Weather Shocks and Migration Intentions in Western Africa: Insights from a Multilevel Analysis*

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Abstract

We use a multilevel approach to investigate whether a general and robust relationship between weather shocks and (internal and international) migration intentions can be uncovered in Western African countries. We combine individual survey data with measures of localized weather shocks for thirteen countries over the 2008-2016 period. A meta-analysis on results from about 51,000 regressions is conducted to identify the specification of weather anomalies that maximizes the goodness of fit of our empirical model. We then use this best specification to document heterogeneous mobility responses to weather shocks. We find that variability in SPEI/rainfall is associated with changing intentions to move locally or internationally in a few countries only. However, the significance, sign and magnitude of the effect are far from being robust and consistent across countries. These differences might be due to imperfections in the data or to differences in long-term climate conditions and adaptation capabilities. They may also suggest that credit constraints are internalized differently in different settings, or that moving internally is not a relevant option as weather conditions are spatially correlated while moving abroad is an option of last resort. Although our multilevel approach allows us to connect migration intentions with the timing and spatial dimension of weather shocks, identifying a common specification that governs weather-driven mobility decisions is a very difficult, if not impossible, task, even for countries belonging to the same region. Our findings also call for extreme caution before generalizing results from specific case-studies.

JEL codes: F22, J61, O13, O15

Keywords: International migration; Migration intentions; Individual-level data; Weather shocks; Western Africa.

*We thank two anonymous referees for helpful comments and suggestions, and Olivier Santoni and Stefanija Veljanoska for providing excellent research assistance. We also acknowledge the Agence Française de Développement for its financial support (convention IRS/ECO/437-2017); S. Bertoli acknowledges the support received through the program "*Investissements d'avenir*" (ANR-10-LABX-14-01); the usual disclaimers apply.

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1 Introduction

It has abundantly been shown that changes in weather conditions induce economic, health and welfare effects within a given spatial unit (Dell et al., 2014). In particular, variations in temperature or rainfall have strong impacts on the level and volatility of income in agriculture-dependent economies, thereby increasing incentives (and sometimes forcing) individuals and families to seek more viable and less vulnerable places to live (IPPC, 2014; Rigaud et al., 2018). The influence of weather shocks and conditions on migration decisions is not specific to the contemporaneous period. Fagan (2008) finds that the 2°C rise in temperatures during the Medieval warm period (between the 9^{th} and 14^{th} century) resulted in large relocation of people and economic activity.[1] Still, the world has changed and the recent literature on climate change and migration has given rise to a wide variety of predictions.[2]

In spite of a growing availability of data on weather shocks and human mobility, important gaps remain in our understanding of the complex nexus between the two. This is mainly due to (i) the difficulty in connecting weather shocks realizations to the relevant exposed populations, and (ii) the difficulty in accounting for the individual and regional contexts that govern mobility decisions. Most existing studies suffer from important limitations (Piguet, 2010). On the one hand, macroeconomic approaches are usually constrained by the fact that migration data are available only at coarse levels of temporal and spatial granularity; hence, correlations measured for a big region might not be true at the local level. Individual survey and census data, on the other hand, suffer from the difficulty to keep track of international migrants; besides, conducting a survey takes time, implying that the date of the interview varies across individuals and is imprecisely connected to the timing of weather realizations.

To bridge the gap between the two approaches and to leverage on their respective strengths, our paper uses a multilevel approach. We combine measures of weather shocks collected from ground weather stations at a relatively detailed level of time and spatial granularity, with individual survey data documenting migration intentions at specific dates and spatial units. Our database covers thirteen Western African countries (Benin, Burkina Faso, Ghana, Guinea, Côte d'Ivoire, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo) over a period of up to eight years. We thus focus on a diversified mix of countries, including former French and British colonies, with heterogeneous levels of civil liberties and political stability, hence increasing the external validity of our study.[3] Furthermore, the multilevel approach allows us to better identify individuals hit by weather shocks, and to investigate the robustness and consistency of migration responses to weather events across countries that are geographically close to each other. It has been used in a few studies focusing on internal migration (Gray and Mueller, 2012a; Mueller et al., 2014); we use this approach to shed light on intentions to migrate internally or internationally and on how to model them.

We conduct the empirical analysis in two steps. First, taking advantage of a large

[1] See also Boustan et al. (2012) on internal migration responses to natural disasters in the US during the 1920s and 1930s, and on the role of public investments to protect against flooding.

[2] Recent literature surveys are provided in Piguet et al. (2011), Millock (2015), Berlemann and Steinhardt (2017), Cattaneo et al. (2019).

[3] We may still fall victims of the "streetlight effect", apparently a frequent tendency among climate change researchers "to focus on particular questions, cases and variables for reasons of convenience or data availability rather than broader relevance, policy importance, or construct validity" (Hendrix, 2017, p.137)). See also Kaplan (1964).

degree of freedom to define the specification of the migration response function, we compare a large set of empirical specifications connecting migration intentions to weather shocks. Considering two dependent variables (i.e., intentions to move within 12 months, and intentions to migrate internationally), our specifications differ in the choice of the weather variables (temperature, precipitation, or standardized precipitation evapotranspiration indices), the direction of the shock (positive, negative, or both), the intensity of the shock (one, two or three relative standard deviation(s) from the long-term mean),[4] the length of the period over which shocks are identified (12, 24 or 36 months prior to the date of the interview), and the treatment of the (local) crop-growing seasons. For each specification, we estimate the sensitivity of migration intentions to weather shocks using country-specific logit models and controlling for individual characteristics. Overall, we run about 51,000 logit regressions, and then conduct a meta-analysis of the regression results to assess the impact of methodological choices on migration responses and of the predictive power of the model. This meta-analysis reveals that the predictive power of the model is maximized when using symmetric SPEI or rainfall shocks and when measuring shocks as the share of months with at least one relative standard deviation from the local long-term value in the 24 months prior to the date of the survey. Moreover, the model performs better when focusing on the sub-sample of individuals living in rural areas, when keeping individuals living in (semi-)arid zones, and when we control for "contentment" (or satisfaction) with local amenities.

Second, we use this preferred specification to analyze the determinants of migration intentions, and to test whether these intentions are consistently affected by weather shocks in the thirteen Western African countries under consideration. We find that the results are far from conclusive in the sense that they lack robustness and consistency across Western African countries at both the extensive (significance) and intensive (sign and magnitude) margins. Variability in SPEI or rainfall is associated with differences in migration intentions to move within 12 months in a minority of countries such as Benin, Liberia, Mali, Mauritania, Niger or Sierra Leone. They influence intentions to move abroad in the same countries, plus Côte d'Ivoire, Guinea and Nigeria. The sign of the relationship varies across countries, and differentiating between positive and negative deviations from the long-run mean sometimes leads to counter-intuitive results. These differences might be due to imperfections in the data, unobserved cultural/anthropological differences, heterogeneous long-term climate conditions and capabilities to adapt to weather anomalies. They may also suggest that moving internally is not a relevant option as weather conditions are spatially correlated, and moving abroad is an option of last resort. Although our multilevel approach allows us to connect migration intentions to the timing and spatial dimension of weather shocks, identifying a common specification that governs weather-driven mobility decisions turns out to be very challenging if not impossible.

Our study is unique in several respects. First, we focus on Western Africa, a region at strong environmental risk and with a strong potential for these risks to translate into massive people displacement (European Commission, 2015). Indeed, Western Africa is heavily dependent on agriculture and has already experienced rising temperatures, shifting precipitation patterns, and increasingly extreme events (Jalloh et al., 2013). Second, we examine migration intentions both domestically and internationally. While migration intentions do not translate systematically into actual migration flows, the two appear strongly correlated (Bertoli and Ruyssen, 2018). Third, we analyze responses to several

[4]We define a relative standard deviation as the ratio between an absolute standard deviation and the long-term mean of the relevant climate variable.

types of weather shocks, provide methodological recommendations to formalize the links between weather shocks and migration intentions, and highlight the strong heterogeneity in the relationship between the two.

The rest of the paper is structured as follows. Section 2 describes the various strands of literature to which our paper relates. Section 3 introduces the data sources that we use for our empirical analysis and provides descriptive statistics. Section 4 describes the econometric model and discusses the results of our meta-regression analysis. Section 5 presents the results of our benchmark model and of a few additional specifications for the thirteen Western African countries in our sample. Finally, Section 6 provides concluding remarks.

2 Related literature

Our paper speaks to the literature on climate change and migration, and to the literature on the determinants of migration intentions.

Turning our attention to (selected) cross-country studies, there is great heterogeneity in the results.[5] Marchiori et al. (2012) show that weather anomalies tend to increase rural-to-urban migration through a decrease in agricultural productivity in sub-Saharan Africa. They also find that this urbanization process induces downward pressure on income in cities, which in turn induces internationally mobile workers to move to other countries.[6] In the same vein, Beine and Parsons (2015) find that natural disasters increase urbanization in developing countries; they also identify some indirect effects on international outflows through a decrease in income in urban areas. Marchiori et al. (2015) show that weather-related income variability has little effect on migration decisions. On the contrary, Coniglio and Pesce (2015) and Backhaus et al. (2015) show that higher variability in rainfall leads to outmigration to OECD countries. Cai et al. (2016) find that increases in the level of temperature boost outmigration to OECD destinations from agriculturally-dependent countries. In contrast, Cattaneo and Peri (2016) report that a gradual increase in the level of temperature only boosts international and rural-to-urban migrations in middle-income countries while the same shocks reduce migration outflows from poor countries.

The disparity in these results reflects the lack of an integrated approach, which partly relates to the scarcity, quality, and coarse spatial aggregation of the data. It also reflects the confluence of factors that cannot be identified separately: the migratory mechanisms involved, the structure of the economy, and the behavioral assumptions about household decisions.[7] Nonetheless, cross-country studies strongly suggest that internal and international migration responses to weather shocks are context-specific. In particular, they depend on the type of economic activity and on the level of development of the country under consideration, without it being possible, however, to assert whether such conditional effects are due to financial constraints, to the skill composition of the population,

[5]Other complementary studies focus on internal migration responses using urbanization rates (Barrios et al. 2006) or data aggregated by region (e.g., Bohra-Mishra et al. (2014) on province-to-province movements in Indonesia; or Bazzi (2017) on village-to-village movements in the same country).

[6]This is consistent with the results in Girsberger et al. (2020) who investigate the effect of migration to the main urban centers of francophone West Africa on wages and wage inequality in that region.

[7]Cattaneo and Peri (2016) argue that the disparity in results can be due to the fact that some studies are over-controlling with variables that are also influenced by weather at origin, and that the effects of weather variables vary with income per capita at origin.

to heterogeneous capabilities of "on-farm" adaptation, to past migration experiences, or even to cultural characteristics governing the perceptions of environmental hazards.

Case studies conducted at the microeconomic level tend to confirm that migration responses are highly heterogeneous (Gray and Bilsborrow, 2013; Piguet, 2010). Due to data constraints, case studies usually focus on the impact of a single type of shock (e.g., drought, high temperatures, low precipitation, natural disasters, etc.) and on rural-to-urban migration in specific countries. The role of household wealth also varies across countries. Just to name a few examples, Gray and Mueller (2012a) use longitudinal survey data spanning over 15 years to estimate the mobility responses to flooding and crop failures in Bangladesh. They find significant effects for women and for the poorest segments of the population. Looking at the case of Pakistan, Mueller et al. (2014) combine satellite-derived measures of weather shocks with longitudinal survey data. They find that flooding has modest to insignificant impacts on migration, while heat stress episodes increase the long-term migration of men, and more so for land- and asset-poor families. In contrast, other studies suggest that liquidity constraints prevent profitable migration in poor households. Bazzi (2017) combines administrative data available at the village level in Indonesia with rainfall shocks. He finds that liquidity constraints limit migration responses. The implied migration costs are suggestive of large inter-regional differences in the prevalence of financial constraints as well as in the potential net income gains from migration. Using South-African census data, Mastrorillo et al. (2016) quantify the effect of temperature and rainfall shocks on inter-district migration flows. They find that increases in temperature and (negative or positive) anomalies in rainfalls enhance out-migration of black, low-income individuals. The effect on white, high-income individuals is either weak or insignificant.

Other related studies highlight differences across skill groups. Due to heterogeneous exposition to climate change, Thiede et al. (2016) find that households with little or no education are more likely to be displaced by weather shocks than individuals with completed primary education. Their analysis relies on 25 censuses collected in eight South-American countries and contradicts panel data analyses relying on international migration flow data (Drabo and Mbaye, 2015). The role of gender is also controversial. While Thiede et al. (2016) and Gray and Bilsborrow (2013) find large migration responses for women, most of the existing studies show that men are more responsive than women, especially when looking at long-distance migration (Dillon et al., 2011) or when accounting for marriage-related moves (Gray and Mueller, 2012b).

In general, methodological choices are strongly affecting the results (Beine and Jeusette, 2018). Moreover, quantifying international migration responses using survey data is a complex task since international migrants disappear from (or are imperfectly captured in) census and register statistics, especially when the entire household is moving (Ibarraran and Lubotsky, 2007).[8] One distinctive feature of our analysis is that we focus on internal and international migration intentions, whose realization takes time. Our conjecture is that potential migrants remain in the pool of respondents in the first months following the shock. There is a large number of case studies in sociology and demography investigating the determinants of migration intentions (among others, see Becerra, 2012; Drinkwater and Ingram, 2009; Jonsson, 2008; Wood et al., 2010). Comparative survey

[8]Two additional sources of under-counting of international migration episodes in population censuses and surveys concern deliberate mis-reporting (Hamilton and Savinar, 2015) and the dissolution of the household of origin of the migrant (Bertoli and Murard, 2020), as retrospective questions are subject to a co-residence condition at the time of migration.

data on migration intentions, together with rich information on the individual characteristics of respondents, come from the Gallup World Polls (GWP), a unique database covering 150 countries since the year 2008. The GWP include "finer" (i.e., sub-regional) and "coarser" regional identifiers as well as interview dates, which allow us to connect respondents with spatial and time variations in weather conditions.

