LUND UNIVERSITY
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No Place to Hide

The Impact of Climate Change on Internal Migration Across Six Sub-Saharan Countries

by

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Abstract

Drawing from 17 rounds of harmonised census data, this paper explores the link between climate variability and internal migration across six Sub-Saharan African countries. This study uses high-resolution precipitation and temperature data to construct two sets of measures capturing climate variability, the intensity of climate anomalies and the exposure to climate extremes. Two complementary hypotheses are tested: (1) whether climate variability increases the likelihood to migrate across provinces, and (2) if this effect is more pronounced for urban-bound migration. Overall, our analysis yields mixed conclusions. First, our results indicate that prolonged exposure to climate extremes such as droughts and cold snaps discourages migration across provinces. Second, most of the climate measures decrease the odds of urban-bound migration, therefore suggesting the existence of an immobilising effect through which climate change lowers the resources needed to finance the cost of migrating. Notwithstanding the limitations of this study, this research provides the first evidence of the climate inhibitor mechanism of internal migration across a large geographical area of relatively poor Sub-Saharan countries.

Key words: Climate Change; Internal Migration; Sub-Saharan Africa; Trapped populations

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Introduction

1.1 Research Problem

It is now widely accepted that we are entering a period of unprecedented change in the Earth's climate, mainly caused by human activity (UNFCCC, 1992). Climate change manifests in more frequent extreme climate events such as floods, storms, droughts and heat waves, to only name a few (UNGA, 2009). The various effects of climate change have and will trigger adverse consequences on our ecosystems, yet much controversy remains concerning its impact on our societies and particularly on human mobility patterns.

On the one hand, some studies have made sweeping predictions about mass migrations to come. Projections on the number of climate migrants by 2050 range from 50 million (Myers, 2002) to 1 billion (Christian Aid, 2007), yet these estimates generally lack strong empirical evidence supporting their claim (Gemenne, 2011; Missirian & Schlenker, 2017). On the other hand, micro-level evidence challenge this simplistic common narrative by revealing complex migration patterns (among others: Baez et al., 2017a; Gray & Mueller, 2012; Nawrotzki et al., 2017). Whereas most studies conclude that climate change can induce migration, evidence shows that migratory responses are not "monolithic and unidirectional" (Gray & Wise, 2016, p.556). As much uncertainty still prevails about the relationship between climate change and migration, this paper seeks to unravel the micro-level evidence at a regional scale for six Sub-Saharan countries. More specifically, this study aims to address three main shortcomings identified in the recent literature on climate change and migration.

First, due to the absence of harmonised migration dataset, a vast majority of these studies are based on single-country analysis and have a geographically-narrow focus. Consequently, the generalisability of much-published research on this issue is problematic as the results are likely to capture results that are either biased, time-specific or country-specific (Gray & Wise, 2016). *Second,* a number of studies focus on a single climate anomaly derived from precipitation data, thus omitting its interdependence with temperature anomalies. Even though the latter tend to have a greater impact on migration in comparison to that of precipitation (Bohra-Mishra, Oppenheimer & Hsiang, 2014). *Third,* most studies generally capture a single aspect of climate variability which does not allow them to capture the different migratory responses to both slow and sudden-onset climate events (Mastrorillo et al., 2016).

1.2 Aim and Scope

This paper addresses these limitations by shedding light on the impact of climate variability on internal migration across six Sub-Saharan African countries. To provide a better framework for this analysis, the research questions of this paper can be formulated as follows: *Does climate variability affect the decision to migrate across provinces? If so, does climate change play a role in the urbanisation of cities?* Therefore, two complementary hypotheses are tested:

(1) *Climate variability has a positive impact on the likelihood to migrate across provinces.*
(2) *Climate variability is more likely to trigger inter-provincial migration to urban areas than to rural ones.*

Using precipitation and temperature data spanning from 1961 to 2012, this study examines two aspects of climate variability. One is gradual climate changes which are referred to as multi-period deviations from a long-term mean. The second captures the length of exposure to climate extremes (Thiede, Gray & Mueller, 2016). Measures of climate variability are merged to harmonised census data for Burkina Faso, Botswana, Kenya, Mozambique, Tanzania, and Zambia, covering roughly 30 years (1979-2012).

Overall, our analysis yields mixed conclusions. While previous evidence had shown that human mobility could serve as an adaptation strategy facing climate change, our results indicate that prolonged exposure to climate extremes such as droughts and cold snaps discourages migration across provinces. Second, most of the climate measures decrease the odds of urban-bound migration, therefore suggesting the existence of an immobilising effect through which climate change lowers the resources needed to finance the cost of migrating. Overall, our results indicate that climate variability is likely to act as a climate inhibitor reducing inter-province migration. While the identification of the channels affecting the relationship is beyond the scope of this research, we suggest that the effect runs through the "agricultural pathway" by lowering agricultural productivity and the resources needed to finance the cost of moving.

Besides overcoming the three limitations of the climate change migration research, this study adds to the literature in several ways. *First*, this research addresses the extensive theoretical literature on the determinants of migration. We argue that climate variability is likely to exacerbate already-existing economic, political and demographic push factors of migration (Black et al., 2011a). *Second*, this paper addresses the growing micro-level literature linking climate change to migration. This study is, to the best of our knowledge, the first study pooling six Sub-Saharan countries over a period of roughly thirty years. Other studies have looked at the climate-migration relationship with fewer Sub-Saharan African countries (Cattaneo & Massetti, 2015; Gray & Wise, 2016; Nawrotzki, Schlak & Kugler, 2016) or have investigated this relationship in other continents (Baez et al., 2017a, 2017b; Thiede, Gray & Mueller, 2016). *Finally*, this study is also relevant to the relatively scarce micro-level evidence dealing with the impact of climate change on urbanisation in Sub-Saharan Africa. By identifying the climate factors preventing individuals from migrating, our study highlights the need for policymakers to reduce the climate vulnerability of people living in rural areas by facilitating migration.

1.3 Outline of the Thesis

The remaining part of the paper proceeds as follows. Section 2 reviews the literature. Section 3 presents the different sources of data used in this paper. Section 4 exposes the construction of the climate variables together with the model used to test the above-mentioned hypotheses. At last, Section 5 discusses the results of the empirical analysis.

2 Literature Review

2.1 Conceptual complexity

The absence of conceptual clarity on the definition of key terms describing the climate-migration phenomenon sparked much debate in the literature. Indeed, the discussion on climate migration is hampered by a lack of consensus on the terms to describe the people affected, whether they should be called refugees, migrants or displaced people (McAdam, 2009). After introducing key definitions of climate change and its manifestations, this section aims at summarising this overarching issue and its implications in the climate change-migration research.

2.1.1 Climate change

Before delving into the nature of the debate, we first define climate change and its manifestations. This paper follows the United Nations Framework Convention on Climate Change (hereafter UNFCCC) definition of climate change which is defined as "a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods" (UNFCCC, 1992, p.7).[i]

Studies assessing the relationship between climate change and migration typically investigate one of the two types of disruptions intensified by climate change: *sudden-onset* or *slow-onset events*. *Sudden-onset events* also referred to as extreme weather events, are due to disasters that are either natural or anthropogenic. They include flash floods, earthquakes, landslides, tsunamis, hurricanes, and wildfires, among others (UNGA, 2016). Climate change also manifests in *slow-onset events* having a gradual and less destructive impact than that of disasters. As recognized in the Cancun Agreement, rising temperatures, droughts, desertification, loss of biodiversity, land and forest degradation, glacial retreat, ocean acidification, sea level rise and salinization capture the long-term effects of climate change (UNFCCC, 2011). Considering both *sudden* and *slow-onset events* allows a diversity of adaptation techniques to be captured. Indeed, evidence shows that different measures of climate change are likely to have multi-directional impacts on migration (Thiede, Gray & Mueller, 2016). In the light of this dichotomy, this paper uses monthly temperature and precipitation data to capture two aspects of climate variability: the intensity of climate anomalies over several periods (*slow-onset events*) together with the cumulative exposure to climate extremes (*sudden-onset events*).

Another significant aspect of climate change stems from its exacerbation of already-existing social, economic and environmental instabilities. Climate change acts as a "threat multiplier" as it widens social and economic inequalities, intensifies political instability over resource management, and increases the frequency and intensity of natural disasters, to only name a few (UNGA, 2009). Populations living in developing countries are therefore particularly vulnerable to the direct and indirect effects of climate change. For instance, as their livelihood is mostly based on agricultural production, they are, by nature, very sensitive to climatic events (Wineman et al., 2015). Additionally, in the absence of access to formal financial services, smallholder farmers have limited means of insurance against unpredicted risks (Ravallion & Chaudhuri, 1997). Consequently, physical mobility and more especially temporary and permanent migration represent an important risk-management strategy to adapt to climate change (Hallegatte, S., Vogt-Schilb, A., Bangalore, M., & Rozenberg, 2017).

2.1.2 Climate refugee debate

Despite the undeniable impact of climate change on migration patterns, categorising the climate displaced people has sparked much debate in the literature. First introduced by Lester Brown of the Worldwatch Institute in the 1970s, the concept of environmental refugees has occasionally been used by researchers to refer to various populations movements linked to climate change (Black, 2001). However, these definitions do not always encapsulate the same patterns. El-Hinnawi (1985) originally defined environmental refugees as "people who have been forced to leave their traditional habitat, temporarily or permanently, because of a marked environmental disruption (natural and/or triggered by people) that jeopardized their existence and/or seriously affected the quality of their life" (El-Hinnawi, 1985, p.4). In comparison, Bates (2002) proposes a rather vague definition of environmental refugees as "people who migrate from their usual residence due to changes in their ambient non-human environment" (Bates, 2002, p.468). Others such as Renaud et al. (2007) first defined environmental refugees based on a differentiation of the type of environmental stressor. Environmental refugees, as opposed to environmentally motivated migrants and environmentally forced migrants, were defined as people that flee the worse environmental events either temporarily or permanently.[ii] Nevertheless, Castles (2002) and Black (2001) claim that since the decision to migrate is influenced by a multitude of interwoven factors, isolating environmental factors to deduce a definition of "environmental refugees" is misleading. Furthermore, the problem also lies in the absence of differentiation with other refugees. As defined by the 1951 United Nations Convention on Refugees and its 1967 Amendment, a refugee is "someone who is unable or unwilling to return to their country of origin owing to a well-founded fear of being persecuted for reasons of race, religion, nationality, membership of a particular social group, or political opinion" (UNHCR, 1967, p.3). The designation of migrant or refugee is therefore ultimately linked to whether people leaving their homes have control over this decision (Bates, 2002). Current research proves that climate change triggers heterogeneous migration patterns, comprising both voluntary and forced population movements, thus supplementing the existing conceptual complexity (Black et al., 2011a).

This on-going academic debate has, as of today, prevented an international recognition of the terms "environmental refugees" or "environmental migrants" which hampers the climate change migration research. Indeed, the lack of conceptualisation ultimately prevents studies from generalising the impact of climate change and therefore from identifying those that are the most affected.[iii] In the light of this debate, the definition of environmental migrants by the International Organisation for Migration is adopted as a working definition. Environmental migrants are defined as "persons or groups of persons who, predominantly for reasons of sudden or progressive changes in the environment that adversely affect their lives or living conditions, are obliged to leave their habitual homes, or choose to do so, either temporarily or permanently, and who move within their country or abroad" (IOM, 2011, p.33). As of today, this definition appears to be broader and more inclusive than previous definitions as it acknowledges the multifaceted, multifactorial and multidirectional relationship between climate change and migration (Renaud et al., 2011). Given this definition, this research aims to determine whether gradual climate changes and climate extremes impact inter-province migration across six Sub-Saharan countries.

