rd quarter	0.652**	0.689**	0.662**	0.695**
	(0.09)	(0.10)	(0.10)	(0.10)
4th quarter	0.495**	0.376**	0.504**	0.384**
	(0.08)	(0.11)	(0.08)	(0.10)
Constant	0.760**	0.560*	0.708**	0.612**
	(0.11)	(0.21)	(0.11)	(0.20)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AIC	2252.947	1941.721	2244.728	1946.504
Joint F test (SPEI)	2.28	0.99	4.91**	0.73
CV rmse	1.425	1.129	1.428	1.138
N	888	806	888	806
N Countries	*37*	*34*	*37*	*34*

Std errors clustered by country. CV rmse null models: 1.358 (agrarian sample) and 1.124 (non-agrarian sample).
+ p<0.10, * p<0.05, ** p<0.01

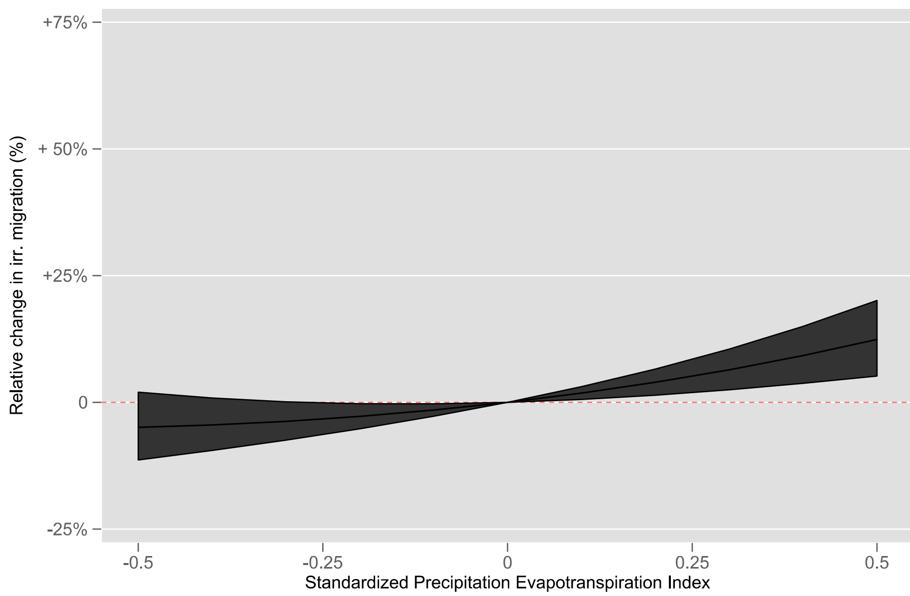

Figure A 27: Adding excluded migration routes — Immediate effects of weather shocks on migration with 95% confidence interval (Model 2, Table A.37).

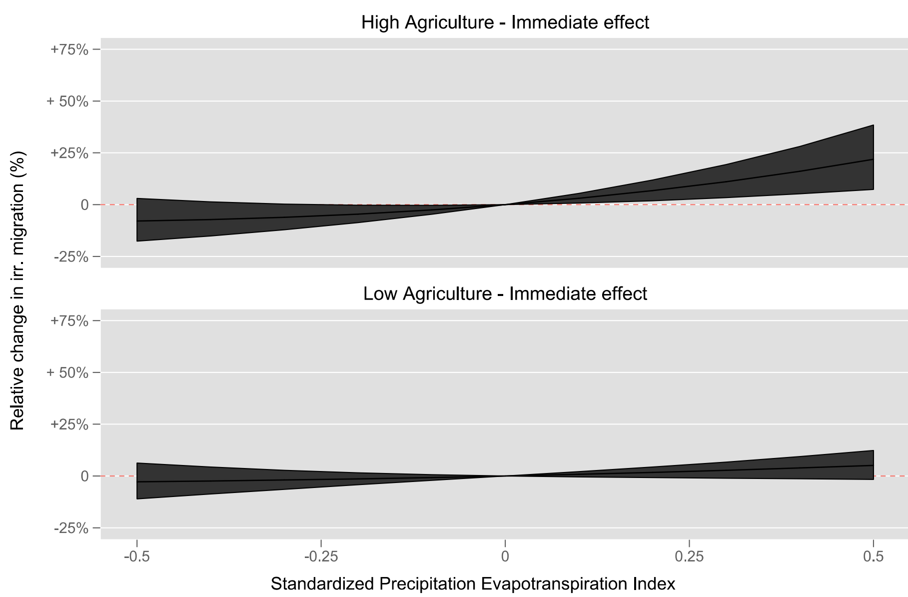

Figure A 28: Adding excluded migration routes — Immediate effects of weather shocks on migration conditional on agriculture reliance with 95% confidence interval (Model 7 and 8, Table A.38)