As the data are relatively new, the literature relying on these data to capture migration intentions is limited. Manchin et al. (2014) investigate the impact of individual wellbeing on the willingness to migrate internationally and locally. Dustmann and Okatenko (2014) study the role of wealth constraints and local amenities in governing migration intentions from sub-Saharan African countries. Docquier et al. (2014) and Dao et al. (2018) study the determinants of migration intentions after aggregating GWP data by country pair and by education level. Docquier et al. (2015) use the GWP data to proxy the number of potential migrants who could respond to a relaxation of migration policy barriers. Bertoli and Ruyssen (2018) and Manchin and Orazbayev (2018) quantify the effect of migrant networks on migration intentions and on migrants' destination choices. Ruyssen and Salomone (2018) investigate whether gender discrimination fosters women's migration intentions and plans. Docquier et al. (2020) investigate whether intended migrants from MENA countries self-select on cultural traits such as religiosity and gender attitudes. Finally, Friebel et al. (2018) study the elasticity of migration intentions to illegal moving costs, exploiting the demise of the Gaddafi regime in 2011 and the ensuing opening of the Libyan route to Europe as a quasi-natural experiment. To the best of our knowledge, our paper is the first to connect the GWP data on migration intentions with weather shocks and to conduct the analysis at relatively low levels of spatial resolution.

3 Data sources and descriptives

Our analysis covers thirteen Western African countries covered by the GWP (namely, Benin, Burkina Faso, Côte d'Ivoire, Ghana, Guinea, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone and Togo) over a period of eight years (from 2008 to 2015).[9] We use micro data on migration intentions of individuals aged 15 to 49 for whom we also have a rich set of individual variables. We connect these data from the GWP surveys with data on weather shocks (or anomalies) at the regional level, at two levels of resolution (for each region we will use either a "fine" or a "coarse" regional identifier, depending on the set of regional characteristics we control for). This section describes our data sources and provides descriptive statistics.

Migration intentions. – The GWP are surveys conducted by Gallup on around 1,000 randomly selected individuals in each wave, either through phone calls or through face-to-face interviews in countries where less than 80 percent of the population has a telephone landline (i.e., virtually all developing countries).[10] The sampling frame represents the entire civilian, non-institutionalized population aged 15 and above covering the entire country including rural areas, but excluding areas where the safety of the interviewing staff might be threatened, scarcely populated islands in some countries, and areas that interviewers can reach only by foot, animal, or small boats. The questionnaire of the

[9] Western African countries that are not covered by the GWP are Cape Verde, the Gambia, Guinea-Bissau, and the dependent territory of Saint-Helena. These countries and territories represent around 5 million inhabitants, i.e. 1.3% of the population of the region.

[10] For a description of the methodology and codebook, see Gallup (2017).

GWP includes a core set of questions that are covered in each country-wave pair and another set of questions that are asked only in some countries and/or waves. Notably, the GWP include two related questions on the intention to move:[11]

1. *In the next 12 months, are you likely or unlikely to move away from the city or area where you live?*

2. *Ideally, if you had the opportunity, would you like to move permanently to another country, or would you prefer to continue living in this country?*

Questions 1 and 2 differ with respect to three key dimensions, namely the time horizon of the intended move, the intended destination, and the duration of stay. Firstly, Question 1 only focuses on a short time horizon, while it does not restrict the answer to a specific (internal or international) type of destination, which prevents us from using destination-specific determinants and/or relying on spatial econometric techniques. By contrast, Question 2 does not specify a time frame for the intended move, but it restricts the focus to foreign countries. We refer to the individuals who express their intention to leave their area (or country) of residence as *would be* internal (or international) migrants.[12] Another difference concerns the duration of the intended move, which is left unspecified in Question 1, which can thus possibly cover also temporary or seasonal migration episodes, while Question 2 only relates to permanent moves. Many would be migrants are willing to emigrate either temporarily or permanently (Delogu et al., 2018). However, we will use Question 1 to build a proxy for the general intention to move, and Question 2 to build a proxy for the (inclusive) intention to migrate internationally.

Besides these key variables of interest, we keep track also of additional individual-level information contained in the GWP. Specifically, we record respondents' age and gender at the time of the interview, whether they are highly educated or not (i.e., have completed four years of education beyond high school and/or received a 4-year college degree or not), whether they live in a rural or urban area (living in a rural area includes living in a farm, small town or village, while an urban area is defined as a large city or a suburb of a large city), and whether they have a distance-one connection abroad (i.e., relatives or friends who are living in another country whom they can count on to help them if needed). We have information on the number of adults (aged 15 and above) and children in the household. In line with Dustmann and Okatenko (2014), we also use information about the respondent's contentment with local amenities, which captures opinion on public services available in the area of residence as well as contentment with area security and living standard. This variable captures dissatisfaction with public policies, including mitigation mechanisms implemented by national and local authorities

[11]The way in which this kind of hypothetical questions is interpreted might vary across countries, as observed by Clemens and Pritchett (2016) who underlines the risk of using contingent value surveys. Typically, respondents may interpret "opportunity" in light of the possibilities currently available to them (legal migration, irregular life-threatening trip, with or without funding, etc.), which vary across regions. For this reason, we only exploit within-country variation in the econometric analysis.

[12]For individuals who provide a positive answer to Question 2 (i.e., would-be international migrants), the GWP also asks the intended destination country. Bertoli and Ruyssen (2018) provide evidence that variations in bilateral migration intentions correlate with variations in actual gross bilateral migration flows to OECD countries. In addition, the GWP also include a question on migration plans: *Are you planning to move permanently to another country in the next 12 months, or not?* However, this question is only asked if the answer related to migrate intention is affirmative, which considerably reduces the number of observations. We will not exploit it in our analysis.

to cope with weather shocks. Note that the GWP also include, but *not* for all country-wave pairs, self-reported information about household income per capita. We do not use this variable in our benchmark specification, as (*i*) this would entail a (for some countries, substantial) reduction in our sample size, (*ii*) self-reported income can be affected by a substantial measurement error, especially in rural areas where subsistence agriculture is predominant, and (*iii*) income is likely to be affected by weather shocks and acts as a channel of transmission governing emigration decisions, so that we would end up over-controlling, as argued by Cattaneo and Peri (2016).

When dealing with mobility issues, a drawback of the GWP is that we cannot differentiate between long-standing residents (i.e., people who have lived for a long time in their current place of residence) and newcomers. Although GWP data allows us to connect migration intentions of residents with the timing and spatial dimension of weather shocks, we cannot exclude the possibility that individuals with the greatest propensity to migrate have already left the most adversely affected regions by the time of the survey, while temporary migrants might consider returning to their regions of origin and leaving regions that are beneficially affected. This may induce biases in our estimated responses to local shocks, or even change the sign of the coefficients. We will partially mitigate these concerns by checking the robustness of our results to the length of the period over which shocks are computed (prior to the survey).

Table 1 describes the main characteristics of the GWP data, and Figure 1 illustrates some key stylized facts. Panel A of Table 1 gives the number of observations per year and per country. Our sample consists of 60,248 observations. Panel B gives the month of the interview, a variable that will be used to connect the timing of migration intentions with the timing of weather realizations. Panel B reveals that there is considerable variation in the period of the year in which the survey is conducted in the various countries and waves.

Furthermore, the GWP includes up to two sets of geographical identifiers (a finer and a coarser one) corresponding to the location of each respondent, which broadly follow the administrative units of each country (i.e. regional or sub-regional administrative entities). We have processed these identifiers, matching them with timely maps from Global Administrative Areas (henceforth GADM).[13] This intermediate step allows us to connect each individual in the sample to the weather conditions prevailing in the GADM region(s) where the interview took place. For this step, we also use the information about the month of the interview, a relevant piece of information to ensure that we correctly match each respondent to relevant past weather conditions.

[13]See `https://gadm.org/`.

Table 1: Gallup data on migration intentions by year and by country

Country	A. Sample size								Total
	2008	2009	2010	2011	2012	2013	2014	2015	
Benin	0	0	0	818	823	763	797	762	3,963
Burkina Faso	759	0	790	828	789	832	788	783	5,569
Côte d'Ivoire	0	811	0	0	0	850	832	697	3,190
Ghana	0	743	0	807	838	797	754	746	4,685
Guinea	0	0	0	285	742	763	732	654	3,176
Liberia	0	0	861	0	0	711	0	740	2,312
Mali	791	791	789	830	836	776	813	759	6,385
Mauritania	0	0	0	1,656	808	744	728	742	4,678
Niger	806	855	832	848	837	801	766	740	6,485
Nigeria	602	657	836	866	1,489	661	762	827	6,700
Senegal	813	809	836	759	822	813	798	762	6,412
Sierra Leone	794	0	790	857	0	734	0	684	3,859
Togo	613	0	0	761	0	0	776	684	2,834
Total	5,178	4,666	5,734	9,315	7,984	9,245	8,546	9,580	60,248

	B. Month of the interview								# Waves
	2008	2009	2010	2011	2012	2013	2014	2015	
Benin	Aug	–	–	Sep	Aug	Jul	Jul	Aug	6
Burkina Faso	Apr	–	May	Sep	May	May	May	May	7
Côte d'Ivoire	–	Apr	–	–	–	Jun	May	Jun	4
Ghana	Apr	Jul	Sep	Apr	May	Jul	Sep	Apr	8
Guinea	–	–	–	May	Oct	Jul	Jul	Jun	5
Liberia	May	–	May	–	–	Nov	–	Jul	4
Mali	Jun	Oct	Oct	Nov	Nov	Oct	Oct	Oct	8
Mauritania	–	Sep	Mar/Sep	Feb/Sep	Feb	Jun	Nov	Apr	9
Niger	Jun	Jun	Nov	Nov	Nov	Sep	Oct	Oct	8
Nigeria	Apr	Aug	Apr	Aug	Mar/Nov	Jul	Jun	Jul	9
Senegal	Apr	Jun	Apr	Apr	Apr	May	Apr	May	8
Sierra Leone	Jun	–	Oct	Oct	–	Nov	Apr	Apr	7
Togo	Aug	–	–	Aug	–	–	Jun	Jun	4

	C. Availability of coarse region ID								# Obs.
	2008	2009	2010	2011	2012	2013	2014	2015	
Benin	No	No	No	Yes	Yes	Yes	Yes	Yes	3,963
Burkina Faso	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	5,569
Côte d'Ivoire	No	No	No	No	No	No	Yes	Yes	1,529
Ghana	No	No	No	No	No	No	No	No	0
Guinea	No	No	No	Yes	Yes	Yes	Yes	Yes	3,176
Liberia	No	No	No	No	No	No	No	No	0
Mali	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	6,385
Mauritania	No	No	No	Yes	Yes	Yes	Yes	Yes	4,678
Niger	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	6,485
Nigeria	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	5,670
Senegal	No	No	Yes	Yes	Yes	Yes	Yes	Yes	4,790
Sierra Leone	Yes	No	Yes	Yes	No	Yes	No	Yes	3,859
Togo	Yes	No	No	Yes	No	No	Yes	Yes	2,834

Source: Authors' elaboration on Gallup World Polls.

Table 1: Gallup data on migration intentions by year and by country (*continued)*

Country	D. Availability of fine region ID								# Obs.
	2008	2009	2010	2011	2012	2013	2014	2015	
Benin	No	No	No	No	No	No	Yes	Yes	1,559
Burkina Faso	No	No	Yes	Yes	Yes	Yes	Yes	Yes	4,810
Côte d'Ivoire	No	Yes	No	No	No	Yes	Yes	Yes	3,190
Ghana	No	Yes	No	Yes	Yes	Yes	Yes	Yes	4,685
Guinea	No	No	No	Yes	Yes	Yes	Yes	Yes	3,176
Liberia	No	No	Yes	No	No	Yes	No	Yes	2,312
Mali	No	No	No	No	No	No	Yes	Yes	1,572
Mauritania	No	No	No	Yes	Yes	Yes	Yes	Yes	4,678
Niger	No	No	No	No	No	No	Yes	Yes	1,506
Nigeria	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	6,098
Senegal	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	6,412
Sierra Leone	No	No	Yes	Yes	No	Yes	No	Yes	3,065
Togo	No	No	No	No	No	No	No	No	0

Source: Authors' elaboration on Gallup World Polls.

Panels C and D of Table 1 give the number of observations for which coarse and/or fine regional identifiers are available by year and by country. The two sets of identifiers are not necessarily available for all country-year pairs. For instance, neither of the two sets of identifiers is available up to 2013 for Côte d'Ivoire. Coarse identifiers are never available in Ghana and Liberia, whereas fine identifiers are never available in Togo. For each country-wave pair, we use the finest identifier that is available. For Togo, we only use coarse identifiers for the years 2011, 2014 and 2015. For some countries, we switch from fine to coarse regional identifiers when the former are not available. This can induce a time-varying measurement error in local weather conditions, increasing the chances of failing to reject the null hypothesis of a zero effect for our variable of interest. However, similar results are obtained when conducting regressions on a restricted sample of country-year pairs for which consistent regional identifiers are available.

Figures 1a and 1b plot the fine and coarse GADM regions for the thirteen Western African countries included in our analysis. Non-colored portions of the country (notably, for Mali and Niger) correspond to areas of the country that have not been covered by the GWP in at least one year between 2008 and 2015. Typically, the GWP exclude areas where the safety of the interviewing staff is threatened. These areas represent between 5 and 10% of the national population.[14] Note that the various countries differ with respect to the level of disaggregation of the two sets of regional identifiers.

Finally, Figures 1c to 1f map the share of respondents in each fine or coarse region who state their intention to move within 12 months and to migrate abroad, respectively. The light-colored areas are regions where the share of intended movers is smaller than 20%. The dark-color areas are regions where this share exceeds 47%. To put these figures in an international context, we can observe that Bertoli and Ruyssen (2018), who analyze the data on the intention to move abroad from the GWP conducted in 147 countries, report that the (population-weighted) average share of the respondents that intend to move abroad stands at 21.1 percent. This average value hides major differences across countries, with one of the countries in our sample (Sierra Leone) having the second highest incidence of respondents that intend to migrate (63.8 percent), and with the share of

[14]See `https://www.gallup.com/services/177797/country-data-set-details.aspx` for more details. The exception is Mali where regions accounting for 15 to 20% of the population were excluded between 2012 and 2016 due to rebel activity.

would-be migrants being negatively and significantly correlated with income per capita.