2.2 Theoretical Background

The determinants of migration are subject to complex interactions of *push* and *pull* factors, which respectively capture forces related to the place of origin or destination (Lee, 1966). We attempt to review these interrelated forces to shed light on the possible incentives to migrate together with the selectivity of migration concerning climate change.

2.2.1 Migration theories

First, migration theories have attempted to summarise the economic *push* and *pull* forces influencing the decision to migrate. Neoclassical models of migration suggest that differences in net economic advantages, namely wages, are the primary motive behind migration (Sjaastad, 1962; Todaro, 1969). In this framework, a cost-benefit calculation determines whether individuals choose to migrate (Massey et al., 1993). That is to say, individuals migrate if the expected benefits in the place of destination (*pull* factor) minus the cost of moving exceed the expected benefits in the place of origin (*push* factor) (Massey et al., 1993). In other words, neoclassical models of migration rely on the rationality of agents that seek to maximize their lifetime utility to increase their earnings in the future.[iv] The selectivity of migration is thus driven by specific individual characteristics such as the level of education, skills or age which lead individuals to self-select destinations based on where they can get higher expected earnings (Massey et al., 1993; Todaro, 1969). Given this theoretical framework, migration from rural to urban areas is considered as a result of wages differentials (Lucas, 2004; Todaro, 1969).

Lacking a more comprehensive analysis of determinants other than expected income, the New Economics of Labour Migration challenged some of the assumptions of previously existing neoclassical models. The starting point of this new theoretical framework lies in the fact that the decision to migrate no longer takes place at the individual level but at the family or household level (Stark & Bloom, 1985). The members of this larger group base their decision to migrate, not because they want to maximize their expected income, but as a strategy to overcome market failures, minimise risks, diversify income sources and loosen financial constraints through remittances (Stark & Bloom, 1985; Stark & Levhari, 1982). Together with other adaptation strategies, climate migration allows households in developing countries to smooth risk and diversify their incomes (Lauby & Stark, 1988; McLeman & Smit, 2006). Nevertheless, contrasting migration patterns have been found given the level of income of households. Indeed, prior evidence shows that individuals' socioeconomic status before a climate shock determines their migration response and ability to do so (Kubik & Maurel, 2016). On the one hand, climate-related shocks act as *push* factors of migration for households with sufficient resources to migrate (Warner & Afifi, 2014). On the other hand, case studies of African countries have shown that climatic variations may also prevent the most vulnerable households from migrating as they lack the means to move, thereby falling in a poverty trap (Gray & Mueller, 2012a; Henry, Schoumaker & Beauchemin, 2004). As such, climate migration is not always under the control of households, as liquidity constraints can restrict the choice of poor individuals (Black et al., 2011b; Cattaneo & Peri, 2016).

Next to the economic *push* and *pull* factors, the migration networks theory supports the idea that social capital and cultural dispositions also influence migration (McLeman & Smit, 2006). Interpersonal connections within families, households, and communities form networks capable of sharing risks and diminishing the cost of migration (Boyd, 1989). Indeed, migrant networks increase the likelihood of human mobility by reducing the cost and risks linked to migration, often referred to as chain migration (Massey et al., 1993). However, studies assessing the impact of migrant networks on climate migration do not reveal such clear-cut relationship. On the one hand, some studies have shown that migrant networks are a statistically significant *pull* factor of climate migration. For instance, Nawrotzki & DeWaard (2018) found that migrant networks have the power to overcome climate-related immobility constraints for poor and disadvantaged people in Zambia. On the other hand, in a previous study on rural Mexico, Nawrotzki et al. (2015) proved that migrant networks suppressed the effect of climate change on international migration as they encouraged adaptation at home. Overall, despite this ambiguous impact that could be country-specific, the influence of social networks on climate-related migration is not consistently taken into account by scholars, which render their results prone to biases (Hunter et al., 2014).

Collectively, these migration theories reveal that several *push* and *pull* factors, ranging from economic, social and cultural behaviour, play a role in shaping migration behaviour. Nevertheless, migration theories remain narrow in focus and do not directly deal with the complex linkages of climate change acting as potential *push* forces (Black, 2001; Castles, 2002; Warner et al., 2010). This inconsistency led scholars to develop conceptual models assessing the complex multilevel linkages between climate change and migration.

2.2.2 Climate migration models

In the past fifteen years, climate migration models have attempted to assess how climate change impacts migration, either via new or already-existing *push* factors. First, conceptual models of migration have considered climate change as a direct *push* factor varying given the vulnerability of individuals. The climate-migration model of McLeman and Smit (2006) suggests that migration is a possible adaptive response to climate change. Based on multiple outcomes, this climate migration model places vulnerability as a function of exposure to a climate-related change and the adaptive capacity of the household. Different adaptation strategies are determined by the household's access to capital endowment and environmental conditions which are dynamically related to migration. By considering multiple factors leading to migration as an adaptation strategy, the model takes into account the heterogeneity of migration responses across sub-groups.[v] Nevertheless, the climate-migration model of McLeman and Smit (2006) fails to consider several types of environmental changes which could form different *push* forces. Renaud et al. (2011) complement this problem by taking into account a wider range of environmental events, namely rapid and slow onset hazards and applies a sub-categorisation of environmental migrants. Applying such dichotomy highlights the diversity of responses possible following different climate events and allows better identification of those in need of assistance (Renaud et al., 2011).

In contrast to the previous climate-migration models, Black, Kniveton & Schmidt-Verkerk (2013) do not start with the environment as a potential *push* factor of migration, but instead, consider already existing *push* forces to determine how environmental changes might affect those. Climate change is therefore comprehended as both a direct influence on migration decision and as an indirect one as it affects four other push forces of migration (economic, political, social and demographic). Overall, the wider framework of Black et al. (2013) acknowledges the extensive range of *push* factors through which climate change impacts migration.

2.2.3 Implications of the theoretical background

The theoretical evidence presented in this section acknowledges that migration is a multidimensional process influenced by interrelated *push* and *pull* factors (Rigaud et al., 2018; Warner et al., 2010). Drawing upon the reviewed theories and models, this paper considers climate variability as an indirect *push* factor of migration across six Sub-Saharan African countries. Indeed, climate variability is likely to exacerbate already-existing economic, political and demographic *push* factors of migration, by, for instance, affecting employment opportunities in the place of origin (Black et al., 2011a). Based on the New Economics of Labour Migration, we assume that while the decision to migrate is taken at the household level, migration is the act of individual responses to climate change. Furthermore, the evidence of migration as a human capital investment has been confirmed in the climate-migration literature focusing on African countries (Shimeles, 2010). Thus the importance of human capital in the decision to migrate is acknowledged by controlling for the age and the education level (either primary or secondary education) of the individuals in the sample. Then, given the wide range of climates in the countries included in our sample, two aspects of climate variability are considered to assess the multidirectionality of climate change on the likelihood to migrate (Bischiniotis et al., 2018). At last, while networks have been found to be a statistically significant *pull* factor for several African countries (Shimeles, 2010), we are unable to control for those. Indeed, due to data restrictions, this paper takes into account the effect of neither remittances nor migrant networks, which could constitute a bias to our analysis.

2.3 Empirical evidence

While a considerable amount of literature has been published on the climate-migration nexus, the relationship has recently gained revival in the light of the debate on climate change induced migration (among others: Baez et al., 2017a, 2017b; Bohra-Mishra, Oppenheimer & Hsiang, 2014; Gray & Mueller, 2012a, 2012b; Hunter et al., 2014; Mastrorillo et al., 2016; Mueller, Gray & Kosec, 2014; Nawrotzki et al., 2017; Nawrotzki & DeWaard, 2018; Thiede, Gray & Mueller, 2016). This section attempts to summarise the main findings of the micro-level empirical literature alongside with its limitations and discusses its implications for this research.

2.3.1 Single-country studies

A first strand of the literature analysed the impact of climate variations as push factors in specific countries. A great deal of previous micro-level research has focused on countries where rain-fed agriculture is predominant, thus where climate variations can have substantial impacts, such as Bangladesh, Burkina Faso, Indonesia, Ethiopia, Kenya, Pakistan, Malawi, and Zambia, to only name a few.

Historically, studies have tended to focus on the impact of one climate stressor, namely rainfall variability, as a push factor of migration (Gray & Mueller, 2012a, 2012b; Henry, Schoumaker & Beauchemin, 2004). Overall, rainfall variability has been found to be significantly related to internal migration, in statistical terms. For instance, Gray & Mueller (2012a) concluded that rainfall deficit (i.e., droughts) increased internal migration in Ethiopia. Similarly, Henry, Schoumaker & Beauchemin (2004) found that droughts increased rural-rural migration in Botswana. However, these studies failed to take into account other climate stressors, such as temperature variability, which is interdependent with rainfall, therefore rendering their results prone to biases (Bohra-Mishra, Oppenheimer & Hsiang, 2014). Attempting to depict a more accurate picture of complex relationships, recent studies have included temperature and rainfall anomalies as potential determinants of internal migration. In fact, these studies found that temperature extremes have a greater effect on migration in comparison to that of precipitations (Bohra-Mishra, Oppenheimer & Hsiang, 2014; Feng, Oppenheimer & Schlenker, 2012; Thiede, Gray & Mueller, 2016). However, the study of Mastrorillo et al. (2016) is an exception as the authors concluded that both positive temperature anomalies and positive as well as negative precipitation anomalies have an identical impact on internal migration in South Africa. This discrepancy could be attributed to the construction of their precipitation anomalies variables that are computed given averages of rainy-season precipitations, instead of considering yearly averages as done in most studies. Nevertheless, as most of these studies are country-specific and capture limited time periods, their results are most likely not applicable to other settings and longer periods of time (Thiede, Gray & Mueller, 2016).

2.3.2 Cross-country studies

A more recent strand of the literature is now addressing the problem of external validity of prior studies by introducing cross-country comparisons capturing a wider geographical scope (Baez et al., 2017b, 2017a; Gray & Wise, 2016; Thiede, Gray & Mueller, 2016). Covering large periods of time at regional scales, these studies aim at generalising the effect of climate change on internal migration while taking into account within-country heterogeneity and potential country-specific effects.

Consistent with single-country studies, cross-country studies found that temperature variability has a greater impact on internal migration in comparison to rainfall variability, yet most results also show that the relationship is not "monolithic and unidirectional" (Gray & Wise, 2016, p.556). So far, cross-country studies linking climate change to migration have focused on countries in Latin America, the Caribbean and Sub-Saharan Africa (Baez et al., 2017b, 2017a; Cattaneo & Massetti, 2015; Garcia et al., 2015; Gray & Wise, 2016; Thiede, Gray & Mueller, 2016). Overall, these studies confirmed the limited impact of precipitation anomalies on migration in comparison to that of temperature (Gray & Wise, 2016; Thiede, Gray & Mueller, 2016). Nevertheless, this second strand of the literature also noted important variations across countries contradicting the argument of a unidirectional impact of climate change. For instance, Gray & Wise (2016) revealed that the direction of the impact of temperature anomalies on migration varies across the five Sub-Saharan countries in their sample. Indeed, they found that heat waves decreased the number of migrants in Kenya and Burkina Faso but have an opposite effect for Uganda, while the effect is statistically insignificant for Senegal and Nigeria. The evidence of potential bi-directionality of climate anomalies in neighbouring countries further contradicts sweeping predictions about mass climate change migration.