Table A 40: Main Models — Adjusting for spatial and serial correlation

	Model 1	*Model 2*	*Model 3*	*Model 4*
N Migr, ln (Q-1)	0.549**	0.548**	0.548**	0.547**
	(0.03)	(0.03)	(0.03)	(0.03)
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
		(0.09)		(0.10)
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
			(0.08)	(0.08)
$SPEI^2$ (Y-2)				0.020
				(0.11)
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**
	(0.08)	(0.08)	(0.08)	(0.08)
4th quarter	0.578**	0.577**	0.577**	0.577**
	(0.08)	(0.08)	(0.08)	(0.08)
Constant	-0.270	1.994**	1.994**	1.983**
	(0.19)	(0.28)	(0.28)	(0.28)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Joint F test (SPEI)	16.59**	8.59**	6.29**	3.36**
N	1536	1536	1536	1536
N Countries	*64*	*64*	*64*	*64*

Std errors adjusted for spatial (cutofff distamce 1,000 km) and serial (2 lags) correlation.
+ p<0.10, * p<0.05, ** p<0.01

Table A 41: Split sample models — Adjusting for spatial and serial correlation

	Model 5	*Model 6*	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agri*	*High Agr.*	*Low Agr.*	*High Agr.*	*Low Agri*
N Migr, ln (Q-1)	0.524**	0.564**	0.524**	0.564**	0.525**	0.562**	0.524**	0.561**
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-2)	-0.062	0.069	-0.063	0.069	-0.060	0.070	-0.062	0.071
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
N Migr, ln (Q-3)	0.137**	0.061	0.136**	0.061	0.140**	0.063	0.140**	0.064
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.008	0.050	0.008	0.050	0.012	0.052	0.012	0.053
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
SPEI (Y0)	0.464**	0.169+	0.467**	0.171+	0.429**	0.158+	0.421**	0.150+
	(0.12)	(0.09)	(0.12)	(0.09)	(0.12)	(0.09)	(0.12)	(0.09)
$SPEI^2$ (Y0)			0.067	0.045			0.086	0.030
			(0.12)	(0.13)			(0.14)	(0.13)
SPEI (Y-1)					-0.159	-0.076	-0.171	-0.074
					(0.13)	(0.11)	(0.12)	(0.11)
$SPEI^2$ (Y-1)							0.049	-0.012
							(0.20)	(0.13)
SPEI (Y-2)					-0.024	0.042	-0.041	0.038
					(0.11)	(0.11)	(0.12)	(0.11)
$SPEI^2$ (Y-2)							0.183	-0.128
							(0.19)	(0.14)
2nd quarter	0.861**	0.824**	0.861**	0.823**	0.860**	0.823**	0.861**	0.822**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
3rd quarter	0.796**	0.845**	0.796**	0.844**	0.791**	0.845**	0.792**	0.844**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
4th quarter	0.654**	0.501**	0.654**	0.502**	0.650**	0.503**	0.650**	0.500**
	(0.09)	(0.11)	(0.09)	(0.11)	(0.09)	(0.11)	(0.09)	(0.11)
Constant	-0.454*	1.719**	-0.468*	1.708**	1.953**	0.987**	2.364**	0.996**
	(0.18)	(0.35)	(0.19)	(0.35)	(0.35)	(0.33)	(0.37)	(0.32)
Cntr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Joint F test (SPEI)	16.04**	3.64+	8.20**	1.90	6.12**	1.41	3.78**	0.99
N	768	768	768	768	768	768	768	768
N Countries	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*

Std errors adjusted for spatial (cutofff distamce 1,000 km) and serial (2 lags) correlation.
+ p<0.10, * p<0.05, ** p<0.01

Table A 42: Large Weather Shocks — Adjusting for spatial and serial correlation

	Model 13	*Model 14*	*Model 15*	*Model 16*
	High Agr.	*Low Agr.*	*High Agr.*	*Low Agr.*
N Migr, ln (Q-1)	0.532**	0.567**	0.527**	0.564**
	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-2)	-0.060	0.069	-0.063	0.078
	(0.05)	(0.05)	(0.05)	(0.05)
N Migr, ln (Q-3)	0.131**	0.061	0.138**	0.063
	(0.04)	(0.05)	(0.04)	(0.05)
N Migr, ln (Q-4)	0.008	0.049	0.009	0.042
	(0.04)	(0.05)	(0.04)	(0.05)
Drought (Y0)	-0.312*	-0.063	-0.267+	-0.103
	(0.14)	(0.11)	(0.15)	(0.11)
Drought (Y-1)			0.230+	-0.130
			(0.14)	(0.14)
Drought (Y-2)			0.068	-0.246+
			(0.14)	(0.14)
Ex. rainfall (Y0)	0.375**	0.155+	0.366**	0.116
	(0.14)	(0.09)	(0.14)	(0.09)
Ex. rainfall (Y-1)			-0.055	-0.110
			(0.11)	(0.10)
Ex. rainfall (Y-2)			0.134	-0.140
			(0.13)	(0.10)
2nd quarter	0.872**	0.825**	0.867**	0.824**
	(0.11)	(0.11)	(0.11)	(0.11)
3rd quarter	0.799**	0.836**	0.800**	0.846**
	(0.10)	(0.10)	(0.10)	(0.10)
4th quarter	0.653**	0.492**	0.655**	0.502**
	(0.09)	(0.11)	(0.10)	(0.11)
Constant	2.381**	1.697**	-0.583**	1.814**
	(0.37)	(0.36)	(0.20)	(0.34)
Cntr FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Joint F test (SPEI)	5.77**	1.79	3.19**	1.84+
N	768	768	768	768
N Countries	*32*	*32*	*32*	*32*