Note that the shares in Figures 1c to 1f are computed using raw GWP data, which do not account for sampling weights. GWP weights are meant to balance the sample averages of a few key variables – related to the demographic composition of the population – with those obtained from the most recent national population censuses. GWP surveys are neither representative of the population size and structure at the regional levels, nor of key variables such as the household size, personal network, etc. Sampling weights are not used in our descriptive and empirical analyses, as they reduce the efficiency of the estimator (Bertoli and Fernández-Huertas Moraga, 2013).

Weather shocks. – We use data on rainfall (P), on temperature (T), and on the Standarized Precipitation Evapotranspiration Index ($SPEI$) (Begueria et al., 2014) to identify weather shocks. Data on rainfall and temperature are available by month and for each GADM region of the countries included in the analysis from the high-resolution gridded dataset CRU-TS v.4.01 built by the Climatic Research Unit of the University of East Anglia (Harris et al., 2014). The data on meteorological conditions at the monthly level are provided at a resolution of 0.5 degrees,[15] and they come from the aggregation of observations collected from (a varying number of) ground weather stations. The weather conditions prevailing in each GADM region have been computed by aggregating the values corresponding to the grids that belong (entirely or partly) to the region, and each grid is assigned a weight that is proportional to the share of its surface that belongs to the GADM region.

More specifically, data on rainfall (temperature) come from up to eight weather stations located within a radius of 400 km (1,200 km) from the centroid of each grid.[16] For each ground weather station, the observations are first transformed into "anomalies" (i.e., distance to the long-term average value calculated over the period January 1901-December 1999). Figure 2a depicts the long-term average temperature level by "fine" region. For the twelve countries under consideration for which fine regional identifiers are available, the average is above $24.7°C$ in all regions. Temperatures around $30°C$ are observed in desert areas of Burkina Faso, Ghana, Mali, Mauritania, Nigeria, Niger and Senegal. Figure 2c maps the average precipitation by fine region. The North region (covering a large part of Mauritania and Niger, and the uncovered part of Mali) is occupied by the Western part of the Sahara desert, where it almost never rains. The middle region is semi-arid due to the African Monsoon, which brings rainfalls in the Summer. In the Southern regions of coastal countries, the rainy season is more intense and longer, and the landscape is greener.

Anomalies corresponding to stations falling within the radius are interpolated. The version 4.01 of the CRU-TS dataset relies on angular distance weighting interpolation for aggregating the anomalies (New et al., 2000): the weight associated to a station declines with its distance from the centroid (observations from closer stations are more informative) and increases with the degree of angular isolation of a station (observations from two stations that form a small angle with the centroid provide duplicated information). The interpolated value of the anomaly is then added to the long-run average for the centroid of the grid to obtain the information on the temperature or rainfall in a given month.

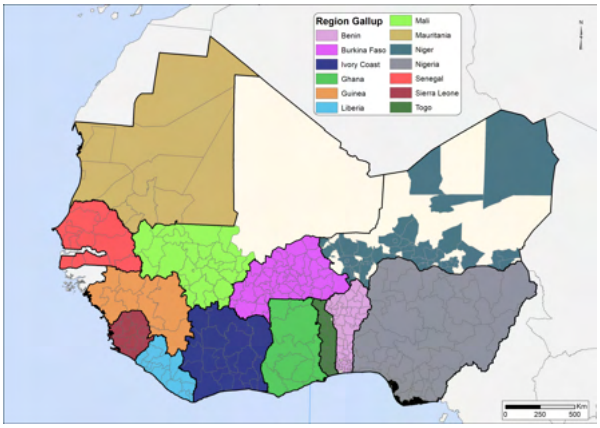
The CRU-TS dataset uses the information from all available ground weather stations

[15]Half a degree of latitude corresponds to approximately 55 km at the equator.

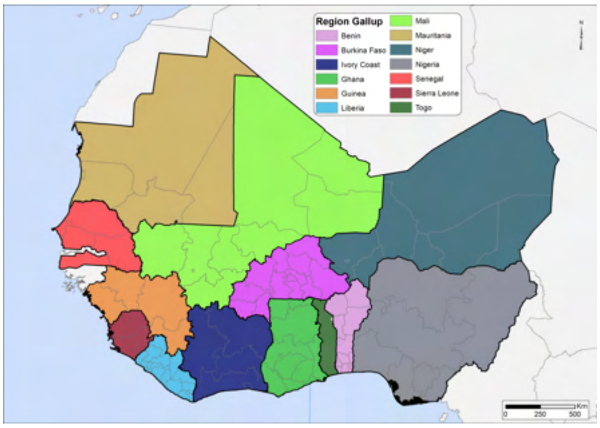
[16]The two radiuses represent the distances beyond which observations from a ground weather station become uninformative about the weather conditions prevailing in the centroid of the grid.

Figure 1: GWP data by region (2008-2015 averages)

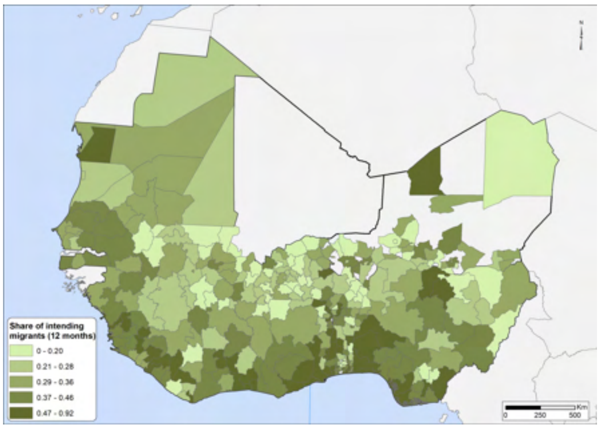
(a) Fine regions by country



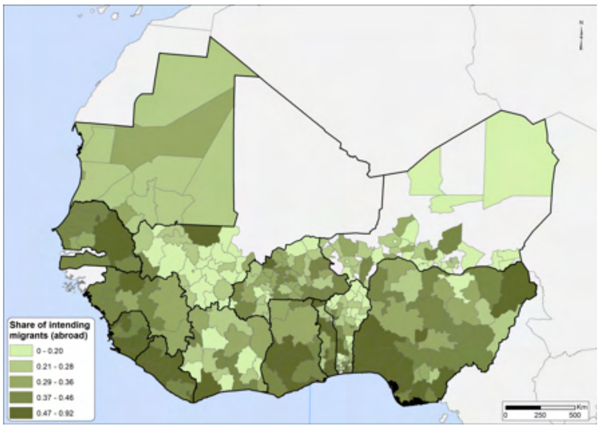
(b) Coarse regions by country



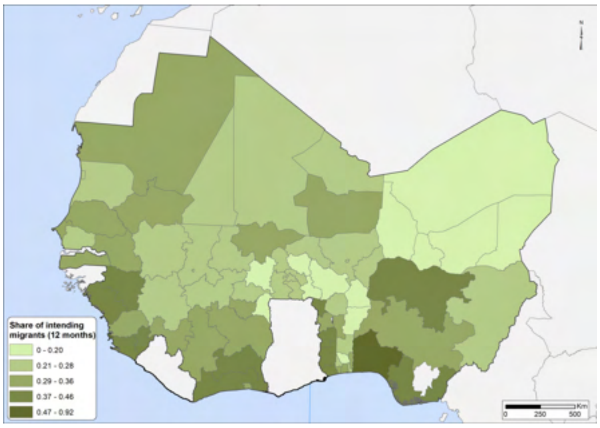
(c) Moving intentions (fine regions)



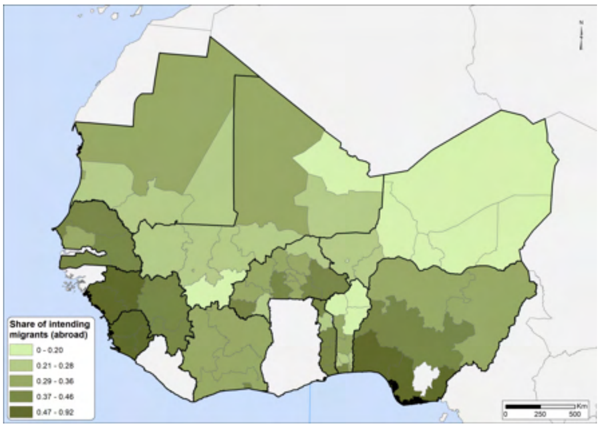
(d) Int'l migration intentions (fine regions)



(e) Moving intentions (coarse regions)



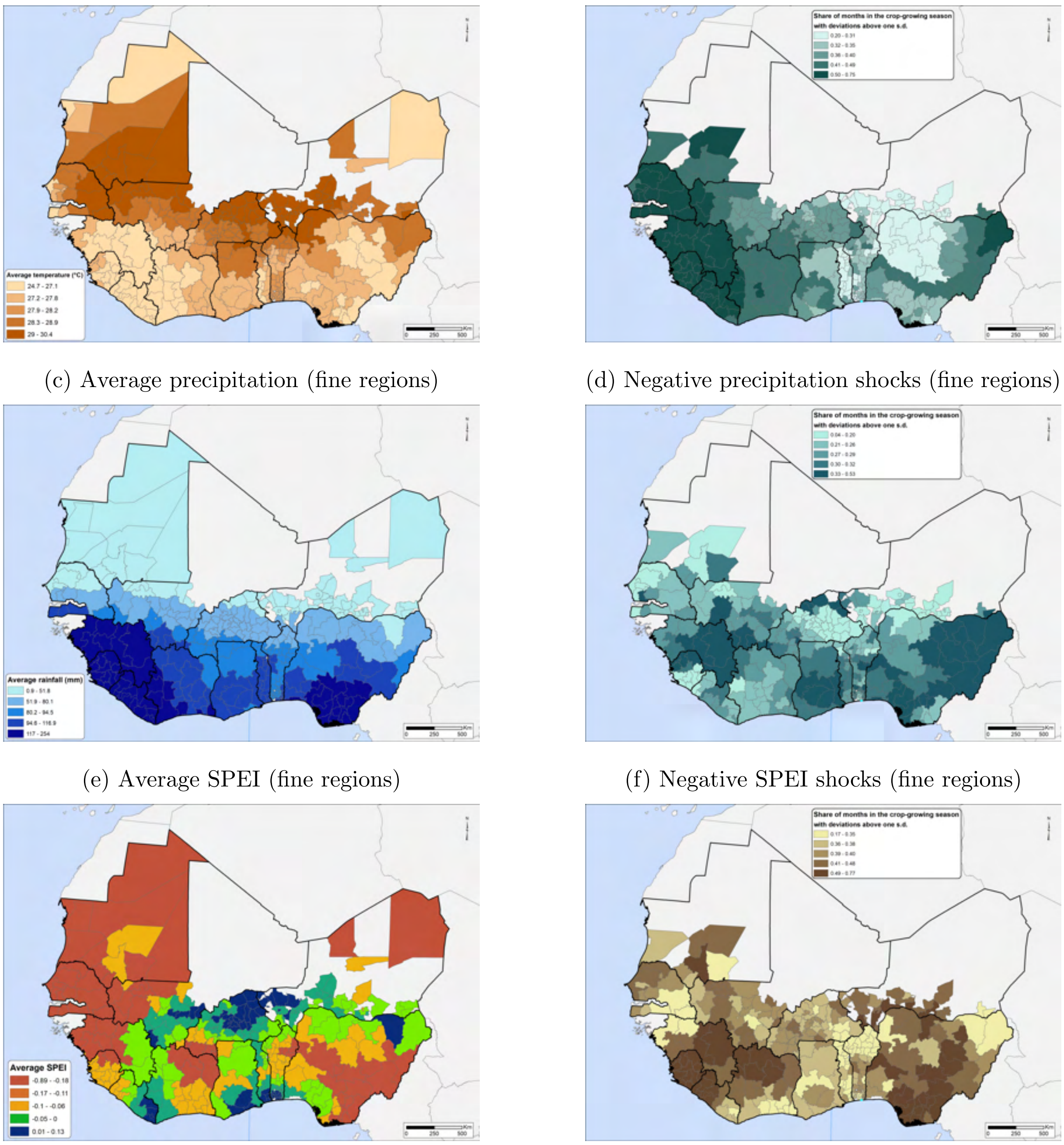
(f) Int'l migration intentions (coarse regions)



Note: Moving intentions = intention to move within 12 months. Int'l migration intentions = International migration intention. We represent here the average percentage of respondents who report an intention to move in the Gallup World Polls between 2008 and 2015.

at each point in time, so that the set of stations that are associated to each grid can vary over time. The dataset contains the information on the number of stations that have been used for each grid (separately for rainfall and temperature), that we have aggregated at the level of (fine and coarse) regions in the GWP data. If no ground weather station was

Figure 2: Data on average weather conditions and adverse shocks



(a) Average temperature (fine regions)

(b) Positive temperature shocks (fine regions)

(c) Average precipitation (fine regions)

(d) Negative precipitation shocks (fine regions)

(e) Average SPEI (fine regions)

(f) Negative SPEI shocks (fine regions)

active in a given month within the pre-specified radiuses (something that is extremely rare), then the grid is assigned a zero anomaly (i.e., the reported values for temperature and rainfall coincide with the long-run average). A zero anomaly is imputed only if no station is active within the radius: this means more than $\pi \times 400^2 \approx 0.5$ million squared kilometers for rainfall, and $\pi \times 1,200^2 \approx 4.5$ million squared kilometers for temperature. This only happens in a very limited number of cases, which are mostly related to spatial heterogeneity in the distribution of the population (and hence in the coverage of ground weather stations). Fluctuations in the density of ground weather stations can influence the reliability of the weather data, but they can also reflect seasonal patterns in the spatial variability of meteorological conditions which require variations in station density to keep the reliability of the data unchanged.

In practice, an adverse weather shock is defined as a month in which the mean temperature exceeds its long-term average value by more than one relative standard deviation (this threshold is guided by the meta-analysis conducted below), or a month in which the total level of precipitation is smaller than the long-term average minus two relative standard deviations. Figure 2b depicts the share of months (over the period 2008-2015) with positive relative temperature shocks, while Figure 2d shows the share of months with negative rainfall shocks.