Furthermore, most cross-country studies fail to take into account the channels linking climate change to migration. Agricultural productivity has been identified as one of the potential channels through which climate change affects migration (Cattaneo & Massetti, 2015; Joarder & Miller, 2013; Mastrorillo et al., 2016). By pooling households from Nigeria and Ghana, Cattaneo & Massetti (2015) observed that temperature and rainfall anomalies are statistically significant determinants of migration for farm households, while they remain insignificant for non-farm households, therefore suggesting that climate change affects migration via agricultural productivity. Going a step further, in the case of Pakistan, Mueller, Gray & Kosec (2014) found that heat waves have a negative impact on agricultural income while excessive rainfall is felt as a positive income shock; which would therefore explain why temperature anomalies have a larger impact on migration than precipitation extremes.[vi] While the identification of mechanisms between climate change and migration is possible in single-country studies, data constraints prevent most cross-national studies from doing so. In other words a majority of cross-country studies have, so far, not been able to identify the specific economic, social and political factors affecting this relationship at a sub-national or national scale.

2.3.3 Heterogeneity

Overall, the climate-migration literature indicates that the association between adverse climatic events and human displacement is highly heterogeneous. Indeed, single and cross-country studies prove that the effect of climate change on migration varies across *sub-groups*, *destinations* and *types of climate anomalies*, suggesting that climate change cannot easily be dissociated from other determinants of migration. By taking into account *individual and household characteristics* such as gender, age, education level, income and wealth, several studies nuanced previously established results (Gray & Wise, 2016; Henry, Schoumaker & Beauchemin, 2004; Mueller, Gray & Kosec, 2014). As the effect of climate change varies depending on the degree of vulnerability of people, studies showed that men and those with a higher income are more likely to migrate in comparison to women and poor individuals (Gray & Mueller, 2012a; Nawrotzki & DeWaard, 2018). For instance, in a macro-level study of 115 countries, Cattaneo & Peri (2016) revealed that higher temperatures are likely to trap populations in poor countries, while the relationship is positive and statistically significant for wealthier countries. By contrast, Thiede et al. (2016) have not found such clear-cut relationship in their cross-country study of 8 Latin American countries. Then, the effect of climate change on migration varies depending on the *type of destination*. For instance, Mueller, Gray & Kosec (2014) found that men are more likely to migrate over longer distances. Other studies confirmed the selectivity of migration theory as they revealed that educated individuals are more likely to migrate towards urban areas (Henry, Schoumaker & Beauchemin, 2004). Lastly, the impact of climate change has been found to vary depending on the *degree of (non)linearity* of the climate measures and across *sources of climate data* (Bohra-Mishra, Oppenheimer & Hsiang, 2014; Gray & Wise, 2016). In the case of Indonesia, Bohra-Mishra et al. (2014) found that temperatures below 25 degrees reduced migration, but if temperatures exceeded 25 degrees the opposite effect took place. A similar non-linear effect was found for precipitations, yet the effect was smaller in magnitude. Besides, by applying the same methodology for two different climate data sources (CRU and MERRA) Gray & Wise (2016) found that the magnitude and statistical significance of their results varied across the five countries included in their study.

2.3.4 Implications of the empirical evidence

Against this background, the reviewed evidence on the climate-migration nexus yields a couple of predictions for the upcoming empirical analysis. In the context of Sub-Saharan Africa, there remain several aspects of the climate change-migration relationship about which relatively little is known. Collectively, these studies outline a critical role for temperature anomalies in comparison to that of precipitation anomalies. We therefore expect temperatures to have a greater impact on the likelihood to migrate across provinces in comparison to precipitations. As for the individual characteristics, we expect men and women to be equally affected by climate anomalies and we expect individuals with higher human capital to migrate to urban areas. At last, similarly to most cross-country studies, data constraints prevent us from identifying the exact social, economic or political mechanisms underlying the migration response to climate change.

2.4 Context of the Sub-Saharan African countries

Focusing on Botswana, Burkina Faso, Kenya, Mozambique, Tanzania and Zambia, three reasons can be identified to explain why these countries are particularly relevant cases for studying the climate-migration link. *First*, as the share of the agricultural sector in each country's economy is predominant, agricultural activities remain a large source of livelihood for households, especially among those living in rural areas (Davis et al., 2007). *Second*, climate change influences climatic variations and climate extremes in each country, thereby increasing the severity and frequency of natural disasters. *Third*, as people living in rural areas are more prone to climate variability, climate change is likely to spur population movements towards urban areas.

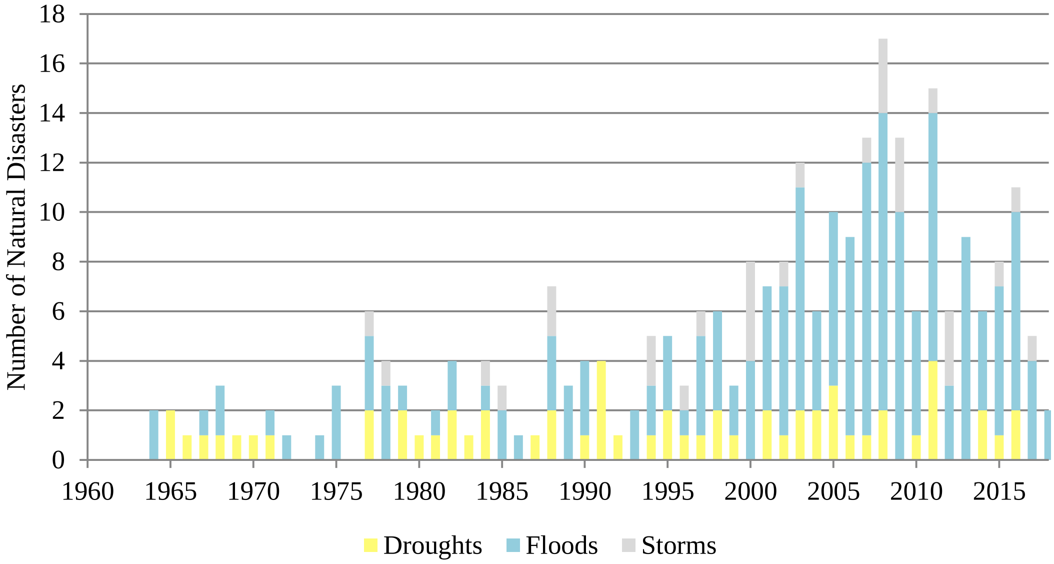
First, Burkina Faso, Kenya, Mozambique, Tanzania, and Zambia rank amongst the poorest countries in the world and suffer from low development (Table 1).[vii] In rural areas, households mostly derive their income from rain-fed agricultural systems (Davis et al., 2007). Indeed, in countries such as Mozambique, Tanzania, and Zambia more than half of the labour force is employed by agricultural sector (World Bank, 2016). Their high agricultural dependence renders households' livelihood particularly vulnerable to climatic changes, by, for instance, affecting agricultural productivity (World Bank, 2013).

Table 1: Country rankings

	HDI rank *(out of 188)*	GDP per capita rank *(out of 175)*
Botswana	108	68
Burkina Faso	185	160
Kenya	146	141
Mozambique	181	169
Tanzania	151	145
Zambia	139	131

Sources: HDI: 2016 estimates for 2015 are sourced from UNDP (2016). GDP per capita ranks for 2015 estimates are retrieved from The World Bank (2016).

Second, despite substantial differences of climates at the regional, national and sub-national level, all six countries are particularly vulnerable to the widespread impact of climate change. Located in various regions of Sub-Saharan African, these countries encompass a wide range of climate and rainfall patterns (Appendix A, Figure 7). Botswana, for instance, has a semi-arid climate with seasonal precipitations from November to March while countries in the Sahel region like Burkina Faso receives most of its annual precipitation from June to September. Countries such as Kenya, Tanzania, and Zambia which are located in Eastern Africa have bimodal rainfall patterns generally peaking in April and November. Despite such diverse climate backgrounds, all countries face high climatic risks due to climate change. Indeed, since the 1960s Sub-Saharan African countries have experienced an increase in *inter-annual climate variability* alongside *extreme climate events* which increase the risk of natural disasters (van Aalst, 2006; World Bank, 2013). Figure 8 and 9 in Appendix B depict the average monthly variations experienced by the countries in our sample from 1961 to 2012. The long-term averages show a significant upward trend in temperatures and a decreasing rainfall trend. This has been the case of Eastern African countries, notably Kenya and Tanzania, which suffer from an increasing rainfall deficit, making this region one of the most vulnerable to droughts in the world (Carrão, Naumann & Barbosa, 2016). Furthermore, the six countries included in this analysis are hit by the increasing intensity and frequency of natural disasters. Figure 1 reveals a steep increase in the number of natural disasters across the six countries of interest, mainly due to an increasing flood trend (Bischiniotis et al., 2018). In the light of this evidence, this study investigates the impact of *climate variability,* as multi-period deviations from long-term averages, and *climate extremes,* as the exposure to highly abnormal climate events, on the decision to migrate across provinces.



Source: International Disaster Database (2018).[viii]

Figure 1: Occurrence of natural disasters across 6 SSA countries, by type, from 1960-2018

Third, as the countries become increasingly more affected by climate change, internal migration is expected to grow, especially between rural and urban areas (Barrios, Bertinelli & Strobl, 2006). Climate change can potentially lower agricultural productivity, increase the variability of food-commodity prices, and ultimately affect economic opportunities of people working in rural areas that are dependent upon the agricultural sector. Altogether, these impacts might intensify human mobility patterns and contribute to the increasing urbanisation trend in the region (Maystadt, Marchiori & Schumacher, 2012; Suckall et al., 2015). In other words, migration to urban areas would be a response to changes in economic opportunities in the agricultural sector, as that individuals migrate to improve their personal outcomes, such as their salary and likelihood of employment (Poelhekke, 2011).