Std errors adjusted for spatial (cutofff distamce 1,000 km) and serial (2 lags) correlation.
+ p<0.10, * p<0.05, ** p<0.01

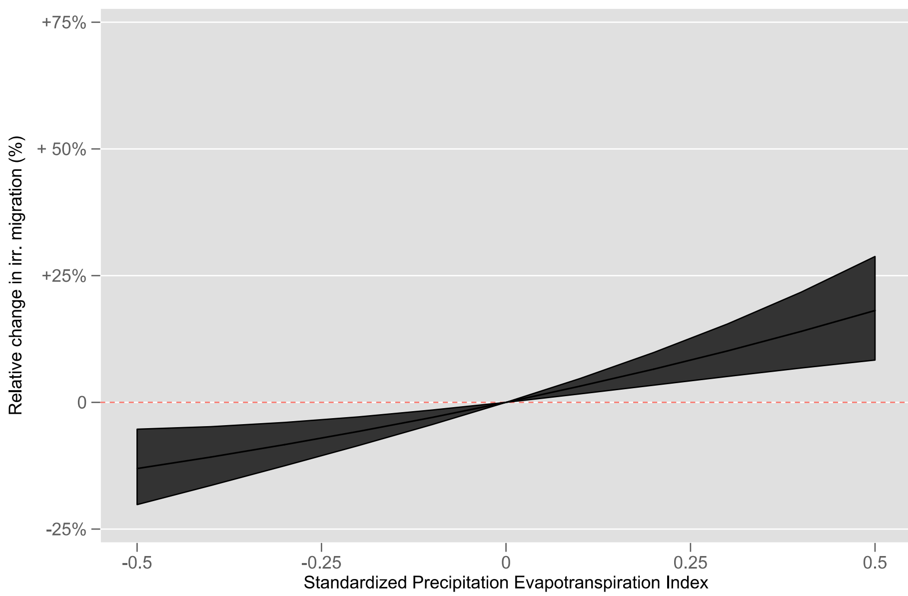

Figure A 29: Adjusting for spatial and serial correlation — Immediate effects of weather shocks on migration with 95% confidence interval (Model 2, Table A.40).

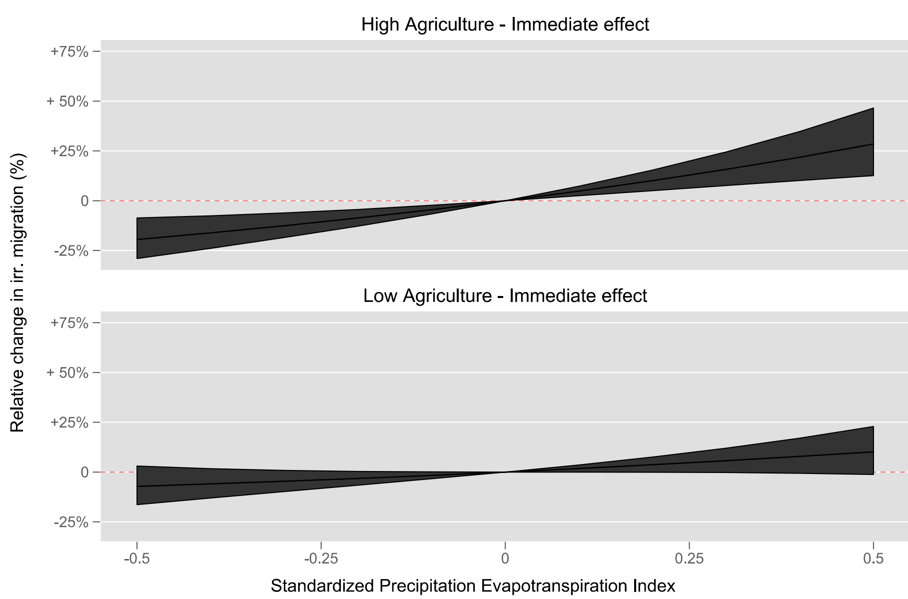

Figure A 30: Adjusting for spatial and serial correlation — Immediate effects of weather shocks on migration conditional on agriculture reliance with 95% confidence interval (Model 7 and 8, Table A.41)