We also use information on the SPEI. This is a multiscalar drought index that is used for determining the onset, duration and magnitude of drought conditions with respect to normal conditions in a variety of natural and managed systems such as crops, ecosystems, rivers, water resources, etc. It depends both on the supply of water to the ground through rainfall, i.e., P_{rt}, and the demand (or use) of water by the atmosphere through evapotranspiration, i.e., $ET0_{rt} = f(T_{rt}, X_r)$, where T_{rt} is the temperature in region r in month t and X_r is a set of other factors (such as latitude or monthly number of sun hours). Let $D_{rt} \equiv P_{rt} - ET0_{rt} = P_{rt} - f(T_{rt}, X_r)$ denote the water balance in region r and in period (month) t. The SPEI is defined over different time horizons: specifically, the $SPEI_{rt}$ is distributed according to a log-logistic distribution:[17]

$$F(D_{rt}) = \left[1 + \left(\frac{a}{D_{rt} - c}\right)^b\right]^{-1}$$

where:

$$D_{rt} \equiv \sum_{s=t-r+1}^{t} D_{rs}$$

and where a, b and c are parameters that are estimated. The SPEI_{rt} has a zero mean and a unitary variance. The distinctive advantage of the SPEI with respect to a separate reliance on rainfall or on temperature to identify extreme weather events is that this variable incorporates the interaction between these two variables in determining agricultural yields: for instance, the effect of a period with below average rainfall (or above average temperature, respectively) on agricultural output could be mitigated by a below average temperature (or above average rainfall, respectively). A drought is characterized by $\text{SPEI}_{rt} < 0$. The long-term average SPEI is depicted in Figure 2e.

Local crop-growing seasons. – Several studies show that the economic effects of weather shocks mostly operate through their influence on crop yields. In particular, weather shocks occurring during the crop-planting and crop-growing seasons are more likely to affect crop production (Iizumi and Ramankutty, 2015). For each GADM region belonging to the 13 countries included in our empirical analysis, we are able to identify the main crop, and then rely on information on the (local) planting and harvesting season for this crop to identify periods of the year in which weather conditions are expected to exert a stronger influence on agricultural yields, and thus possibly on stated migration intentions. More specifically, we proceed as follows: we rely on EARTHSTAT data to identify the main crop cultivated for the thirteen countries on the basis of a 5 minute ×

[17] In words, the SPEI at 3 months for January 2019 is a function of the sum of the water balance from November 2018 to January 2019.

5 minute (10 km $\times$ 10 km) latitude/longitude gridded dataset.[18] We then aggregate the grid data up to the regional level, thus identifying the main crop grown in each region (e.g., groundnut, millet, rice and sorghum for the various regions in Senegal) and use a crop calendar dataset to attach planting and harvesting seasons accordingly to each region (via its main crop).[19] The cropping season dataset is based on different sources that cover the 1990s or early 2000s; it allocates one value per grid and per crop. The harvested crop area data are computed using census data between 1997-2003 to obtain an average value before the start of our period of analysis. For perennial crops, such as cocoa and coffee, the growing season spans the entire year. Hence, in our empirical analysis, the weather shocks illustrated in Figures 2b, 2d and 2e can be weighted by a dummy equal to one if the corresponding month belongs to the crop-planting or crop-growing season.

4 Model specification

Our goal is to analyze the determinants of migration intentions, and to test whether these intentions are affected by weather shocks in the thirteen Western African countries under consideration. This section develops the micro-foundations underlying our empirical model, and describes the meta-analysis used to motivate our benchmark specification choices.

4.1 From theory to empirics

Consider an individual i, residing at time t in region r of country j. At this stage, we leave the country index aside. The choice set D of individual i includes her home region (which we refer to as $k = 0$ without loss of generality), the rest of country, i.e., $R/\{r\}$ where R is the set of regions of the country of origin (we refer to this second alternative in the choice set as $k = 1$), and the set W of other countries of the world ($k = 2$). Thus, the choice set D includes three alternatives: staying put, moving domestically, and migrating to an international destination. Let V_{irkt} denote the utility that individual i from region r would derive if opting for alternative $k \in D$ at time t. We assume that this alternative-specific utility includes a deterministic component V_{irkt} and a stochastic component ϵ_{irkt}. If the stochastic component follows an independent and identically distributed EVT-1, or double-exponential, distribution, then the probability p_{irkt} that $k \in D$ will be the utility-maximizing alternative is given by:

$$p_{irkt} = \frac{e^{V_{irkt}}}{\sum_{l \in D} e^{V_{irlt}}} \tag{1}$$

The relative probability of migrating domestically over staying put is given by:

$$\frac{p_{ir1t}}{p_{ir0t}} = e^{V_{ir01t} - V_{ir00t}} \tag{2}$$

The relative probability of migrating to the foreign destination $k = 2$ over staying put is given by:

$$\frac{p_{ir2t}}{p_{ir0t}} = e^{V_{ir02t} - V_{ir00t}} \tag{3}$$

[18]See http://www.earthstat.org/harvested-area-yield-175-crops/ (accessed on December 2, 2018).

[19]See https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/netCDF5min.php (accessed on December 2, 2018).

The relative probability of intending to move (irrespective of the destination) over staying put is given by:

$$\frac{p_{ir1t} + p_{ir2t}}{p_{ir0t}} = e^{V_{ir01t} + V_{ir02t} - V_{ir00t}} \tag{4}$$

Relative choice probabilities are solely determined by the difference in the levels of utility associated to each pair of alternatives (and not by the levels themselves); this, in turn, entails that we can normalize the utility associated to the baseline option (staying) to zero. Thus, the estimated coefficient for all the regressors give us the differential effect of each variable on the attractiveness of moving versus staying.

Let d_{irt}^{move} and d_{irt}^{abroad} represent two dummy variables taking the value one if individual i residing in region r and interviewed at time t expresses respectively the intention to move within 12 months (to an unspecified location) or the intention to move abroad (within an unspecified time horizon). We estimate logit models separately for each country:

$$\Pr\left(d_{irt} = 1\right) = \frac{e^{V_{irt}}}{1 + e^{V_{irt}}} \tag{5}$$

where $d_{irt} = \left\{d_{irt}^{\text{move}}, d_{irt}^{\text{abroad}}\right\}$.

Denoting the country-of-origin index by j, the reduced-form expression for the utility differential between moving options and staying writes as:[20]

$$V_{irjt} = \alpha_j + \gamma_j X_i + \beta_j WS_{rt} + \delta_{j1} d_m + \delta_{j2} d_y + \delta_{j3} d_r \tag{6}$$

where individual-specific controls (X_i) include dummies for age groups (i.e., 25-34 and 35+, with 15-24 being the reference category) and gender (with females being the reference category), a dummy for education (i.e., college-educated, with the less educated being the reference category), a dummy for living in an urban area (living in a rural area is the reference category, a dummy for having a distance-one connection abroad (i.e., a friend or family member whom one can count on when needed), and two continuous variables describing the size of the household and the number of children in the household to which individual i belongs. The variable WS_{rt} represents the preferred specification of our measure of past weather shocks defined for region r at time t. It is the number of weather shocks between month $t - n$ and the month of the interview t, where the lag n and the type of month to be considered (all months vs. crop-growing-season months) are the outcomes of the meta-analysis of the next sub-section.

Our specification of the deterministic component of the utility associated to moving includes dummies for the month-of-the-year m (d_m) and for the year y in which individual i was interviewed (d_y). We thus control for possible seasonal effects in the stated intentions to migrate and for time-varying country-level determinants of these intentions, respectively. It also includes a dummy for the region (d_r) to control for time-invariant spatial heterogeneity in the intentions to move.

If the estimated coefficient $\widehat{\beta}_j$ associated to the weather shock measure is positive and significant, this means that weather shocks make the origin location relatively less attractive than intended destinations. It is worth emphasizing that the GWP do not provide any information on the intended domestic destination of potential internal migrants. This prevents us from using the dyadic dimension, adding weather shocks in the destination

[20]To avoid cluttering the notation, we omit the dependency of the estimated coefficients with respect to the choice of the dependent variable; all coefficients clearly vary depending on whether $d_{irjt} = d_{irjt}^{12}$ or $d_{irjt} = d_{irjt}^{\text{abroad}}$ in Eq. (5).

region, or dealing with spatial correlation in weather conditions. The marginal effect on the probability of intending to move is given by $\widehat{\beta}_j p_{ijkt}(1-p_{ijkt})$, with $k=1,2$ depending on the choice of the dependent variable, while $\widehat{\beta}_j$ itself represents the partial derivative of the logarithm of the relative choice probability with respect to our variable of interest, that we interpret as a causal impact of weather shocks on migration intention.

Although weather shocks are usually assumed to be exogenous in the literature, it could be argued that stated migration intentions are just a way to express dissatisfaction with mitigation and coping strategies implemented by a national government or local authorities. As the latter influence the extent to which weather shocks translate into economic damages, there is a risk that our coefficient of interest picks up a spurious correlation. We mitigate this problem by including time-invariant regional dummies as well as a variable that captures individual contentment with local amenities, area security and living standard.[21] These factors prove to influence migration intentions, as shown in Dustmann and Okatenko (2014). We conduct a principal component analysis on these variables and keep the first component as an index of contentment with local policies.

The econometric analysis is conducted on prime-age individuals (i.e., between 15 and 49 years old); each individual is matched to the (past) weather conditions prevailing in the GADM region in which he or she is interviewed. The sample is also restricted to individuals for whom at least a coarse regional identifier is available. In the baseline specification, we match individuals to weather conditions using the finest available regional identifier, we always use fine regions if they are available, and we only resort to coarse identifiers if the former are not available.[22] Standard errors are clustered at the regional level (fine or coarse).[23]

4.2 Meta-analysis

We have a large degree of freedom to define the specification of the response functions in general, and the definition of the weather shock variable (WS_{rt}) in particular. To maximize the chance of uncovering a relevant effect of weather shocks on migration intentions, we consider a large number of specifications and conduct a meta-analysis of the regression results to assess the impact of methodological choices on migration responses at the extensive and intensive margins. For both dependent variables (intention to move within 12 months and intention to migrate abroad), our set of specifications covers different ways of measuring weather shocks, and different sub-samples of respondents. Letting $\widehat{\beta}$ represent the estimated coefficient for weather shocks, we analyze whether the various analytical

[21]More precisely, respondents provide an answer to the following questions: (*i*) Are you satisfied or dissatisfied with the city or area in which you live? (WP83); (*ii*) Would you recommend the city or area in which you live to a friend or associate as a place to live or not? (WP86); (*iii*) In the city or area in which you live, are you satisfied or dissatisfied with the educational system or the schools? (WP93); (*iv*) In the city or area in which you live, are you satisfied or dissatisfied with the availability of quality health care? (WP97); (*v*) In the city or area in which you live, are you satisfied or dissatisfied with the availability of good affordable housing? (WP98); (*vi*) In the city or area in which you live, are you satisfied or dissatisfied with the quality of air? (WP94).

[22]Notice that this entails that individuals interviewed in different waves can be matched to (past) weather conditions with a varying level of precision; using only the waves for each country for which consistent regional identifiers are available does not influence our results; these additional estimates are available from the Authors upon request.

[23]The limited number of (especially coarse) regions could entail a risk of over-rejection (Cameron et al., 2008); the relevance of this concern is mitigated by absence of evidence a systematic relationship between weather shocks and migration intentions that emerges from our econometric analysis.

choices related to our variable of interest and of sub-sample are governing its significance and/or size through a meta-regression analysis. Results for the intention to move within 12 months are reported in Table 2, while results for the intention to migrate abroad are reported in Table 3.

In particular, our meta-analysis distinguishes between:[24]

- 13 Western African countries: Benin (BEN), Burkina Faso (BFA), Côte d'Ivoire (CIV), Ghana (GHA), Guinea (GIN), Liberia (LBR), Mali (MLI), Mauritania (MRT), Niger (NER), Nigeria (NGA), Senegal (SEN), Sierra Leone (SLE), Togo (TGO);
- Nine weather variables of interest: deviations from the long-term trends in temperature (our reference in Tables 2 and 3) or in precipitations, and 5 variants of the SPEI shocks (7 methods to compute the long-term trend);
- Three types of weather shocks: both negative and positive shocks taken in a symmetric way (our reference), positive shocks only, or negative shocks only;
- Three measures of the intensity of the shock: at least two standard deviations from the long-term average (our reference), one standard deviation, or three standard deviations;
- Three possibilities for the length of the period over which deviations from the long-term average are computed: 24 months (our reference), 12 months, or 36 months;
- Two types of relevant months: identifying weather anomalies in all months (our reference), or in months falling in the crop-growing season;
- Six samples: full sample (including all individuals from all regions), sub-samples excluding (semi-)arid zones, or sub-samples covering only rural areas, urban areas, low-educated respondents and high-educated respondents.[25]

Exploring all combinations involves comparing 51,740 separate regressions for the general intention to move, and 51,761 for intentions to migrate internationally. Focusing on the coefficient of interest ($\widehat{\beta}$), only a fraction of them can be estimated due to the absence of identifying variation in the weather variable under some specifications. For example, some countries have never experienced shocks of at least two or three standard deviations over our time span. This is particularly the case when we consider asymmetric shocks (positive or negative) during the crop growing season. To maximize the comparability of our results, we focus on a sub-sample of 24,505 regressions for which the effect of weather shocks on general intentions to move within 12 months (and 24,188 for intentions to migrate internationally) can always be estimated.

[24]Some of the characteristics of the various specifications that we bring to the data that we consider in our meta-regressions are not covered by Beine and Jeusette (2018), who code around 80 variables for 45 papers on the relationship between weather conditions and migration; in particular, we analyze whether the significance, sign and size of the estimated coefficient for our variable of interest, i.e., WS_{rt}, depends on the length of the period over which we measure weather conditions, and on the thresholds that are set to identify extreme weather events.

[25]The last point in this list requires that we flag a warning: when we re-estimate our two logit models on sub-samples of observations (defined, for instance, on the basis of the level of education), we obtain a partition of the two samples into two parts of markedly different size. This, in turn, entails that (simply because of statistical power) the odds of finding a significant effect of past weather conditions on, say, highly-educated individuals residing in rural areas, are smaller than the odds of finding a significant effect for low-educated individuals.