3 Data

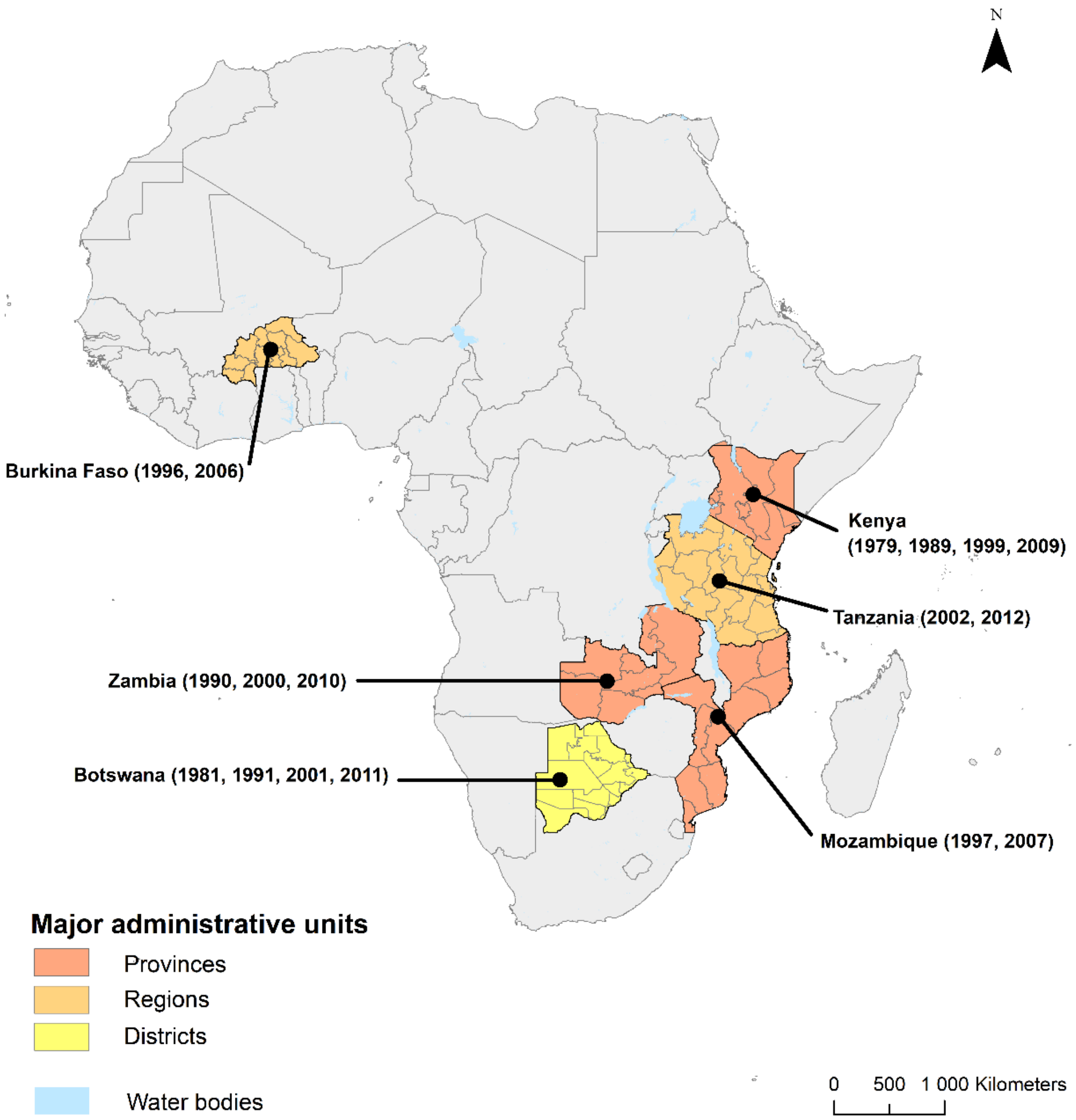
3.1 Individual-level data

3.1.1 Source

Individual-level data is extracted from the Integrated Public Use Microdata Series (IPUMS) International dataset (Minnesota Population Center, 2015). IPUMS collects and harmonises nationally-representative censuses conducted by the national statistical agency of each country. Pooling the different IPUMS samples produces repeated cross-sectional dataset for multiple countries which facilitates cross-national and cross-temporal research (Sobek, 2016). Due to the comparability of the individual and household level variables, the IPUMS dataset has been used in numerous cross-national migration studies (among the most recent ones: Baez et al., 2017a, 2017b; Thiede, Gray & Mueller, 2016).

Focusing on Sub-Saharan Africa, the sample is limited to countries for which detailed migration information is available. That is, the sample is restricted to countries for which the administrative unit of origin and destination is known, prior to and following internal migration. Furthermore, to allow the use of fixed effects, only countries for which two or more censuses had collected information on the migration status of individuals are selected. After these restrictions, the sample includes more than 23 million observations from 17 rounds of census microdata from six Sub-Saharan African countries (Botswana, Burkina Faso, Kenya, Mozambique, Tanzania, and Zambia). Our multi-country cross-sectional dataset, therefore, allows us to generalise the impact of climate change on internal migration across a large diversity of national settings, and so over a period of roughly thirty years (1979-2012).

Figure 2 depicts the location of the selected Sub-Saharan African country alongside with their associated census years. The spatial resolution of our measure of inter-province migration is shown for each country. As changes of boundaries would be a serious issue in the analysis of internal migration, IPUMS International harmonises each administrative boundary to allow meaningful cross-temporal comparisons. To do so, IPUMS aggregates small administrative units into larger ones that are consistent over time (Sobek, 2016). Variables capturing the place of current and previous residence match the temporally-stable boundaries depicted in Figure 2. Despite the differences in the names of the major administrative units in each country, this analysis will refer to inter-provincial migration for all countries for ease of understanding. Provinces are in different sizes and number across regions, for instance, there are 23 provinces in Tanzania, 21 in Botswana, 13 in Burkina Faso, 11 in Kenya and Mozambique and 8 in Zambia.



Map layout and compilation: Fanny Teppe (2018).

Source: IPUMS Terra (Minnesota Population Center, 2016).

Figure 2: Spatial resolution of internal migration

3.1.2 Inter-provincial migration variable

The main dependent variable of this analysis is captured by a retrospective measure of migration. Harmonised for all countries in the sample, the outcome variable *migrate* is equal to 1 if the individual reported having migrated to another major administrative unit a year before the census and is equal to 0 otherwise. While the data does not indicate the exact timing of the move but captures migration over a one-year window, it contains information on the province of origin and destination of each individual. Based on this information, two additional outcome variables are defined: whether the individual migrated to a *rural* or *urban* area. The absence of information on the exact timing of migration prevents us from capturing a more temporally accurate effect of climate change on migration. However, we believe that the one-year retrospective migration variable in our dataset is more precise than most studies using a five-year window (Baez et al., 2017b, 2017a; Thiede, Gray & Mueller, 2016; White & Lindstrom, 2005).

3.1.3 Control variables

Table 2: Definitions of the control variables and their expected signs

Variables	Unit	Definition	Expected Sign
Male	1|0	Dummy variable equal to 1 if the individual is a male, otherwise equal to 0	(+)/(-)
Age	Years	Age at the time of migration	(+)/(-)
Primary education	1|0	A dummy variable equal to 1 if individuals have between 1 and 6 years of schooling, otherwise equal to 0	(+)
Secondary education	1|0	A dummy variable equal to 1 if individuals have between 7 and 11 years of schooling, otherwise equal to 0	(+)
Dependency ratio	%	Proportion of people per household aged less than 15 years old and older than 64 years old relative to the total household size	(-)

Note: As the results in the upcoming empirical analysis will be reported as odds ratios and the signs in this table are to be understood as follows: an odds ratio below 1 reflects a negative relationship, and an odds ratio above 1 reflects a positive relationship.

Source: IPUMS International (Minnesota Population Center, 2015).

Gender. The gender of each individual in the sample is captured by the dummy variable *Male*.

Age. IPUMS International records the age of each individual at the time of the census. Based on this, we compute the age at the time of migration by subtracting 1 to the age of the census. Since the decision to migrate is taken by adults and climate change is likely to impact migration through its effect on labour opportunities, the analysis is restricted to working-age individuals aged between 15 and 64 years old at the time of migration, as done by Mastrorillo et al. (2016). We, therefore, expect this group to be the most responsive to climate variability. The selected sample used in the empirical analysis captures 53.2 percent of observations of our raw sample (i.e., 12,467,530 observations out of the initial 23,451,268).

Education. Together with *Age*, *Education* captures the human capital of each individual. Evidence shows that individuals with higher levels of education have a higher propensity to migrate (White & Lindstrom, 2005). Because of large differences in the sample in terms of years of education, the dummies *Primary education* and *Secondary education* are included to indicate whether the individual has between 1-6 or 7-11 years of schooling, respectively.

Dependency ratio. The dependency ratio was constructed as the proportion of household members aged between 0-14 and more than 64 years old, relative to the household size (UNDP, 2012). As our only household-level control variable, we expect the dependency ratio to capture the impact of household composition on the decision to migrate. Since a high dependency ratio is likely to be correlated with lower economic resources, we expect it to lower the propensity to migrate, as individuals might not be able to afford the cost of moving.[ix]

3.2 Climate data

The climate data used in this analysis is extracted from the Climatic Research Unit's (CRU) of the University of East Anglia time series version 3.21 (Harris et al., 2014). The CRU climate data is chosen for two reasons. *First*, using location-based information, IPUMS Terra converts the CRU time series from raster data to micro-data and averages them at the major administrative unit of each country (Minnesota Population Center, 2016). The use of the CRU time series in a population-based analysis is therefore facilitated by IPUMS Terra, unlike no other climate data source (Nawrotzki, Schlak & Kugler, 2016). *Second*, the CRU climate series has been proven to depict reliable climate estimates for Africa, despite the lower density of weather stations (Los, 2015; Zhang, Körnich & Holmgren, 2013). Given these two reasons, the CRU dataset has been popular in the climate-migration literature focusing on African countries (Cattaneo & Massetti, 2015; Garcia et al., 2015; Gray & Wise, 2016; Nawrotzki, Schlak & Kugler, 2016).

Using IPUMS Terra, we extract monthly precipitation and temperature CRU time series averaged at the province level for each country in the sample from 1961 to 2012. Figure 8 and 9 in Appendix B depict the long-term trajectory of average precipitation and temperature for each country together with linear trends. The construction of the climate variables capturing the intensity of climate variability and the exposure to climate extremes is detailed in Section 4.1. Individuals in the multi-country repeated cross-sectional data are linked to the climate measures by census year and province of origin (i.e., the province individuals reported living in a year prior to the census).

3.3 Limitations of the data

The combined dataset of individual-level data and climate data is prone to several limitations. *First*, the general drawback when using census data lies in the absence of information prior to the census. To avoid the risk of reverse causality, we only include control variables that are fixed prior to migration, which are therefore not an outcome of migration themselves. Notably, besides having information on the residence of individuals a year prior to migration, we do not include measures of individuals' income, wealth and occupation. Furthermore, as the data does not indicate whether the previous place of residence is located in a rural or urban area, we are unable to distinguish rural-urban from urban-urban migration patterns (idem for migration to rural areas).

Second, our cross-province measure of migration is likely to underestimate the true impact of climate anomalies as both international and within-provinces migration patterns are excluded from the analysis (Baez et al., 2017b). While international migration has been shown to be less common than internal migration, short-distance moves are particularly sensitive to climate shocks (Fussell, Hunter & Gray, 2014; Priya Deshingkar & Sven Grimm, 2005). *Third,* the lack of temporal dimension in the dataset prevents us from differentiating short-term from long-term moves, and we, therefore, assume that all moves are permanent. *At last*, the climate data is retrieved at the provincial level, which therefore omits within-province variations, while often sizeable.

4 Methodology

4.1 Climate measures

This section details the methodology behind the construction of the climate variables used in the upcoming empirical analysis. To allow the comparison of our results with a similar cross-national study using the same data sources for 8 Latin American countries, we follow the methodology applied by Thiede, Gray & Mueller (2016). That is to say, based on the precipitation and temperature time series retrieved at the province level, two sets of climate measures are constructed, which capture either (1) the intensity of climate variations (2) the cumulative exposure to climate extremes. Those measures of climate variability are constructed in the period prior to the census (i.e. when the decision to migrate takes place).

4.1.1 Intensity of climate variations

Climate variation intensity measures are computed as the multi-monthly deviations of precipitation and temperature from a 30-year (1961–1990) long-term climate normal period. These province-level variables are standardised with z-scores to allow meaningful cross-country comparisons.

The steps to constructing the climate variability z-scores for each country are as follows. First, the province-level average of precipitation and temperature over 1961-1990 is computed. We use this 30 year-climate normal period as our benchmark against which climate variability is assessed, as recommended by the World Meteorological Organization (2007). We retrieve the standard deviations of the climate normal averages of temperature and precipitation. Then, we compute the province-level average of temperature and precipitation for the relevant observation windows prior to the census. We consider two different observation windows: *(A)* one year (12 months) prior to the census during which migration took place; *(B)* three years (36 months) prior to the census to allow for a potentially lagged migration response, as argued in the literature (among others: Nawrotzki et al., 2017; Nawrotzki, Schlak & Kugler, 2016; Thiede, Gray & Mueller, 2016).[x] At last, for each observation window, the standardised z-score is given by subtracting the province-level average over the observation window value minus the province-level long-run climate normal average, divided by the climate normal standard deviation:

$$Z - score_{i,j,k,l} = \frac{Mean\ Observation\ Window_{i,j,k,l} - Mean\ Climate\ Normal_{i,l}}{Standard\ Deviation\ Mean\ Climate\ Normal_{i}}$$

Where i stands for either the precipitation or temperature series; j captures the observation period *(A)* or *(B)*; k is the census year, and l is the province. While Thiede, Gray & Mueller (2016) do not consider the following sub-specifications, we recode the standardised z-scores as done by Mastrorillo et al. (2016) to capture the unidirectional impact of climate variations on the likelihood to migrate. In other words, based on these z-scores, a set of four climate intensity variables are computed: the intensity of *negative precipitation anomalies, positive temperature anomalies* and their respective symmetrical effect (Table 3).

Negative precipitation anomalies z-scores capture the magnitude of negative precipitation variations in the observation window relative to the 30-year (1961-1990) period. Positive temperature z-scores are replaced with zeros, and absolute values are taken for ease of interpretation in the upcoming analysis (Baez et al., 2017b; Mastrorillo et al., 2016). Therefore, the *negative precipitation anomalies z-score* measures, for each observation window, the number of standard deviations below the average precipitation of the climate normal period (in absolute terms). A z-score of 0.5 means that the average precipitation during the observation period was 0.5 standard deviations below the average precipitation in 1961-1990, which indicates a relatively drier period than usual.

Positive temperature anomalies z-scores capture the magnitude of positive temperature variations in the observation window relative to the 30-year (1961-1990) period). Subsequently, negative temperature z-scores are replaced with zeros and only positive values are kept. The *positive temperature anomalies z-score* measures the number of standard deviations over the average temperature during the climate normal period. For instance, a z-score of 1 would indicate that the temperature during the observation window was one standard deviation above the 30-year climate normal period in this province, and therefore reflects a warmer period than usual.

The two symmetrical measures are recoded similarly. *Negative temperature anomalies z-scores* account for negative temperature variations relative to the 30-year (1961-1990) period. Positive temperature z-scores are replaced with zeros, and absolute values are taken. *Positive temperature anomalies* z-scores capture positive precipitation variations relative to the 30-year (1961-1990) period. Negative precipitation z-scores are replaced with zeros and only positive values are kept.

To summarise, a set of 8 different climate intensity z-scores are computed. That is to say, z-scores are computed for four types of climate anomalies that are likely to have an impact of internal migration, namely *negative precipitation anomalies* and *positive temperature anomalies* together with their symmetric counterparts and for the two observation windows prior to the census, *(A)* 12 months and *(B)* 36 months. However, the climate variability z-scores capture climate anomalies over the observation window and do not necessarily single out climate extremes such as droughts or heat waves, which we have seen are particularly frequent in the sampled countries (Figure 1).

Therefore, we introduce another set of climate measures capturing the cumulative exposure to climate extremes.

Table 3: Definitions of the climate variables

Variables	Unit	Definition
Intensity of climate variations		
Neg. Precip anomalies z-score	Std. dev.	Intensity of negative precipitation anomalies in the observation window, relative to 1961-1990, in absolute values
Pos. Precip anomalies z-score	Std. dev.	Intensity of positive precipitation anomalies in the observation window, relative to 1961-1990
Pos. Temp. anomalies z-score	Std. dev.	Intensity of positive temperature anomalies in the observation window, relative to 1961-1990
Neg. Temp. anomalies z-score	Std. dev.	Intensity of negative temperature anomalies in the observation window, relative to 1961-1990, in absolute values
Exposure to climate extremes		
Monthly precipitation < (-)2 SD	Count	Number of months in the observation window < 2 SD, relative to 1961-1990
Monthly precipitation > 2 SD	Count	Number of months in the observation window > 2 SD, relative to 1961-1990
Monthly temperature > 2 SD	Count	Number of months in the observation window > 2 SD, relative to 1961-1990
Monthly temperature < (-)2 SD	Count	Number of months in the observation window < 2 SD, relative to 1961-1990

Source: IPUMS Terra (Minnesota Population Center, 2016).

4.1.2 Cumulative exposure to climate extremes

Following the methodology generally applied in the literature investigating climate shocks, we compute the cumulative exposure to climate extremes as the number of months exceeding a certain threshold relative to the climate normal average (1961-1990).

As done by Thiede, Gray & Mueller (2016), we first compute monthly z-scores for each province as monthly deviations from the 30-year climate normal period, standardised at the province level. Then, for each observation window, which is 12 or 36 months before the census, we count the number of months exceeding two standard deviations above and below the 30-year mean (1961-1990) (i.e., months for which the z-score is either greater than 2 or lower than -2).

Similarly to the climate intensity measures, our two predictors of interest are *Monthly precipitation $<$ (-)2 SD* and *Monthly temperature $>$ 2 SD*, for which we also consider their symmetrical manifestation (Table 3). Choosing a threshold of two standard deviations rather than one standard deviation, as done in most studies (among others: Nawrotzki et al., 2017; Nawrotzki & DeWaard, 2018), allows us to identify the most extreme climate events, rather than more typical climate variations (Thiede, Gray & Mueller, 2016). In other words, this second set of climate variables capture the exposure to four climate extremes: *droughts*, *heat waves* together with their symmetrical counterparts *excessive precipitations* and *cold snaps*. If the number of *Monthly precipitation $<$ (-)2 SD* is equal to 1, individuals are exposed to a one-time single drought, but a value greater than 1 would indicate that individuals are either experiencing repeated droughts over the observation window or that they are exposed to a prolonged multi-months drought.

All climate variables are then merged to the IPUMS micro dataset by year of census and province of origin of each individual. Overall, these climate variables allow us to determine whether gradual climate variations or the cumulative exposure to climate extremes increase the likelihood to migrate across major provinces and if this relationship varies given the type of destination. Furthermore, as climates measures are computed for two distinct observation windows, we are able to capture potential lags in the decision to migrate.

4.2 Goal of the analysis

This study exploits exogenous spatiotemporal climate data and the characteristics of individuals from six Sub-Saharan countries to determine whether climate variability increases the likelihood to migrate across provinces. The goal of the upcoming empirical analysis is twofold: On the one hand, the aim is to determine whether climate anomalies and the exposure to climate extremes weight in the decision to migrate across provinces. On the other hand, this paper seeks to determine whether climate anomalies and extremes are more likely to trigger migration to urban areas than to rural ones. Consequently, the hypotheses tested are the following:

(1) Climate variability has a positive impact on the likelihood to migrate across provinces.
(2) Climate variability is more likely to trigger inter-provincial migration to urban areas than to rural ones.

4.3 Empirical strategy

The model aims at assessing the role of climate anomalies and the exposure to climate extremes as push factors of migration, conditional on individual and household-level characteristics. The likelihood of inter-province migration is determined by a general specification of the multinomial logit model:

$$log\left(\frac{\pi_{i,p,t,r}}{1-\pi_{i,p,t}}\right) = \beta_0 + \beta_1(C_{\ p,t}) + \beta_2(X_{i,t}) + \delta_i + \mu_t + \varepsilon_t$$

Where $\pi_{i,p,t}$ is the odds of migrating across provinces for individual *i* from province *p* in year *t* while $1 - \pi_{i,p,t}$ is the odds of not moving. To test our second hypothesis, we also estimate two additional outcomes (1) whether the individual migrated to an urban area or did not migrate; (2) whether the individual migrated to a rural area or did not migrate. Given those sub-specifications, $\pi_{i,p,t,r}$ captures the odds of migrating across provinces to either an urban or rural area *r* for individual *i* from province *p* in year *t*. β_0 is the intercept term, β_1 capture the impact of the climate measures introduced in Section 4.1 on inter-provincial migration. $X_{i,t}$ is a vector of control variables operating at the individual and household level (sex, age, education, and dependency ratio) and β_2 is the vector of parameters of the control variables. As climate measures are not idiosyncratic but common to all individuals living in the same province of origin, standard errors ε_t are clustered at the level of the province of origin to control for spatial autocorrelation across provinces.

Additionally, we control for any geographical or temporal factor which could influence the decision to migrate. Therefore we include province of origin δ_i and census-decade fixed effects μ_t. Province of origin fixed effects control for time-invariant factors which could push individuals to migrate. Besides, the inclusion of province of origin fixed effects lower the risks of having an omitted variable bias affecting the climate estimates. Furthermore, we follow Thiede et al., (2016) and include census decade fixed effects rather than year fixed effects as censuses in each country were not recorded on the same years but each country has observations over two or more decades (with decades being defined as ten years interval starting from 1979). Therefore, census decade fixed effects account for any unobservable time-specific shock, such as the El Niño Southern Oscillation (ENSO), which is likely to be correlated with the climate measures and the decision to migrate.

In all regressions, individuals are weighted by the inverse probability of selection. The coefficients of the multinomial logit are exponentiated to be reported as odds ratios. Odds ratios can be interpreted as the multiplicative effect of one unit increase in *x* on the odds of migrating across provinces in comparison to not migrating.

5 Empirical Analysis

5.1 Descriptive statistics

5.1.1 Individual-level descriptive statistics

Table 4 presents the descriptive statistics of the individual-level data used in the analysis. Since adults take the decision to migrate, the statistics are restricted to the individuals aged between 15 and 64 years old at the time of migration, as done by Mastrorillo et al. (2016).

Table 4: Individual-level descriptive statistics for adults aged 15-64

	Pooled	**BW**	**BF**	**KE**	**MZ**	**TZ**	**ZM**
Dependent variables							
Migrate	0.036	0.192	0.014	0.040	0.015	0.037	0.031
Migrate to an urban area	0.020	0.088	0.005	0.024	0.009	0.019	0.016
Migrate to a rural area	0.017	0.104	0.009	0.016	0.006	0.018	0.015
Control variables							
Male	0.474	0.469	0.454	0.487	0.458	0.470	0.481
Age (years)	31.000	31.610	31.610	30.570	31.540	31.400	30.180
Age (15-30)	0.571	0.548	0.552	0.589	0.549	0.554	0.597
Age (31-46)	0.269	0.281	0.272	0.258	0.278	0.280	0.260
Age (46-64)	0.160	0.171	0.177	0.153	0.173	0.167	0.143
Dependency ratio	0.340	0.293	0.405	0.299	0.361	0.358	0.371
Primary education	0.484	0.436	0.105	0.485	0.471	0.628	0.423
Secondary education	0.177	0.284	0.068	0.253	0.041	0.127	0.266
Share of the sample	100.0%	2.5%	9.3%	29.5%	13.7%	32.8%	12.1%

Notes: As most of the variables presented in this table are dummies, standard deviations are omitted and only the means are reported. The table is restricted to adults aged between 15-64 years old. The country codes are as follows: BW: Botswana; BF: Burkina Faso; KE: Kenya; MZ: Mozambique; TZ: Tanzania; ZM: Zambia. All statistics presented in this table were reweighted by the inverse probability of selection.
Source: IPUMS International (Minnesota Population Center, 2015).

Across all countries and censuses, the one-year inter-provincial migration rate is 3.6 percent. The share of individuals migrating in such large sample is consistent with those obtained by prior cross-country studies encompassing a similar period (Baez et al., 2017a, 2017b; Thiede, Gray & Mueller, 2016). While all countries have a relatively similar rate of migration, Botswana stands out as 19 percent of the individuals reported having migrated across provinces a year prior to the census. We cannot completely rule out the possibility that these differences are driven by differences in sizes of provinces. Our analysis also considers whether individuals migrated to a rural or urban area. Overall, there is a slightly larger share of people migrating to urban areas in comparison to those migrating to rural areas across the six countries in the sample. However, this relationship does not hold across all countries, as it is likely to be driven by the context specific to each country.