Table 2: Meta-analysis on intentions to move within 12 months

	Balanced sample					Full sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	β^*	$\beta^* > 0$	$\beta^* < 0$	$\lvert\hat{\beta}\rvert$	Pred	$\beta\nexists$	Pred
Weather shocks (ref. = SPEI, symmetric, 2 sd-intensity, last 24 month)							
Temperature	0.048***	0.007	0.041***	-0.186***	0.300*	0.046***	-0.018
	(0.010)	(0.008)	(0.008)	(0.056)	(0.167)	(0.005)	(0.037)
Rainfall	0.010	-0.007	0.017***	-0.068	0.297**	-0.204***	0.065*
	(0.008)	(0.006)	(0.006)	(0.050)	(0.138)	(0.005)	(0.037)
Relative deviation	-0.047***	-0.034***	-0.013	-0.198***	-0.024	-0.116***	0.063
	(0.011)	(0.009)	(0.009)	(0.063)	(0.188)	(0.005)	(0.039)
Adverse shocks only	0.022***	-0.013**	0.035***	-0.212***	-0.023	0.335***	-0.128***
	(0.007)	(0.005)	(0.006)	(0.038)	(0.119)	(0.004)	(0.029)
Benef. shocks only	0.034***	0.019***	0.015**	-0.034	-0.102	0.393***	-0.191***
	(0.008)	(0.006)	(0.006)	(0.040)	(0.126)	(0.004)	(0.029)
Intensity = 1sd	-0.016**	0.015***	-0.031***	0.195***	0.013	-0.245***	0.094***
	(0.007)	(0.005)	(0.005)	(0.035)	(0.114)	(0.004)	(0.029)
Intensity = 3sd	-0.069***	-0.028***	-0.040***	0.087**	-0.009	0.325***	-0.049*
	(0.009)	(0.007)	(0.007)	(0.043)	(0.148)	(0.004)	(0.029)
Last 12 months	-0.030***	-0.015***	-0.015***	0.003	-0.022	0.028***	-0.007
	(0.007)	(0.005)	(0.005)	(0.031)	(0.113)	(0.004)	(0.029)
Last 36 months	-0.010	-0.011**	0.001	-0.065*	-0.030	-0.012***	-0.010
	(0.007)	(0.005)	(0.005)	(0.035)	(0.110)	(0.004)	(0.029)
Growing season only	0.017***	0.012***	0.005	0.038	-0.022	0.059***	-0.031
	(0.005)	(0.004)	(0.004)	(0.026)	(0.091)	(0.003)	(0.023)
Sub-sample variants (ref. = all regions, all individuals aged 15 and over)							
Arid zones excluded	0.008	-0.004	0.011	-0.039	0.132	0.022***	-0.187***
	(0.015)	(0.012)	(0.012)	(0.081)	(0.255)	(0.006)	(0.045)
Rural regions only	-0.005	-0.000	-0.005	0.025	1.362***	0.001	1.348***
	(0.009)	(0.007)	(0.007)	(0.042)	(0.157)	(0.006)	(0.043)
Urban regions only	0.004	-0.019**	0.022***	-0.162***	-2.901***	0.027***	-2.988***
	(0.010)	(0.007)	(0.007)	(0.048)	(0.160)	(0.006)	(0.043)
College-educ. only	-0.069***	-0.032***	-0.037***	0.095	1.080***	0.072***	0.464***
	(0.010)	(0.008)	(0.008)	(0.070)	(0.168)	(0.006)	(0.043)
Less educated only	0.007	-0.002	0.009	-0.009	0.044	-0.000	0.041
	(0.009)	(0.007)	(0.007)	(0.041)	(0.157)	(0.006)	(0.043)
Additional control in first-stage regressions							
Contentment	0.017*	0.007	0.010	-0.007	1.867***	0.002	1.835***
	(0.009)	(0.007)	(0.007)	(0.041)	(0.157)	(0.006)	(0.043)
Adjusted R^2	0.013	0.007	0.010	0.004	0.043	0.435	0.866
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$1/s.e.\_\beta$				Yes			
Observations	24,505	24,505	24,505	24,505	24,505	51,740	51,740

Notes: Meta-regressions of $\hat{\beta}$ on specification characteristics. All meta-regressions include country dummies. Estimation of $|\hat{\beta}|$ using weighted regressions (observations are weighted by the inverse of the standard errors of $\hat{\beta}$). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All first-stage regressions include weather shocks (with coefficient $\hat{\beta}$), country dummies, and a common set of controls: household size (continuous variable), number of children (continuous variable), age (ref. = 15-24, 25-34, 35+), gender (ref. = female vs. male), education (ref. = no college vs. college), region (ref. = rural vs. urban), network (ref. = 0, 1).

Table 3: Meta-analysis on intentions to migrate abroad

	Balanced sample					Full sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	β^*	$\beta^* > 0$	$\beta^* < 0$	$\lvert\hat{\beta}\rvert$	Pred	$\beta\nexists$	Pred
Weather shocks (ref. = SPEI, symmetric, 2 sd-intensity, last 24 month)							
Temperature	0.008	0.000	0.008	-0.268***	0.216	0.041***	-0.000
	(0.011)	(0.008)	(0.009)	(0.073)	(0.185)	(0.005)	(0.035)
Rainfall	-0.023***	-0.023***	0.000	-0.137**	0.234	-0.211***	0.077**
	(0.009)	(0.006)	(0.007)	(0.064)	(0.150)	(0.005)	(0.034)
Relative deviation	-0.096***	-0.072***	-0.024**	-0.404***	-0.044	-0.119***	0.056
	(0.012)	(0.009)	(0.009)	(0.082)	(0.205)	(0.005)	(0.036)
Adverse shocks only	0.054***	-0.005	0.059***	-0.248***	0.019	0.338***	-0.107***
	(0.008)	(0.006)	(0.006)	(0.050)	(0.130)	(0.004)	(0.026)
Benef. shocks only	0.024***	0.035***	-0.012*	-0.070	-0.098	0.393***	-0.150***
	(0.008)	(0.006)	(0.006)	(0.053)	(0.136)	(0.004)	(0.026)
Intensity = 1sd	-0.031***	0.002	-0.034***	0.263***	0.013	-0.248***	0.064**
	(0.007)	(0.005)	(0.006)	(0.045)	(0.124)	(0.004)	(0.026)
Intensity = 3sd	-0.017*	-0.022***	0.005	0.022	0.087	0.321***	-0.073***
	(0.009)	(0.007)	(0.007)	(0.056)	(0.160)	(0.004)	(0.026)
Last 12 months	0.002	-0.010**	0.012**	-0.014	-0.072	0.029***	-0.061**
	(0.007)	(0.005)	(0.006)	(0.041)	(0.123)	(0.004)	(0.026)
Last 36 months	-0.013*	-0.010**	-0.003	-0.063	-0.014	-0.013***	-0.003
	(0.007)	(0.005)	(0.005)	(0.046)	(0.119)	(0.004)	(0.026)
Growing season only	-0.027***	-0.002	-0.024***	0.102***	0.067	0.057***	0.036*
	(0.006)	(0.004)	(0.005)	(0.035)	(0.099)	(0.003)	(0.022)
Sub-sample variants (ref. = all regions, all individuals aged 15 and over)							
Arid zones excluded	0.017	0.007	0.010	0.018	-0.018	0.023***	-0.136***
	(0.016)	(0.012)	(0.013)	(0.106)	(0.275)	(0.006)	(0.041)
Rural regions only	-0.039***	-0.012*	-0.027***	0.064	0.430**	0.006	0.392***
	(0.010)	(0.007)	(0.008)	(0.056)	(0.169)	(0.006)	(0.040)
Urban regions only	0.006	-0.007	0.013	-0.051	-1.276***	0.034***	-1.335***
	(0.010)	(0.007)	(0.008)	(0.063)	(0.173)	(0.006)	(0.040)
College-educ. only	-0.054***	-0.028***	-0.026***	-0.159*	3.005***	0.075***	2.830***
	(0.011)	(0.008)	(0.009)	(0.087)	(0.183)	(0.006)	(0.040)
Less educated only	-0.003	-0.003	-0.000	0.003	0.010	0.000	-0.008
	(0.010)	(0.007)	(0.008)	(0.054)	(0.169)	(0.006)	(0.040)
Additional control in first-stage regressions							
Contentment	0.014	0.003	0.011	-0.026	1.025***	0.002	1.015***
	(0.010)	(0.007)	(0.008)	(0.055)	(0.169)	(0.006)	(0.040)
Adjusted R^2	0.010	0.007	0.010	0.004	0.023	0.452	0.899
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$1/s.e.\_\beta$				Yes			
Observations	24,188	24,188	24,188	24,188	24,188	51,761	51,761

Notes: Meta-regressions of $\hat{\beta}$ on specification characteristics. All meta-regressions include country dummies. Estimation of $|\hat{\beta}|$ using weighted regressions (observations are weighted by the inverse of the standard errors of $\hat{\beta}$). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All first-stage regressions include weather shocks (with coefficient $\hat{\beta}$), country dummies, and a common set of controls: household size (continuous variable), number of children (continuous variable), age (ref. = 15-24, 25-34, 35+), gender (ref. = female vs. male), education (ref. = no college vs. college), region (ref. = rural vs. urban), network (ref. = 0, 1).

We refer to this restricted sample of specifications as the balanced sample. In Cols. (1-3), we identify the conditions under which $\widehat{\beta}$ is significantly different from zero (β^*), is significant and positive ($\beta^* > 0$), or significant and negative ($\beta^* < 0$), respectively. In Col. (4), we analyze whether the magnitude ($|\hat{\beta}|$) of the estimated effect also depends on other characteristics of the model that we bring to the data. For the latter regression, we weigh observations by the inverse of the standard error of the coefficient in order to give higher weight to highly significant values of $\widehat{\beta}$. Maximizing the size or the significance of $\widehat{\beta}$ is not an objective *per se*. Hence, in Col. (5), we go beyond an exclusive focus on our variable of interest by analyzing a measure of the overall goodness of fit of each specification of the model, which also depends on the ability of other individual-level regressors to help us predict migration intentions. Specifically, let $\widehat{p_i}$ be the predicted probability that individual i intends to migrate, and let D_i represent a dummy variable taking the value one if individual i has stated an intention to migrate. We consider that our model correctly predicts migration intentions when $\widehat{p_i} \geq 0.5$ and $D_i = 1$, or $\widehat{p_i} < 0.5$ and $D_i = 0$. For each specification of our logit model, we can thus compute the share of observations in the sample that have been correctly predicted, and regress it on the characteristics of the model. The latter results govern the choice of our benchmark specification choice.

When focusing on general intentions to move within 12 months (Table 2), our meta-analysis reveals that the predictive power of the model is maximized when using symmetric SPEI or rainfall shocks – on average, the latter are more significant at the 5% level – in all months. Note that using rainfall shocks does not increase the probability to obtain a significant level of β^*. By contrast, considering adverse or beneficial shocks both increase the probability to obtain a significant level of β^*, but with somewhat counter-intuitive signs (adverse shocks lead to $\beta^* > 0$ and beneficial shocks lead to $\beta^* < 0$). Symmetric shocks capture the variability in weather conditions. Considering shocks occurring during the crop-growing season does not improve the predictive power of the model, though it increases the probability to obtain $\beta^* > 0$. This suggests that the effect of weather shocks is not limited to crop yields; they may affect welfare through other channels. The intensity and sign of the shock as well as the length of the period have little influence on the predictive power of the model. Considering shocks over the last 24 months increases the probability that β^* is significant.

Similar findings are found when focusing on intentions to migrate internationally in Table 3. The greatest predictive power is obtained with symmetric shocks in all months. In the balanced sample, choices regarding weather proxies (SPEI or rainfall), shock intensity and length of the period do not influence the predictive power of the model. Less importantly, the predictive power is always better when the sample includes (semi-)arid regions, when it is restricted to rural regions and highly educated individuals, and when we control for contentment with local amenities. Including the latter control does not affect the significance, the sign and the magnitude of $\widehat{\beta}$.

In Cols. (6-7), we report results for the full sample of regressions. We first identify the variables affecting the probability that the coefficient of interest, $\widehat{\beta}$, cannot be estimated ($\widehat{\beta}\nexists$). This is the case when we consider asymmetric shocks during the crop growing season, and when using temperature as a proxy. Using the full set of regressions, symmetric shocks are also desirable, and considering shocks of one standard deviation maximizes the size of the sample (i.e., avoid losses of observations) and the predictive power of the model. Considering shocks over the last 24 months is also desirable.

Overall, the meta-analysis suggests that weather shocks in our benchmark specification can be defined as relative and symmetric SPEI shocks of one standard-deviation intensity over 24 months prior to the date of the survey. In the Appendix B, we produce results from the meta-analysis for each country separately. The goal is to identify potential heterogeneous patterns and alternative specifications of the weather variables that are worth investigating. Results for the two outcome variables are presented in Tables A.1 and A.2. We consider that a variant is worth investigating when a different specification improves the predictive power of the model (at the 5% level) in at least 3 countries. Considering rainfall shocks (rather than SPEI) is desirable in 5 countries for general intentions to migrate within 12 months, and in 3 countries for intentions to migrate internationally. There is no strong reason to consider additional variants. This suggests that modelling the effect of weather shocks on migration intentions does not require drastically different country-specific specifications.

5 Weather shocks and migration intentions

The results of our meta-analysis are used to guide the choice of the proxy used to measure past weather shocks for region r at time t, WS_{rt}. In our benchmark specification, we proxy WS_{rt} with the share of months in the 24 months before the interview in which the SPEI (measured over one month) was at least one standard deviation above or below its long-term average value of zero. This implies that we are focusing on the effect of SPEI variability on moving intentions. Hence, if $\widehat{\beta}$ is positive (or negative, respectively), this means that weather shocks make the origin location relatively less (or more, respectively) attractive than other intended destinations. The first column of Tables 4 and 5 uses the full sample, and presents the results of our benchmark specification for the intention to move within 12 months and for the intention to move internationally, respectively. We only report the coefficient of the variable of interest, WS_{rt}. The coefficients for the full set of controls are provided in Tables B.1 and B.2 in the Appendix.

In the rest of Tables 4 and 5, we consider alternative specifications. In Col. (2), we use the same symmetric specification but we replace SPEI by rainfalls as a weather proxy. In Cols. (3-4), we get back to the SPEI proxy, and differentiate between positive shocks and negative shocks. The latter are usually assimilated to adverse shocks (i.e., droughts) causing agricultural and economic damages. Finally, in Cols (5-6), we estimate the model on rural regions only, and exclude one potential *bad control* which may indirectly capture the effect of weather shocks on intentions to move, namely the contentment with local amenities. This choice is guided by the fact that agricultural productivity is commonly perceived as highly sensitive to weather conditions.