Furthermore, on average adults have a slightly lower chance to be a male and are 31 years old at the time of migration. The dependency ratio ranges from 29 to 40 percent across all countries, which indicates that a large proportion of household members are dependent on adults and are therefore likely to weight in the decision to migrate. Moreover, 49 percent of the adults reported having some primary education and 18 percent reported having some secondary education. At last, a third of the adults in the sample live in Tanzania, followed by Kenya that represents 29.5 percent of the total number of adults aged 15-64 in the sample. Adults from Burkina Faso, Mozambique and Zambia have relatively equal weight. Despite having four census years, only 2 percent of the individuals in the sample live in Botswana, which is consistent with the fact that Botswana has the smallest population among the six countries.

Table 5: Balance table between migrants and non-migrants, aged 15-64

	Migrants	**Non-Migrants**	**Mean Difference**
Control variables			
Male	0.508	0.473	***
Age (years)	27.515	31.120	***
Age (15-30)	0.707	0.566	***
Age (31-46)	0.206	0.271	***
Age (46-64)	0.087	0.163	***
Dependency ratio	0.239	0.344	***
Primary education	0.479	0.485	***
Secondary education	0.309	0.172	***
N	439,609	12,027,921	

Notes: A similar analysis for migrants to urban and rural areas yields identical results. All statistics presented in this table were reweighted with individual weights. *Significant at 10%; ** significant at 5%; *** significant at 1%.
Source: IPUMS International (Minnesota Population Center, 2015).[xi]

To further justify the use of individual and household-level controls in the regression, we compare the means of characteristics of migrants and non-migrants, for individuals aged between 15-64 years old. Recall that only characteristics that are fixed at the time of migration are included. As expected, characteristics such as sex, age, level of education and the proportion of dependent household members differ significantly across migrants and non-migrants. Indeed, adult migrants are significantly younger and more educated than non-migrants. Migrants also have fewer household dependent members. Table 5, therefore, provides the first hint that internal migrants are selected over their sex, age, education level and the proportion of dependents in the household, relatively to non-migrants aged between 15-64 years old (White & Lindstrom, 2005).

5.1.2 Climate measures descriptive statistics

Next to the description of the individual-level variables, Table 6 presents the average climate measures in the sample as well as in each country. First, while we focus on the exposure to climate anomalies and extremes at the provincial level, an overview of the climatic conditions at the national level gives us an indication of historical averages against which climate anomalies are being compared. On average, all countries confounded, the monthly temperature during the climate normal period 1961-1990 was 23 degrees Celsius, and the monthly precipitation was around 73mm. Nevertheless, these averages mask large temporal within-country variations. At the national level only, there are considerable monthly (Figure 7 in Appendix A) and annual variations (Figure 8 and 9 in Appendix B). The wide-range of climatic conditions across all countries justifies the inclusion of symmetrical climate measures. Indeed, including the symmetrical effect of our climate measures of interest allows us to capture the potential bi-directional impact of climate anomalies and extremes across countries, which has been reported in previous studies (Mastrorillo et al., 2016; Thiede, Gray & Mueller, 2016).

Overall, the two sets of climate measures capturing the intensity of climate anomalies and exposure to climate extremes indicate that on average individuals have experienced more periods of rainfall deficit and positive temperature anomalies than their symmetrical counterparts. This observation is consistent with the respective upward and downward trends in temperature and precipitation since 1990 depicted in Figure 8 and 9 in Appendix B.

The climate anomalies z-scores reveal that the effect of the intensity of climate variability on migration might differ given the observation period preceding the census. Unlike positive temperature anomalies, negative precipitation anomalies are, on average, more intense during the 12 months preceding the census than during a period of 36 months before the census. Indeed, during the 12 and 36 months prior to the census, the average precipitation was respectively 0.31 and 0.24 standard deviations below the climate normal period (in absolute values). By contrast, the average temperature was 0.42 to 0.46 standard deviations above the 30-year climate normal period during the 12 and 36 months before the census. The differential intensity across observation periods justifies the need to observe migratory responses with and without a time lag. Furthermore, it is important to stress that negative temperature anomalies appear to be extremely unlikely across all six countries. This is consistent with the upward trend in temperatures depicted in Figure 8 and 9 in Appendix B.

The exposure to climate extremes is measured by the number of months exceeding the threshold of (-)2 standard deviations above or below the long-term mean of 1961-1990. On average, individuals in the sample are exposed to 3 months of drought and 1.5 months of extremely warm temperature during the year preceding the census, relative to the climate normal period.

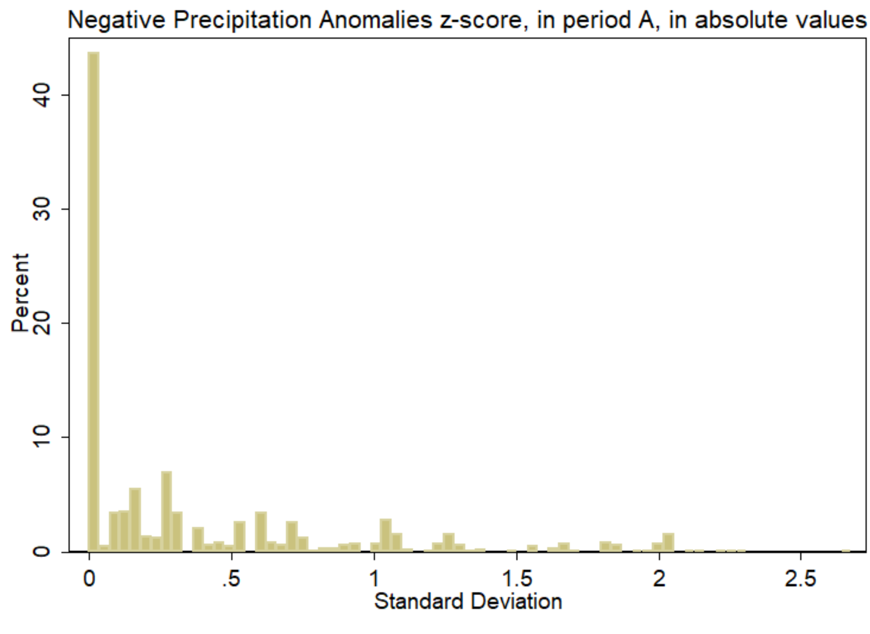
Table 6: Descriptive statistics for the climate measures

	Pooled	BW	BF	KE	MZ	TZ	ZM
Historical climate averages (1961-1990)							
Monthly precipitation in mm	73.3	36.5	66.9	82.3	80.2	90.5	83.0
	(19.56)	(6.49)	(14.10)	(34.37)	(17.37)	(17.80)	(16.57)
Monthly temperature in °C	23.3	21.1	28.1	22.1	23.6	23.3	21.6
	(2.55)	(0.94)	(0.50)	(3.86)	(0.69)	(2.05)	(0.66)
Climate measures, 12 months prior to census (A)							
Neg. Precip anomalies z-score	0.307	0.203	0.413	0.072	0.539	0.477	0.459
	(0.482)	(0.296)	(0.785)	(0.110)	(0.699)	(0.475)	(0.612)
Pos. Precip anomalies z-score	0.155	0.152	0.825	0.184	0.172	0.069	0.116
	(0.274)	(0.228)	(0.864)	(0.236)	(0.228)	(0.167)	(0.211)
Pos. Temp. anomalies z-score	0.417	1.270	0.604	0.133	0.594	0.368	0.607
	(0.456)	(0.832)	(0.431)	(0.066)	(0.212)	(0.125)	(0.540)
Neg. Temp. anomalies z-score	0.008	0.004	0.038	0.007	0.000	0.000	0.042
	(0.039)	(0.030)	(0.109)	(0.017)	-	-	(0.091)
Count, monthly precipitation < (-)2 SD	3.124	4.14	3.906	1.139	5.689	3.769	4.307
	(2.048)	(1.750)	(1.025)	(1.119)	(1.084)	(1.114)	(1.575)
Count, monthly precipitation > 2 SD	0.992	2.443	1.589	0.367	1.507	0.494	2.556
	(1.136)	(0.827)	(1.122)	(0.520)	(0.843)	(0.762)	(1.141)
Count, monthly temperature > 2 SD	1.540	3.538	5.713	0.000	4.936	0.130	4.073
	(2.172)	(0.925)	(0.483)	-	(0.943)	(0.336)	(1.156)
Count, monthly temperature < (-)2 SD	0.942	2.850	3.526	0.000	2.323	0.000	2.953
	(1.382)	(0.874)	(0.521)	-	(0.542)	-	(0.790)
Climate measures, 36 months prior to census (B)							
Neg. Precip anomalies z-score	0.242	0.028	0.125	0.025	0.438	0.517	0.239
	(0.334)	(0.071)	(0.221)	(0.041)	(0.318)	(0.385)	(0.247)
Pos. Precip anomalies z-score	0.066	0.245	0.221	0.077	0.023	0.025	0.015
	(0.120)	(0.172)	(0.296)	(0.102)	(0.069)	(0.055)	(0.027)
Pos. Temp. anomalies z-score	0.458	0.996	0.682	0.157	0.767	0.399	0.818
	(0.409)	(0.661)	(0.470)	(0.087)	(0.342)	(0.145)	(0.366)
Neg. Temp. anomalies z-score	0.001	0.003	0.043	0.000	0.000	0.000	0.000
	(0.017)	(0.023)	(0.092)	-	-	-	-
Count, monthly precipitation < (-)2 SD	9.778	11.390	12.470	4.340	16.830	11.630	13.540
	(5.339)	(3.611)	(3.304)	(2.438)	(2.663)	(2.622)	(4.149)
Count, monthly precipitation > 2 SD	3.126	8.136	4.025	1.322	3.871	1.757	7.841
	(2.985)	(1.726)	(2.075)	(1.273)	(1.872)	(1.699)	(1.605)
Count, monthly temperature > 2 SD	4.902	9.858	16.310	0.000	15.510	0.725	13.860
	(6.680)	(1.370)	(1.658)	-	(2.131)	(0.878)	(3.796)
Count, monthly temperature < (-)2 SD	2.726	7.884	10.030	0.000	6.986	0.000	8.562
	(3.972)	(2.642)	(1.330)	-	(1.599)	-	(1.925)

Notes: Standard errors are reported in parentheses. The table is restricted to adults aged between 15-64 years old. The country codes are as follows: BW: Botswana; BF: Burkina Faso; KE: Kenya; MZ: Mozambique; TZ: Tanzania; ZM: Zambia. All statistics presented in this table were reweighted by the inverse probability of selection to make each sample nationally representative. Source: IPUMS Terra (Minnesota Population Center, 2016).

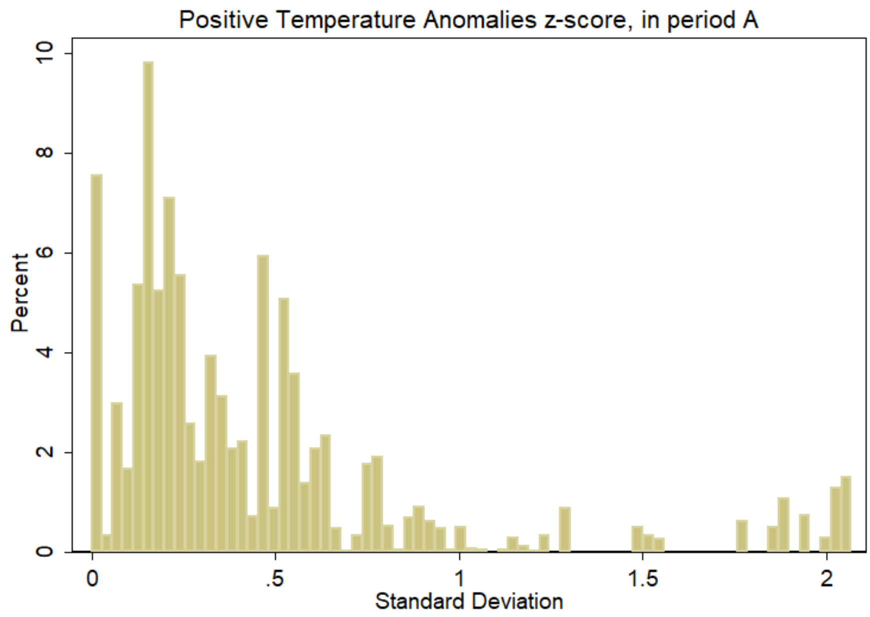
The exposure to cold snaps is very low, and sometimes inexistent (i.e., Eastern African countries such as Kenya or Tanzania generally do not experience such cold episodes). The length of exposure to climate extremes varies widely across countries, as they all capture context specific climate trends and do not include the same shocks as the censuses for each country were not recorded on the same year (Figure 2). Consequently, as a direct country-comparison is misleading, the upcoming analysis focuses on the pooled sample to capture the average impact of climate variability on inter-provincial across all countries.

Figure 3 and Figure 4 illustrate the distribution of the two climate anomalies z-scores of interest to this analysis, namely negative precipitation anomalies and positive precipitation anomalies (The distribution of these variables for observation B can be found in Figure 10 in Appendix C). About 50 percent of all negative precipitation anomalies z-scores are equal to 0, either because the z-score captured negative values or because no climatic deviation from the long-term mean (1961-1990) was captured in this period. The different intensity range, captured by the standard deviations on the x-axis, reveal that the periods of positive temperature anomalies prior to the census are more severe than those of negative temperature anomalies. Besides, Figure 4 captures several outliers; those are the 12-months period in which the average temperature was around 2 standard deviations higher than the long-term average (1961-1990), these are likely to reflect periods of heat waves.



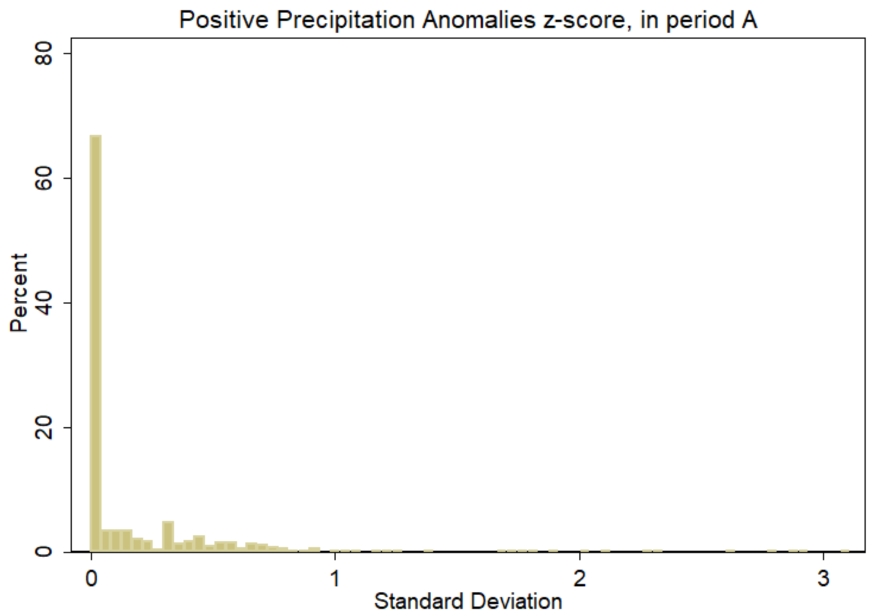
Source: IPUMS Terra (Minnesota Population Center, 2016).

Figure 3: Distribution of the negative precipitation anomalies z-score



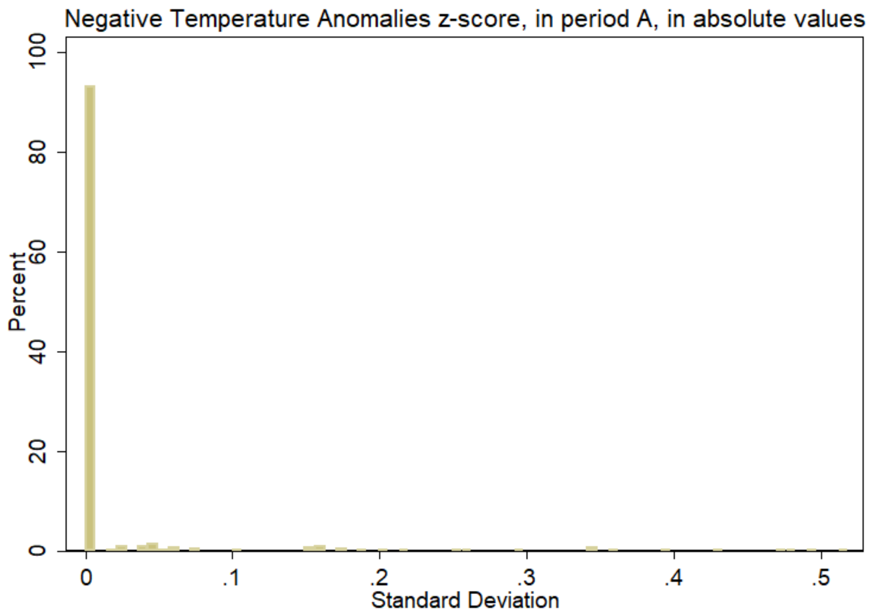
Source: IPUMS Terra (Minnesota Population Center, 2016).

Figure 4: Distribution of the positive temperature anomalies z-score



Source: IPUMS Terra (Minnesota Population Center, 2016).

Figure 5: Distribution of the positive precipitation anomalies z-score



Source: IPUMS Terra (Minnesota Population Center, 2016).

Figure 6: Distribution of the Negative Temperature anomalies z-score

Similarly, Figure 5 and Figure 6 show the distribution of the symmetrical z-scores, which are positive precipitation anomalies and negative temperature anomalies. Positive precipitation anomalies are not as intense as its symmetrical counterpart. Nevertheless, several outliers are recorded at around 2 and 3 standard deviations above the long-term mean. Furthermore, the distribution of negative temperature anomalies confirms our previous observation that such anomalies have a very limited occurrence across the six countries in our sample. As negative temperature anomalies have a very small range and hardly vary over the dataset, we decide to remove it from the subsequent analysis as it would otherwise inflate the odds ratios and produce inaccurate estimates.

5.2 Results

5.2.1 Likelihood to migrate across provinces

As the first step in our analysis, we explore the impact of climate variability on inter-provincial migration across six countries in Sub-Saharan Africa. Two aspects of climate variability are considered, namely the intensity of climate anomalies and the exposure to climate extremes. Climate measures are computed in two distinct observation windows, 12 months (Table 7) and 36 months prior to the census (Table 8) which allows us to explicitly test for a potential lagged migratory response. For both observation windows, Models A and C capture our baseline specifications as they include the two climate predictors of interest, while Model B and D include their symmetrical counterparts. The latter are included separately to avoid the problem of multicollinearity which could inflate the standard errors and reduce the precision of our estimates. Recall that negative temperature anomalies are not included due to their extremely low predictive power. All models are restricted to adults aged between 15 and 64 years old and include province of origin and census decade fixed effects.

Climate intensity measures

Expressed in z-scores, the climate intensity measures capture climate deviations from the 30-year long-term average. Overall, we find that our two measures of interest, namely negative precipitation anomalies and positive temperature anomalies are statistically insignificant, and so regardless of the observation window. Looking solely at the magnitude of the odds ratios, our results do not support previous evidence on the stronger effect of temperature with respect to precipitations (Bohra-Mishra, Oppenheimer & Hsiang, 2014; Thiede, Gray & Mueller, 2016). Interestingly, the magnitude of the odds ratio of positive temperature anomalies changes over a one year or 36-months window. This could indicate that if positive temperature anomalies are experienced over a longer period, they decrease the likelihood to migrate across provinces. However, these results are to be considered carefully as the coefficients are not significant. Furthermore, while research has tended to focus on the effect of negative deviations from precipitation averages, our findings support the case of a potential asymmetric effect of precipitation anomalies. Indeed, the magnitude of the odds ratios indicates that higher precipitations than usual increase the likelihood to migrate, while the opposite effect takes place when precipitations are lower than average (note that the latter has a stronger effect on the odds of not migrating).

Climate shock exposure

Overall, results from Table 7 and 8 reveal that adults are less likely to migrate when they are exposed to negative precipitation shocks, which we refer to as droughts. Indeed, Table 7 indicates that for every additional month exposed to a drought, the odds of inter-province migration decreased by 8 percent. This finding indicates that droughts have an immobilising power, and so particularly within a one year window. A possible reading of this result could be that extremely low precipitations are extremely harmful to agriculture, which could eventually decrease the income of farm households and prevent them from mobilising resources needed to finance the cost of moving (Cattaneo & Massetti, 2015). However, since we are not able to distinguish individuals based on their occupation before the census, these are only suggested interpretations. Similarly, we find that the prolonged exposure to extremely cold temperatures, such as cold snaps, decreases the likelihood to migrate through a lagged effect (Table 8). In summary, these results provide important insight into the holding power exercised by abnormally low precipitations or temperatures such as droughts and cold snaps.

Control variables

In both Table 7 and 8, the control variables enter with the expected sign, confirming the selectivity of migration over younger ages, higher levels of education and fewer household dependent members. As expected, having some primary or secondary education are positively associated with a higher propensity to migrate. Considering our baseline specification in Model A, the odds to migrate of someone having some primary or secondary education are 16 and 70 percent higher than for those that respectively do not have some primary or secondary education. Besides, gender enters insignificantly regardless of the specification or observation window, albeit the magnitude of the odds ratio indicates that men aged 15-64 are slightly more likely to migrate than women of the same age.

Summary

Taken together, the results in Table 7 and Table 8 provide little support to our first hypothesis which is whether climate anomalies and extremes increase the likelihood to migrate across provinces. Next to the absence of statistical significance for most estimates, we find that the exposure to extremely low temperature or precipitation decreases the likelihood to migrate. Since the significance level is not consistent with negative temperature and precipitation anomalies, it indicates that the differential impact of climate variability on migration stems from differences in the severity of the climate event. In other words, the results suggest that, unlike climate variations, a longer exposure to droughts and cold snaps discourage migration and are likely to immobilise individuals. This finding is in accordance with those of Nawrotzki & DeWaard (2018) that use the same individual level and climate data sources for Zambia. Furthermore, the estimates do not generally support a potential lagged migratory response to our different climate measures. As results from Table 7 and Table 8 rather suggest the evidence of a climate inhibitor mechanism reducing inter-province migration, we reject our first hypothesis.