Weather shocks and general intentions to move. – Focusing on the intention to move within 12 months, Table B.1 in the Appendix shows that moving intentions are always greater for males, always decrease with age (at least when considering individuals aged 35 and over), increase with the network variable,[26] and decrease with the contentment with local amenities.[27] It is worth noticing that we correctly predict moving intentions

[26]Notice that this applies also to the intention to move, although the (unspecified) destination might be internal, while this control variable related to the existence of distance-one connections outside one's own country.

[27]We have also estimated a specification with self-reported household income per capita among the regressors; the inclusion of this variable entails a reduction in the sample size in most countries, as this variable is either not covered in the questionnaire or it is unavailable for a large share of the respondents.

for a share of the sample varying between 66.2 percent (Sierra Leone) and 81.8 percent (Niger).

Focusing on our main variable of interest, however, Table 4 provides contrasting results. Variability in SPEI is associated with a significantly higher probability of intending to move within 12 months for Liberia, Mali and Sierra Leone. By contrast, the same variable reduces intentions to move in Niger, and has no significant impact in the other countries. Despite the fact that our benchmark specification maximizes the predictive power of the model, the effect of weather shocks on intentions to move is far from being robust and consistent across Western African countries. There are several possible explanations for this result. First, the quest for a common migration technology can be elusive, as average weather conditions/trends differ drastically across regions, and the effect of weather shocks might be non-linear. Second, cultural and anthropological disparities across countries and regions can be such that the migration option can be perceived as a relevant strategy or as a strategy of last resort. Third, the data on migration intentions might be imperfect.

To investigate the role of the migration technology and highlight possible cross-country heterogeneity, we use alternative specifications that can be seen as close substitutes to the benchmark one coming out of our meta-analysis. When using the variability in rainfalls in Col. (2), we obtain a negative association with intentions to move in four countries, Benin, Liberia, Mauritania and Sierra Leone, and insignificant effects elsewhere. Importantly, using rainfalls does not increase the share of correctly predicted observations. Furthermore although the meta-analysis suggests that the greatest predictive power is obtained when considering symmetric shocks, regressions in Cols. (3-4) show that differentiating positive and negative shocks does not lead to more homogeneous results. It appears that negative SPEI shocks (assimilated to droughts) have insignificant effects in virtually all countries except Benin, where droughts surprisingly reduce intentions to move. By contrast, positive SPEI shocks decrease intentions to move in Mauritania and Sierra Leone, while increasing intentions in Guinea and Togo. Finally, focusing on rural areas only does not lead to more conclusive effects. Droughts increase intentions to move in Mauritania and Sierra Leone, while having a negative impact in Benin. Similarly, positive SPEI shocks have contrasting effects in Mauritania and Niger, and insignificant effects elsewhere. Similar findings are obtained when considering shocks of greater intensity (2 standard deviations).

A possible concern in these regressions on the intention to move (irrespective of the destination) is the following: if an individual considers moving to a neighboring region, then weather conditions at origin could be positively correlated with weather conditions at destination, and this correlation confounds the effect of the estimated coefficient, possibly biasing it towards zero and reducing its statistical significance. Thus, when individuals have incentives to move, potential (internal) destinations may appear less attractive. This problem can be reinforced by the fact that gridded weather data are interpolated, as the data for region r can actually come from ground weather stations located in neighboring regions. This, in turn, entails that the estimated coefficient for WS_{rt} that we obtain when using d_{irjt}^{move} as our dependent variable is likely to be downward biased, so that our estimates could be interpreted as a lower bound of the true size of the effect. As discussed below, this concern is less pressing when investigating the determinants of intentions to move abroad.

A further concern related to the data is that individuals might have moved between the occurrence of an extreme weather event, and the date in which they are interviewed by

Results are available from the Authors upon request.

Table 4: Effect of weather shocks on intentions to move within 12 months ($\widehat{\beta}$)

	SPEI	Rainfall	SPEI		SPEI (rural only)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Symmetric	Symmetric	Positive	Negative	Positive	Negative
BEN	0.534	**-2.825*****	0.316	**-2.018*****	0.007	**-1.739*****
	(0.64)	(-4.56)	(0.25)	(-4.43)	(0.01)	(-4.24)
	[0.772]	[0.772]	[0.777]		[0.765]	
BFA	-0.973	-1.075	1.051	-3.134*	1.196	-2.995*
	(-1.25)	(-0.78)	(0.79)	(-1.74)	(0.94)	(-1.87)
	[0.794]	[0.794]	[0.795]		[0.783]	
CIV	0.062	-0.885	0.790	-1.229	0.873	-0.825
	(0.08)	(-0.92)	(0.65)	(-1.07)	(0.67)	(-0.72)
	[0.685]	[0.692]	[0.683]		[0.660]	
GHA	-0.266	0.745	0.290	0.984	0.410	1.045
	(-0.68)	(1.12)	(0.30)	(0.98)	(0.43)	(1.04)
	[0.666]	[0.664]	[0.668]		[0.620]	
GIN	0.140	1.421	**2.314****	1.021	2.082*	0.114
	(-0.17)	(0.97)	(1.97)	(1.28)	(1.79)	(0.17)
	[0.686]	[0.683]	[0.682]		[0.676]	
LBR	**3.082****	**-3.454****	-3.708	-0.854	-2.106	-0.719
	(2.27)	(-2.02)	(1.21)	(-0.46)	(-0.73)	(-0.41)
	[0.692]	[0.692]	[0.682]		[0.636]	
MLI	**1.077*****	-0.036	-0.398	-1.240	-0.568	-0.876
	(2.96)	(-0.06)	(35)	(-1.46)	(-0.56)	(-1.41)
	[0.761]	[0.760]	[0.760]		[0.756]	
MRT	0.610	**-1.384*****	**-1.290****	0.864	**-1.201*****	**2.861****
	(0.64)	(-5.09)	(-2.49)	(0.82)	(-2.81)	(2.34)
	[0.732]	[0.733]	[0.737]		[0.726]	
NER	**-1.062****	1.321*	0.663	0.569	**0.878****	1.024
	(-2.12)	(1.82)	(1.36)	(0.69)	(1.97)	(1.25)
	[0.818]	[0.815]	[0.816]		[0.812]	
NGA	-0.236	-0.262	0.871	0.063	0.648	-0.096
	(-0.53)	(-0.33)	(1.19)	(0.08)	(0.90)	(-0.14)
	[0.678]	[0.675]	[0.677]		[0.659]	
SEN	1.163	0.028	0.484	1.064	-0.187	1.217
	(1.44)	(0.02)	(-0.82)	(1.06)	(-0.33)	(1.12)
	[0.708]	[0.709]	[0.710]		[0.671]	
SLE	**4.254****	**-2.558****	**-7.312*****	7.372	-2.854	**18.804*****
	(2.31)	(-2.03)	(2.65)	(1.35)	(-0.81)	(4.82)
	[0.662]	[0.655]	[0.654]		[0.621]	
TGO	0.549	-	**1.356*****	-1.276	0.310	-1.588*
	(1.16)	-	(2.73)	(-1.37)	(0.063)	(-1.69)
	[0.675]	-	[0.664]		[0.632]	

Notes: Logit estimation by country. We only report the coefficient of the weather-shock variable, defined as a one standard deviation from the trend over the last 24 months. All regressions include a common set of controls: household size (continuous variable), number of children (continuous variable), age (ref. = 15-24, 25-34, 35+), gender (ref. = female vs. male), education (ref. = no college vs. college), region (ref. = rural vs. urban), network (ref. = 0, 1), contentment with local amenities. In the last two columns, we focus on the sample of rural regions only, and exclude the contentment variable from the set of controls. Country codes: Benin (BEN), Burkina Faso (BFA), Côte d'Ivoire (CIV), Ghana (GHA), Guinea (GIN), Liberia (LBR), Mali (MLI), Mauritania (MRT), Niger (NER), Nigeria (NGA), Senegal (SEN), Sierra Leone (SLE), Togo (TGO). Standard errors in parentheses are robust and clustered across regions. The share of correctly predicted intentions is reported between square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients significant at the least at the 5% level are reported in bold characters.

Gallup. If individuals with the highest propensity to migrate abroad have already moved by the time of the survey, then we would be missing them entirely.[28] If they moved internally (to a different region) in reaction to a negative weather shock, they might still be included in the sample, but we would be incorrectly matching them to the wrong weather conditions (the GWP do *not* provide information on the individual past migration history), that is, those prevailing in the region in which they moved to rather than in their region of origin, where they got exposed to a negative weather shock. A wrong association between an individual and past weather conditions introduces a measurement error in our variable of interest WS_{rt}. The ensuing implications for the size of the estimated coefficient are, however, ambiguous. Let us assume that internal migrants have moved to a region that has *not* been recently affected by a past negative weather shock; if these internal migrants intend to stay there (i.e., do not express the intention to move (again) within 12 months), then this would induce an upward bias in our estimated coefficients. But if these internal migrants have moved only on a temporary (or even seasonal) basis out of their region of origin, they might express the intention to move (return) within 12 months, thus inducing a downward bias in our estimated coefficient. Thus, the overall effect of the possible mismatch between a respondent in the GWP and past weather conditions exterted on the size (and significance) of the coefficient of our variable of interest is ambiguous. In addition, it is worth noticing that reducing the number of months over which weather shocks are computed to 12 months does not improve the significance and consistency of the results.

Weather shocks and intentions to migrate internationally. – The concern about a downward bias in the size of the estimated coefficient of interest is much less pressing when we consider intentions to migrate abroad, as the attractiveness of foreign destinations should be largely unaffected by local weather conditions. Table 5 provides the estimates for the main variable of interest, while Table B.2 in the Appendix provides the entire set of results related to Col. (1). It shows that intentions to migrate internationally are always greater for males, always decrease with age and increase with the network variable. They decrease with the contentment with local amenities. The model correctly predicts migration intentions for a share of the sample varying between 62.1 percent (Ghana) and 83.2 percent (Niger).

In Table 5, Col. (1) shows that SPEI symmetric shocks are never significantly associated with intentions to migrate. In Col. (2), we consider variability in rainfalls and find contrasting results: a positive effect on migration intentions is found in Guinea, Mauritania, Niger and Nigeria, whereas a significant negative association is found in Benin, Côte d'Ivoire and Sierra Leone. When differentiating positive and negative shocks, the effects are rarely significant and have different signs. In Cols (3-6), differentiating between positive and negative SPEI shocks does not lead to significant and consistent results. Droughts increase intentions to migrate in Niger, while the opposite effect is found in Benin. Again, it can be argued that the most mobile individuals might have moved between the occurrence of weather shocks and the date in which they are interviewed by Gallup. However, migrating abroad usually requires more and longer preparation, and similar results are obtained when weather shocks are computed over the last 12 months. With the exception of Mauritania and Sierra Leone, the association between weather shocks and international

[28]When estimating our logit model with d^{abroad}_{irjt} as our dependent variable, the fact that individuals whose location choices are more reactive to past local weather conditions might have disappeared from the sample would induce a downward bias in the size of our estimate for the coefficient of WS_{rt}.

Table 5: Effect of weather shocks on intentions to move abroad ($\widehat{\beta}$)

	SPEI	Rainfall	SPEI		SPEI (rural only)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Symmetric	Symmetric	Positive	Negative	Positive	Negative
BEN	0.528	**-3.787*****	-0.337	**-2.589*****	-0.404	**-2.590*****
	(0.44)	(-4.76)	(-0.21)	(-3.94)	(-0.26)	(-4.07)
	[0.759]	[0.765]	[0.763]		[0.760]	
BFA	-1.377	0.815	0.306	0.090	0.168	-0.079
	(-1.44)	(0.70)	(0.23)	(0.06)	(0.14)	(-0.06)
	[0.720]	[0.722]	[0.722]		[0.701]	
CIV	0.388	**-2.089*****	0.097	-1.139	-0.063	-0.871
	(0.38)	(-3.12)	(0.05)	(-1.26)	(-0.03)	(-0.84)
	[0.715]	[0.718]	[0.716]		[0.701]	
GHA	0.304	-0.137	0.422	0.040	0.473	0.035
	(1.00)	(-0.21)	(0.36)	(0.04)	(0.41)	(0.04)
	[0.621]	[0.620]	[0.619]		[0.620]	
GIN	-0.630	**3.060****	1.141	-2.032	0.847	-2.054
	(-1.20)	(2.38)	(1.15)	(-1.48)	(0.70)	(-1.59)
	[0.680]	[0.677]	[0.674]		[0.659]	
LBR	-0.150	-0.314	-0.736	-1.495	0.119	-0.866
	(-0.13)	(-0.22)	(-0.44)	(-0.58)	(0.08)	(-0.35)
	[0.666]	[0.665]	[0.665]		[0.629]	
MLI	0.169	1.000*	0.046	0.250	-0.165	0.512
	(0.52)	(1.75)	(0.06)	(0.34)	(-0.19)	(1.00)
	[0.774]	[0.777]	[0.775]		[0.777]	
MRT	0.683	**1.764****	0.146	0.154	0.413	2.215
	(0.67)	(2.48)	(0.31)	(0.09)	(1.03)	(1.39)
	[0.761]	[0.763]	[0.762]		[0.763]	
NER	-0.689	**1.733****	0.436	**2.482*****	0.666	**2.809*****
	(-1.24)	(2.30)	(0.87)	(3.17)	(1.32)	(3.64)
	[0.832]	[0.833]	[0.833]		[0.832]	
NGA	-0.594	**1.644****	0.417	0.020	-0.046	-0.168
	(-1.15)	(1.97)	(0.55)	(0.03)	(-0.06)	(-0.24)
	[0.654]	[0.653]	[0.654]		[0.639]	
SEN	0.556	0.356	0.256	-1.323	0.499	-1.074
	(0.77)	(0.28)	(0.79)	(-0.81)	(1.44)	(-0.68)
	[0.682]	[0.684]	[0.684]		[0.660]	
SLE	2.511	**-3.414*****	-4.733	15.953	-5.074	16.240
	(1.03)	(-3.33)	(-0.89)	(1.02)	(-1.48)	(1.54)
	[0.636]	[0.635]	[0.644]		[0.627]	
TGO	-0.554	-	**1.507****	0.012	1.287	-0.488
	(-0.84)	-	(2.08)	(0.02)	(1.56)	(-0.45)
	[0.663]	-	[0.667]		[0.657]	

Notes: Logit estimation by country. We only report the coefficient of the weather-shock variable(s), defined as a one standard deviation from the trend over the last 24 months. All regressions include a common set of controls: household size (continuous variable), number of children (continuous variable), age (ref. = 15-24, 25-34, 35+), gender (ref. = female vs. male), education (ref. = no college vs. college), region (ref. = rural vs. urban), network (ref. = 0, 1), contentment with local amenities. In the last two columns, we focus on the sample of rural regions only, and exclude the contentment variable from the set of controls. Country codes: Benin (BEN), Burkina Faso (BFA), Côte d'Ivoire (CIV), Ghana (GHA), Guinea (GIN), Liberia (LBR), Mali (MLI), Mauritania (MRT), Niger (NER), Nigeria (NGA), Senegal (SEN), Sierra Leone (SLE), Togo (TGO). Standard errors in parentheses are robust and clustered across regions. The share of correctly predicted intentions is reported between square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients significant at least at the 5% level are reported in bold characters.

migration intentions is rather weak.

6 Conclusion

In this paper, we use a multilevel approach to characterize the relationship between weather shocks and (internal and international) migration intentions. Focusing on thirteen Western African countries over a period of 8 years, we combine individual survey data on migration intentions with various types of weather shocks measurable at a relatively detailed spatial scale. We firstly conduct a meta-analysis to identify the specification of weather anomalies that maximize the goodness of fit of our empirical model. Comparing results from about 51,000 regressions, we find that the highest predictive power is obtained when defining weather anomalies as symmetric SPEI shocks, when measuring shocks as the share of months with at least 1 standard deviation with respect to the local long-term value over the last 24 months. We secondly use this best specification to identify mobility responses to weather shocks.

We find that variability in rainfalls are associated with smaller intentions to move within 12 months in countries such as Benin, Liberia, Mali, Mauritania, Niger or Sierra Leone. They are associated with differences in intentions to move abroad in the same countries, plus Côte d'Ivoire, Guinea or Nigeria. However, results are far from being robust and consistent across Western African countries at the extensive (significance) and intensive (sign and magnitude) margins. In particular, the sign of the effect varies across countries, and differentiating between positive and negative shocks sometimes leads to counter-intuitive results. This can be due to several reasons. Differences in culture or adaptation capabilities can require a region-specific specification, although we mitigate this concern by showing that the country-specific meta-analyses lead to converging findings. Data on migration intentions might be imperfect as the most mobile people might have already left their region of origin at the date in which they are interviewed. However, we mitigate this concern by showing that the same lack of robustness and consistency arises when computing shocks over a shorter period before the interview.

Our prior when starting this project was that it would have been possible to identify a stable relationship connecting the exposure in the recent past to extreme weather events with stated intentions to migrate as we were focusing on countries belonging to the same region (rather than on the whole developing world). Our analysis actually delivers a negative result: such a stable relationship does not emerge even from an attempt to maximize predictive power out of 51 thousand alternative specifications that have been estimated. The extent of the variations (in terms of measure of the variable of interest, composition of the sample and additional controls) implies that such "common technology" is *un*likely to exist, and all the more so in a larger and more diverse set of developing countries. Our interpretation is that the relationship between stated intentions to migrate (abroad or over the next year) and weather conditions is probably strongly context-specific. This pertains, possibly, to the strong heterogeneity across countries (and respondents) in the extent to which respondents internalize the prevailing liquidity constraints (possibly affected themselves by extreme weather events) when reporting their intentions to move. However, Clemens and Mendola (2020) show that moving from a question on "intentions" to a question on "making active plans" in the GWP – with the latter question supposedly internalizing credit constraints – does not change the pattern of self-selection, suggesting that credit constraints are indeed anticipated when stating one's migration intentions.[29] Their result is robust to accounting for people's networks, which have been shown to render selection more negative (McKenzie and Rapoport, 2010). Another possible interpretation is that moving within one's country is not a relevant option as weather conditions are spatially correlated, and moving abroad is an option of last resort. Is this is correct, our results reinforce even more the call for efficient local policies in responding to the challenge of climate change.

[29]We do not employ this variable as a dependent variable in our analysis because few respondents declare to be making active plans for migrating abroad, something that is problematic given the level of spatial and temporal granularity of our measure of extreme weather events.

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Appendix

A Additional meta-regressions

Tables A.1 and A.2 provide produce results from the meta-analysis for each country separately. The goal is to identify potential heterogeneous patterns and alternative specifications of the weather variables that are worth investigating.

Table A.1: Heterogeneity in predictive power by country – Intentions to move within 12 months

	BEN	BFA	CIV	GHA	GIN	LBR	MLI	MRT	NER	NGA	SEN	SLE	TGO
	Weather shocks (ref. = SPEI, symmetric, 2 sd-intensity, last 24 month)												
Temperature	-0.048	0.022	-0.023	0.122***	0.441***	-0.087**	0.036*	-0.025	0.016	-0.453***	0.017	-0.075***	0.000
	(0.044)	(0.045)	(0.033)	(0.025)	(0.032)	(0.037)	(0.021)	(0.044)	(0.079)	(0.064)	(0.027)	(0.026)	(.)
Rainfall	0.060	0.148***	0.251***	0.106***	-0.011	0.054	0.021	-0.010	-0.054	-0.178***	0.056**	0.418***	0.000
	(0.044)	(0.045)	(0.033)	(0.025)	(0.032)	(0.037)	(0.021)	(0.044)	(0.079)	(0.064)	(0.027)	(0.026)	(.)
Relative deviations	-0.009	0.061	0.066*	0.097***	0.041	0.006	0.072***	0.027	0.121	0.040	0.015	0.133***	0.000
	(0.046)	(0.048)	(0.035)	(0.026)	(0.034)	(0.039)	(0.022)	(0.045)	(0.081)	(0.067)	(0.028)	(0.028)	(.)
Adverse shocks only	-0.251***	-0.223***	-0.052**	-0.012	-0.072***	0.234***	-0.063***	-0.064*	-0.241***	0.067	-0.216***	-0.167***	-0.472***
	(0.034)	(0.035)	(0.026)	(0.019)	(0.025)	(0.029)	(0.016)	(0.035)	(0.063)	(0.050)	(0.021)	(0.020)	(0.066)
Benef. shocks only	-0.183***	-0.183***	0.012	-0.046**	-0.206***	0.003	-0.043***	-0.041	-0.279***	-0.520***	-0.237***	-0.171***	-0.016
	(0.034)	(0.035)	(0.026)	(0.019)	(0.025)	(0.029)	(0.016)	(0.035)	(0.063)	(0.050)	(0.021)	(0.020)	(0.066)
Intensity = 1sd	0.204***	0.109***	-0.077***	0.000	0.105***	-0.153***	0.016	0.048	0.091	0.148***	0.122***	0.162***	0.065
	(0.034)	(0.035)	(0.026)	(0.019)	(0.025)	(0.029)	(0.016)	(0.035)	(0.063)	(0.050)	(0.021)	(0.020)	(0.066)
intensity = 3sd	-0.105***	-0.033	-0.126***	-0.045**	-0.019	-0.255***	-0.054***	-0.018	-0.108*	-0.123**	-0.125***	0.001	0.148**
	(0.034)	(0.035)	(0.026)	(0.019)	(0.025)	(0.029)	(0.016)	(0.035)	(0.063)	(0.050)	(0.021)	(0.020)	(0.066)
Last 12 months	0.067*	-0.135***	0.026	-0.017	-0.187***	0.031	-0.038**	-0.006	-0.091	-0.129***	-0.069***	-0.160***	-0.102
	(0.034)	(0.035)	(0.026)	(0.019)	(0.025)	(0.029)	(0.016)	(0.035)	(0.063)	(0.050)	(0.021)	(0.020)	(0.066)
Last 36 months	-0.018	0.024	0.041	0.029	-0.050**	0.009	0.051***	0.001	-0.054	0.047	-0.030	-0.092***	-0.004
	(0.034)	(0.035)	(0.026)	(0.019)	(0.025)	(0.029)	(0.016)	(0.035)	(0.063)	(0.050)	(0.021)	(0.020)	(0.066)
Growing season only	0.287***	-0.273***	-0.000	-0.080***	0.018	0.014	-0.029**	1.233***	-0.492***	-0.155***	-0.020	0.002	0.002
	(0.028)	(0.029)	(0.021)	(0.016)	(0.020)	(0.023)	(0.013)	(0.029)	(0.051)	(0.041)	(0.017)	(0.017)	(0.054)
	Sub-sample variants (ref. = all regions, all individuals)												
Arid zones only	-0.035	-0.833***	-0.000	0.000	0.000	0.000	0.154***	-0.001	0.049	-0.285***	-0.525***	0.000	-0.000
	(0.052)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.025)	(0.073)	(0.130)	(0.076)	(0.032)	(0.031)	(0.101)
Rural regions only	1.511***	0.160***	2.681***	-0.305***	0.975***	-2.826***	0.403***	0.669***	-0.040	0.132*	1.615***	-2.122***	3.300***
	(0.052)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.025)	(0.051)	(0.091)	(0.076)	(0.032)	(0.031)	(0.101)
Urban regions only	-9.670***	-0.734***	-7.139***	0.578***	-2.338***	5.153***	-1.643***	-1.474***	0.235***	0.745***	-0.848***	5.459***	-8.163***
	(0.052)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.025)	(0.051)	(0.091)	(0.076)	(0.032)	(0.031)	(0.101)
College-educ. only	-3.624***	9.454***	-0.291***	1.086***	-0.691***	6.852***	-1.001***	1.948***	3.864***	0.559***	7.133***	1.907***	13.527***
	(0.052)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.025)	(0.051)	(0.092)	(0.076)	(0.032)	(0.031)	(0.101)
Less educated only	0.089*	-0.110**	0.316***	-0.165***	0.108***	-0.197***	0.066***	-0.122**	-0.023	0.007	-0.057*	-0.018	0.012
	(0.052)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.025)	(0.051)	(0.091)	(0.076)	(0.032)	(0.031)	(0.101)
	Additional control in first-stage regressions												
Contentment	0.289***	1.164***	0.349***	-0.101***	1.926***	3.661***	0.264***	0.637***	-0.027	0.700***	2.582***	1.442***	-0.096
	(0.052)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.025)	(0.051)	(0.091)	(0.076)	(0.032)	(0.031)	(0.101)
Adjusted R^2	0.941	0.930	0.946	0.452	0.783	0.948	0.739	0.641	0.444	0.130	0.958	0.944	0.949
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4158	4158	4158	4158	4158	4158	4158	3780	3755	4158	4158	4158	2646

Notes: Meta-regressions of $\hat{\beta}$ on specification characteristics by country. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All first-stage regressions include weather shocks (with coefficient $\hat{\beta}$), country dummies, and a common set of controls: household size (continuous variable), number of children (continuous variable), age (ref. = 15-24, 25-34, 35+), gender (ref. = female vs. male), education (ref. = no college vs. college), region (ref. = rural vs. urban), network (ref. = 0, 1).

Table A.2: Heterogeneity in predictive power by country – Intentions to move abroad

	BEN	BFA	CIV	GHA	GIN	LBR	MLI	MRT	NER	NGA	SEN	SLE	TGO
	Weather shocks (ref. = SPEI, symmetric, 2 sd-intensity, last 24 month)												
Temperature	-0.113***	-0.016	-0.058*	0.028	0.400***	0.003	-0.013	-0.052	-0.124	-0.221***	-0.052**	-0.075***	0.000
	(0.043)	(0.044)	(0.032)	(0.024)	(0.031)	(0.036)	(0.020)	(0.044)	(0.078)	(0.061)	(0.026)	(0.026)	(.)
Rainfall	-0.005	0.110**	0.217***	0.013	-0.052*	0.144***	-0.028	-0.037	-0.194**	0.054	-0.013	0.418***	0.000
	(0.043)	(0.044)	(0.032)	(0.024)	(0.031)	(0.036)	(0.020)	(0.044)	(0.078)	(0.061)	(0.026)	(0.026)	(.)
Relative deviations	-0.009	0.061	0.066*	0.097***	0.041	0.006	0.072***	0.027	0.121	0.040	0.015	0.133***	0.000
	(0.046)	(0.048)	(0.035)	(0.026)	(0.034)	(0.039)	(0.022)	(0.045)	(0.081)	(0.067)	(0.028)	(0.028)	(.)
Adverse shocks only	-0.067	-0.177***	-0.029	0.062**	0.013	0.038	-0.011	-0.028	-0.096	-0.261***	-0.103***	-0.262***	-0.406***
	(0.053)	(0.054)	(0.040)	(0.030)	(0.038)	(0.044)	(0.025)	(0.052)	(0.093)	(0.075)	(0.032)	(0.032)	(0.071)
Benef. shocks only	-0.172***	-0.166***	0.032	-0.059***	-0.205***	0.005	-0.033**	-0.039	-0.236***	-0.504***	-0.164***	-0.200***	-0.116
	(0.036)	(0.037)	(0.027)	(0.020)	(0.026)	(0.030)	(0.017)	(0.037)	(0.066)	(0.051)	(0.022)	(0.021)	(0.073)
Intensity = 1sd	-0.192***	-0.109***	-0.064**	0.037*	-0.177***	0.077***	-0.101***	-0.044	0.032	-0.580***	0.074***	-0.146***	-0.198***
	(0.035)	(0.036)	(0.026)	(0.020)	(0.025)	(0.029)	(0.016)	(0.035)	(0.064)	(0.049)	(0.021)	(0.021)	(0.073)
Intensity = 3sd	0.191***	0.148***	0.123***	-0.077***	0.144***	-0.052*	0.113***	0.043	0.137**	0.511***	0.210***	0.008	-0.102
	(0.037)	(0.038)	(0.028)	(0.021)	(0.027)	(0.031)	(0.017)	(0.038)	(0.069)	(0.053)	(0.023)	(0.022)	(0.073)
Last 12 months	0.067*	-0.135***	0.026	-0.017	-0.187***	0.031	-0.038**	-0.006	-0.091	-0.129***	-0.069***	-0.160***	-0.102
	(0.034)	(0.035)	(0.026)	(0.019)	(0.025)	(0.029)	(0.016)	(0.035)	(0.063)	(0.049)	(0.021)	(0.021)	(0.066)
Last 36 months	-0.018	0.024	0.041	0.029	-0.050**	0.009	0.051***	0.001	-0.055	0.047	-0.030	-0.092***	-0.004
	(0.034)	(0.035)	(0.026)	(0.019)	(0.025)	(0.029)	(0.016)	(0.035)	(0.063)	(0.049)	(0.021)	(0.021)	(0.066)
Growing season only	0.287***	-0.273***	0.000	-0.080***	0.018	0.014	-0.029**	1.233***	-0.491***	-0.155***	-0.020	0.002	0.002
	(0.028)	(0.029)	(0.021)	(0.016)	(0.020)	(0.023)	(0.013)	(0.029)	(0.051)	(0.040)	(0.017)	(0.017)	(0.054)
	Sub-sample variants (ref. = all regions, all individuals)												
Arid zones only	-0.035	-0.833***	-0.000	0.000	0.000	0.000	0.154***	-0.001	0.049	-0.285***	-0.525***	0.000	-0.000
	(0.053)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.024)	(0.073)	(0.130)	(0.074)	(0.032)	(0.031)	(0.101)
Rural regions only	1.511***	0.160***	2.681***	-0.305***	0.975***	-2.826***	0.403***	0.669***	-0.040	0.132*	1.615***	-2.122***	3.300***
	(0.053)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.024)	(0.051)	(0.091)	(0.074)	(0.032)	(0.031)	(0.101)
Urban regions only	-9.670***	-0.734***	-7.139***	0.578***	-2.338***	5.153***	-1.643***	-1.474***	0.235**	0.745***	-0.848***	5.459***	-8.163***
	(0.053)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.024)	(0.051)	(0.091)	(0.074)	(0.032)	(0.031)	(0.101)
College-educ. only	-3.624***	9.454***	-0.291***	1.086***	-0.691***	6.852***	-1.001***	1.948***	3.863***	0.559***	7.133***	1.907***	13.527***
	(0.053)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.024)	(0.051)	(0.092)	(0.074)	(0.032)	(0.031)	(0.101)
Less educated only	0.089*	-0.110**	0.316***	-0.165***	0.108***	-0.197***	0.066***	-0.122**	-0.023	0.007	-0.057*	-0.018	0.012
	(0.053)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.024)	(0.051)	(0.091)	(0.074)	(0.032)	(0.031)	(0.101)
	Additional control in first-stage regressions												
Contentment	0.289***	1.164***	0.349***	-0.101***	1.926***	3.661***	0.264***	0.637***	-0.027	0.700***	2.582***	1.442***	-0.096
	(0.053)	(0.054)	(0.039)	(0.030)	(0.038)	(0.044)	(0.024)	(0.051)	(0.091)	(0.074)	(0.032)	(0.031)	(0.101)
Adjusted R^2	0.940	0.930	0.946	0.453	0.784	0.948	0.741	0.641	0.443	0.169	0.958	0.943	0.949
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4158	4158	4158	4158	4158	4158	4158	3780	3755	4158	4158	4158	2646

Notes: Meta-regressions of $\hat{\beta}$ on specification characteristics by country. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All first-stage regressions include weather shocks (with coefficient $\hat{\beta}$), country dummies, and a common set of controls: household size (continuous variable), number of children (continuous variable), age (ref. = 15-24, 25-34, 35+), gender (ref. = female vs. male), education (ref. = no college vs. college), region (ref. = rural vs. urban), network (ref. = 0, 1).

B Country-specific regressions

Tables B.1 and B.2 report the estimated coefficients for the full set of controls used in Col. (1) of Tables 4 and 5, respectively.

Table B.1: Intentions to move within 12 months - symmetrical definition based on SPEI (plus or minus one standard deviation)

	BEN	BFA	CIV	GHA	GIN	LBR	MLI	MRT	NER	NGA	SEN	SLE	TGO
SPEI	0.534	-0.973	0.062	-0.266	0.140	3.082**	1.077***	0.610	-1.062**	-0.236	1.163	4.254**	0.549
	(0.64)	(-1.25)	(0.08)	(-0.68)	(0.17)	(2.27)	(2.96)	(0.64)	(-2.12)	(-0.53)	(1.44)	(2.31)	(1.16)
Age 25-34	-0.104	-0.237***	-0.071	-0.106*	-0.555***	-0.031	-0.595***	0.128	-0.051	-0.078	-0.116	-0.211**	-0.291***
	(-0.87)	(-3.16)	(-0.57)	(-1.79)	(-3.72)	(-0.20)	(-7.87)	(0.91)	(-0.74)	(-1.14)	(-1.15)	(-2.20)	(-3.49)
Age 35+	-0.778***	-0.710***	-0.673***	-0.457***	-1.002***	-0.368***	-1.153***	-0.388**	-0.634***	-0.570***	-0.705***	-0.518***	-0.544***
	(-7.35)	(-5.70)	(-4.17)	(-6.97)	(-4.62)	(-2.64)	(-11.25)	(-2.21)	(-6.52)	(-5.85)	(-5.01)	(-4.28)	(-5.33)
Male	0.206*	0.445***	0.040	0.031	0.365***	0.198*	0.706***	0.470***	1.167***	0.268***	0.681***	0.124	0.237***
	(1.95)	(5.08)	(0.47)	(0.36)	(3.91)	(1.75)	(5.59)	(2.75)	(9.43)	(4.82)	(9.56)	(1.39)	(5.44)
College	0.169	0.179	0.091	0.328	0.425	0.599**	0.147	0.301	-0.138	-0.149	-0.102	-0.214	-0.198
	(0.37)	(0.63)	(0.18)	(1.55)	(1.51)	(2.41)	(0.47)	(0.92)	(-0.38)	(-0.69)	(-0.54)	(-1.10)	(-0.42)
Urban	0.542**	-0.269*	0.136	-0.375**	0.091	-0.137	0.126	0.063	0.033	0.240**	0.101	0.043	0.524**
	(2.05)	(-1.70)	(0.77)	(-2.54)	(0.53)	(-0.48)	(0.72)	(0.13)	(0.19)	(2.55)	(0.50)	(0.26)	(2.00)
N. adults	0.004	-0.033	0.020	-0.032*	0.028*	0.019	-0.020	0.073***	0.048**	-0.023*	0.023	0.023*	-0.010
	(0.16)	(-1.60)	(1.01)	(-1.79)	(1.96)	(0.78)	(-1.54)	(5.00)	(2.43)	(-1.74)	(1.17)	(1.84)	(-0.84)
N. children	0.003	-0.021	-0.024	-0.022	0.005	0.059***	0.006	-0.031	0.004	-0.033*	-0.005	0.005	-0.008
	(0.11)	(-1.39)	(-1.20)	(-0.87)	(0.27)	(4.54)	(0.55)	(-1.03)	(0.34)	(-1.94)	(-0.51)	(0.35)	(-0.43)
Network	0.373***	0.232**	0.272***	0.218**	0.180*	0.146	0.450***	0.113	0.478***	0.505***	0.348***	0.473***	0.601***
	(3.38)	(2.57)	(3.81)	(2.36)	(1.83)	(0.77)	(7.01)	(0.83)	(5.64)	(6.42)	(5.13)	(4.80)	(7.17)
Contentment with local amenities	-0.421***	-0.506***	-0.429***	-0.414***	-0.374***	-0.576***	-0.352***	-0.511***	-0.453***	-0.306***	-0.510***	-0.414***	-0.467***
	(-7.80)	(-9.96)	(-8.84)	(-10.05)	(-5.12)	(-6.44)	(-4.88)	(-11.19)	(-11.93)	(-7.70)	(-16.70)	(-6.81)	(-8.08)
Constant	-0.943*	-1.888***	-0.989***	-0.269	-1.534***	-4.250***	-2.253***	-1.954***	-2.836***	0.339*	-2.107***	-1.506***	-1.465***
	(-1.96)	(-6.98)	(-3.00)	(-0.85)	(-5.25)	(-3.66)	(-5.42)	(-5.65)	(-14.08)	(1.70)	(-3.87)	(-5.02)	(-9.63)
Pseudo R^2	0.139	0.108	0.093	0.084	0.088	0.128	0.090	0.082	0.120	0.092	0.106	0.076	0.087
Correctly predicted	77.218	79.350	68.508	66.586	68.571	69.164	76.120	73.241	81.803	67.770	70.812	66.221	67.492
Observations	3630	5385	3131	4561	2870	2189	6252	2160	6166	5951	6328	3736	2667

Notes: Logit estimation by country. Country codes: Benin (BEN), Burkina Faso (BFA), Côte d'Ivoire (CIV), Ghana (GHA), Guinea (GIN), Liberia (LBR), Mali (MLI), Mauritania (MRT), Niger (NER), Nigeria (NGA), Senegal (SEN), Sierra Leone (SLE), Togo (TGO). Standard errors in parentheses are robust and clustered across regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Intentions to move abroad - symmetrical definition based on SPEI (plus or minus one standard deviation)

	BEN	BFA	CIV	GHA	GIN	LBR	MLI	MRT	NER	NGA	SEN	SLE	TGO
SPEI	0.528	-1.377	0.388	0.304	-0.630	-0.150	0.169	0.683	-0.689	-0.594	0.556	2.511	-0.554
	(0.44)	(-1.44)	(0.38)	(1.00)	(-1.20)	(-0.13)	(0.52)	(0.67)	(-1.24)	(-1.15)	(0.77)	(1.03)	(-0.84)
Age 25-34	-0.550***	-0.498***	-0.438***	-0.301**	-0.545***	-0.070	-0.624***	-0.341*	-0.340***	-0.276***	-0.470***	-0.309***	-0.360***
	(-4.40)	(-6.12)	(-5.73)	(-2.45)	(-6.55)	(-0.52)	(-6.63)	(-1.88)	(-3.95)	(-4.31)	(-10.76)	(-4.14)	(-3.60)
Age 35+	-1.086***	-1.095***	-0.963***	-0.649***	-1.068***	-0.457***	-1.313***	-1.133***	-0.984***	-0.626***	-1.184***	-0.471***	-0.811***
	(-8.61)	(-11.40)	(-7.61)	(-4.22)	(-9.78)	(-5.44)	(-10.04)	(-9.95)	(-10.78)	(-8.67)	(-8.75)	(-4.30)	(-13.10)
Male	0.443***	0.629***	0.391***	0.372***	0.389***	0.185*	0.824***	0.572***	1.448***	0.423***	0.713***	0.170***	0.375***
	(4.58)	(7.22)	(4.95)	(4.35)	(4.38)	(1.88)	(7.00)	(3.98)	(9.80)	(6.95)	(5.90)	(2.62)	(3.90)
College	-0.050	-0.616*	0.509***	-0.195	0.398***	0.001	0.169	0.303	-0.086	-0.018	-0.434**	-0.039	-0.527
	(-0.16)	(-1.93)	(2.75)	(-1.44)	(2.64)	(0.00)	(0.52)	(1.14)	(-0.27)	(-0.10)	(-2.52)	(-0.21)	(-0.66)
Urban	0.435*	-0.099	0.034	-0.001	0.482*	0.415**	0.154	0.257	0.085	0.099	-0.127	0.125	0.780***
	(1.65)	(-0.76)	(0.21)	(-0.01)	(1.84)	(2.54)	(1.00)	(1.59)	(0.30)	(1.10)	(-1.02)	(0.94)	(3.06)
N. adults	0.056***	0.020	0.063*	0.024	0.066***	0.058**	0.013	-0.010	0.031**	0.009	0.053***	0.029	0.020
	(2.84)	(1.28)	(1.70)	(0.99)	(2.99)	(2.11)	(1.34)	(-0.29)	(2.24)	(0.56)	(3.98)	(1.63)	(0.69)
N. children	0.004	-0.039**	-0.026	0.015	0.030***	0.020	-0.000	0.022	0.016	-0.049**	-0.025*	0.007	-0.018
	(0.19)	(-2.48)	(-1.48)	(0.55)	(2.59)	(0.77)	(-0.02)	(0.59)	(1.43)	(-2.43)	(-1.73)	(0.45)	(-1.53)
Network	0.389***	0.442***	0.182*	0.346***	0.193**	0.303**	0.383***	0.384**	0.575***	0.444***	0.527***	0.386***	0.384**
	(2.92)	(6.52)	(1.85)	(3.78)	(2.11)	(2.16)	(3.86)	(2.51)	(6.81)	(5.17)	(7.79)	(3.27)	(2.38)
Contentment with local amenities	-0.276***	-0.390***	-0.343***	-0.148***	-0.361***	-0.312***	-0.310***	-0.346***	-0.423***	-0.158***	-0.409***	-0.220***	-0.245***
	(-4.94)	(-8.05)	(-6.95)	(-4.42)	(-4.10)	(-6.58)	(-6.28)	(-5.71)	(-8.62)	(-5.88)	(-11.35)	(-5.75)	(-4.76)
Constant	-0.683	-0.774***	-1.810***	-0.140	-1.221***	-0.228	-1.392***	-1.816***	-2.709***	0.409**	-0.735	-0.409	-1.303***
	(-1.14)	(-2.68)	(-3.85)	(-0.56)	(-5.55)	(-0.22)	(-2.94)	(-4.84)	(-12.44)	(2.46)	(-1.43)	(-1.18)	(-6.79)
Pseudo R^2	0.135	0.110	0.109	0.060	0.106	0.083	0.104	0.085	0.149	0.090	0.129	0.072	0.076
Correctly predicted	75.947	71.975	71.536	62.070	68.004	66.566	77.453	76.139	83.287	65.391	68.247	63.566	66.337
Observations	3642	5488	3190	4685	2891	2312	6338	2238	6181	6273	6412	3859	2834

Notes: Logit estimation by country. Country codes: Benin (BEN), Burkina Faso (BFA), Côte d'Ivoire (CIV), Ghana (GHA), Guinea (GIN), Liberia (LBR), Mali (MLI), Mauritania (MRT), Niger (NER), Nigeria (NGA), Senegal (SEN), Sierra Leone (SLE), Togo (TGO). Standard errors in parentheses are robust and clustered across regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.