Table 7: Likelihood of inter-provincial migration. observation period A

	Model A	**Model B**	**Model C**	**Model D**
Climate intensity measures				
Neg. Precip anomalies z-score	0.955			
	(0.052)			
Pos. Precip anomalies z-score		1.015		
		(0.044)		
Pos. Temp. anomalies z-score	1.004			
	(0.11)			
Climate shock exposure				
Count, monthly rainfall < (-)2 SD			0.921**	
			(0.032)	
Count, monthly rainfall > 2 SD				1.045
				(0.058)
Count, monthly temperature > 2 SD			1.001	
			(0.053)	
Count, monthly temperature < (-)2 SD				0.867
				(0.082)
Control variables				
Male	1.012	1.010	1.012	1.011
	(0.020)	(0.019)	(0.020)	(0.020)
Age (years)	0.979***	0.979***	0.979***	0.979***
	(0.0020)	(0.0020)	(0.0021)	(0.0020)
Dependency ratio	0.209***	0.204***	0.208***	0.209***
	(0.055)	(0.054)	(0.055)	(0.056)
Primary education	1.159***	1.160***	1.155***	1.155***
	(0.056)	(0.056)	(0.057)	(0.056)
Secondary education	1.715***	1.720***	1.711***	1.709***
	(0.15)	(0.15)	(0.15)	(0.15)
N	12467540	12467540	12467540	12467540

Notes: Odds ratios and their standard errors clustered at the province of origin level are reported in parentheses. The regressions include census decade and province of origin fixed effects. Observations are weighted by the inverse probability of selection. The following six countries are included in the regressions: Botswana, Burkina Faso, Kenya, Mozambique, Tanzania and Zambia. The sample is restricted to adults aged between 15 and 64 years old. Climate measures are computed over observation A, that is 12 months before the census took place.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: IPUMS International combined with IPUMS Terra (Minnesota Population Center, 2015; 2016).

Table 8: Likelihood of inter-provincial migration, observation period B

	Model A	**Model B**	**Model C**	**Model D**
Climate intensity measures				
Neg. Precip anomalies z-score	0.834			
	(0.12)			
Pos. Precip anomalies z-score		1.010		
		(0.11)		
Pos. Temp. anomalies z-score	0.971			
	(0.13)			
Climate shock exposure				
Count, monthly rainfall < (-)2 SD			0.991	
			(0.014)	
Count, monthly rainfall > 2 SD				1.022
				(0.031)
Count, monthly temperature > 2 SD			0.981	
			(0.020)	
Count, monthly temperature < (-)2 SD				0.931***
				(0.028)
Control variables				
Male	1.011	1.011	1.011	1.011
	(0.020)	(0.020)	(0.020)	(0.020)
Age (years)	0.979***	0.979***	0.979***	0.979***
	(0.0020)	(0.0020)	(0.0020)	(0.0021)
Dependency ratio	0.208***	0.205***	0.208***	0.210***
	(0.055)	(0.056)	(0.055)	(0.056)
Primary education	1.157***	1.158***	1.158***	1.159***
	(0.056)	(0.056)	(0.056)	(0.056)
Secondary education	1.715***	1.720***	1.721***	1.716***
	(0.15)	(0.15)	(0.15)	(0.15)
N	12467540	12467540	12467540	12467540

Notes: Odds ratios and their standard errors clustered at the province of origin level are reported in parentheses. The regressions include census decade and province of origin fixed effects. Observations are weighted by the inverse probability of selection. The following six countries are included in the regressions: Botswana, Burkina Faso, Kenya, Mozambique, Tanzania and Zambia. The sample is restricted to adults aged between 15 and 64 years old. Climate measures are computed over observation A, that is 12 months before the census took place.

*** p < 0.01, ** p < 0.05, * p < 0.1

Source: IPUMS International combined with IPUMS Terra (Minnesota Population Center, 2015; 2016).

5.2.2 Likelihood to migrate across provinces, by type of destination

As a second step in our analysis, we determine whether climate change increases migration to urban areas. Recall that due to data constraints, we are not able to identify the type of origin of individuals, be it rural or urban, but we only know about the type of destination. As such, we are not able to deduce potential rural-urban migration patterns. As Table 8 showed no significant evidence of a lagged migratory response for our predictors of interest, the subsequent analysis focuses on climate measures computed over a year before the census (Observation period A). Similarly to the previous analysis, the same Model specifications are compared, for rural (Table 9) and urban-bound destinations (Table 10).

Climate intensity measures

First, comparing Table 9 and Table 10 reveals that climate anomalies have opposite effects given the destination and also confirms that gradual climate variations can immobilise individuals. Table 10 shows that one standard deviation increase in positive temperature variations decreases the odds to migrate to urban areas by 18.6 percent. The opposite effect is found for individuals migrating to rural areas (Table 9). Indeed, a one standard deviation increase in either positive precipitation or temperature anomalies increases the odds of inter-province moves to rural destinations by 11.5 and 34.5 percent respectively. This result is contrary to that of Thiede et al. (2016) who found that, for eight Latin American countries, positive temperature anomalies decrease the likelihood to migrate to rural areas and inversely for urban-bound destinations. We cannot rule out that this effect might be country or region specific. Taken together, the climate intensity measures, therefore, provide little evidence supporting our second hypothesis.

Climate shock exposure

Then, measures capturing the exposure to extreme climate shocks also highlight that the effect goes in opposite directions depending on the destination of individuals. For instance, prolonged exposure to excessive precipitations increases the odds of migrating to rural areas while it decreases the odds of migrating to an urban-bound destination, albeit this last estimate being insignificant. This result could potentially stem from an increase in labour opportunities in rural areas, as excessive precipitations could be beneficial to agricultural production. Table 10 indicates that extremely colder temperatures than usual have a positive impact on the odds of inter-province migration to urban areas. An additional month of exposure to cold snaps increases the odds of inter-province migration to urban areas by 14.1 percent. This effect was also reported by Thiede et al. (2016) in their cross-country study on Latin America.

Control variables

As for the control variables, Table 9 and Table 10 highlight a clear gender pattern. While men have higher odds to migrate toward rural areas than women, an opposite effect is revealed for urban destinations. Furthermore, individuals with a high dependency ratio are much less likely to migrate to urban than to rural areas. At last, education is a significant push factor for individuals migrating to urban areas but has an insignificant effect on the odds to migrate to rural areas.

Summary

Overall, our results provide very little evidence for our second hypothesis, which states that individuals exposed to climate anomalies or extremes are more likely to migrate across provinces to urban areas. On the contrary, we identify the exposure to cold snaps as being the only statistically significant climate-related push factors of urban-bound migration. Interestingly, this analysis also revealed several asymmetric effects of our climate measures given the type of destination of individuals.

5.2.3 Robustness check

To assess the robustness and relevance of the results presented in the previous sections, we run a similar analysis on a smaller subset of the population, for individuals aged between 15 and 30 years old at the time of migration. Indeed, we expect those individuals to be particularly more responsive to shocks than the individuals aged between 30 and 64 years old. We, therefore, test the likelihood to migrate across provinces for individuals aged between 15-30 years old (Table 11, Appendix D) and we assess whether this alters our previous findings on urban-bound migration (Table 12, Appendix D).

Results shown in Table 11 are almost identical to those in Table 7. The statistical significance of our climate measures is unaffected. Indeed, similarly, we find that the exposure to droughts inhibits inter-province migration, which is statistically significant at the 5 percent level. Only the odds ratio of the control variables change as we find that younger women aged 15-30 are less likely to migrate, and age no longer enters significantly.

As for the impact of our climate measures on the likelihood to migrate to urban areas, the results are mostly unchanged in comparison to Table 8. The only significant difference stems from the exposure to abnormally low precipitation which decreases the odds of inter-province migration to urban areas at a 10 percent significance level. Taken together, this robustness check shows that our findings are robust regardless of the adult population considered, which thus reinforces further our conclusions.

Table 9: Likelihood of inter-provincial migration to rural areas

	Model A	Model B	Model C	Model D
Climate shock intensity				
Neg. Precip anomalies z-score	0.871*			
	(0.069)			
Pos. Precip anomalies z-score		1.115*		
		(0.069)		
Pos. Temp. anomalies z-score	1.345*			
	(0.22)			
Climate shock exposure				
Count, monthly rainfall < (-)2 SD			0.873**	
			(0.048)	
Count, monthly rainfall > 2 SD				1.125*
				(0.068)
Count, monthly temperature > 2 SD			1.094	
			(0.092)	
Count, monthly temperature < (-)2 SD				0.623***
				(0.086)
Control variables				
Male	1.172***	1.173***	1.173***	1.172***
	(0.027)	(0.027)	(0.027)	(0.027)
Age (years)	0.986***	0.986***	0.986***	0.986***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Dependency ratio	0.604**	0.607*	0.597**	0.616*
	(0.15)	(0.16)	(0.15)	(0.16)
Primary education	1.085	1.086	1.082	1.087
	(0.071)	(0.073)	(0.070)	(0.071)
Secondary education	1.126	1.128	1.126	1.128
	(0.10)	(0.10)	(0.10)	(0.10)
N	12467540	12467540	12467540	12467540

Notes: Odds ratios and their standard errors clustered at the province of origin level are reported in parentheses. The regressions include census decade and province of origin fixed effects. Observations are weighted by the inverse probability of selection. The following six countries are included in the regressions: Botswana, Burkina Faso, Kenya, Mozambique, Tanzania and Zambia. The sample is restricted to adults aged between 15 and 64 years old. Climate measures are computed over observation A, that is 12 months before the census took place.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: IPUMS International combined with IPUMS Terra (Minnesota Population Center, 2015; 2016).

Table 10: Likelihood of inter-provincial migration to urban areas

	Model A	Model B	Model C	Model D
Climate shock intensity				
Neg. Precip anomalies z-score	1.005			
	(0.049)			
Pos. Precip anomalies z-score		0.972		
		(0.051)		
Pos. Temp. anomalies z-score	0.814**			
	(0.078)			
Climate shock exposure				
Count, monthly rainfall < (-)2 SD			0.958	
			(0.026)	
Count, monthly rainfall > 2 SD				0.980
				(0.049)
Count, monthly temperature > 2 SD			0.942	
			(0.044)	
Count, monthly temperature < (-)2 SD				1.141*
				(0.079)
Control variables				
Male	0.894***	0.892***	0.893***	0.894***
	(0.026)	(0.025)	(0.026)	(0.026)
Age (years)	0.974***	0.974***	0.974***	0.974***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Dependency ratio	0.089***	0.087***	0.089***	0.089***
	(0.020)	(0.020)	(0.020)	(0.020)
Primary education	1.251***	1.252***	1.247***	1.250***
	(0.093)	(0.094)	(0.094)	(0.093)
Secondary education	2.295***	2.300***	2.285***	2.293***
	(0.24)	(0.24)	(0.24)	(0.24)
N	12467540	12467540	12467540	12467540

Notes: Odds ratios and their standard errors clustered at the province of origin level are reported in parentheses. The regressions include census decade and province of origin fixed effects. Observations are weighted by the inverse probability of selection. The following six countries are included in the regressions: Botswana, Burkina Faso, Kenya, Mozambique, Tanzania and Zambia. The sample is restricted to adults aged between 15 and 64 years old. Climate measures are computed over observation A, that is 12 months before the census took place.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: IPUMS International combined with IPUMS Terra (Minnesota Population Center, 2015; 2016).

5.3 Discussion

This study constitutes the first empirical research linking climate variability to internal migration across six Sub-Saharan African countries over a period of 30 years. Overall, we find no significant climate effect on inter-province migration across the six countries in our sample but rather the evidence that climate change can exert immobilising forces on individuals. As the six Sub-Saharan countries in our sample depict high poverty rates together with a large rural population, we assume that their livelihood is primarily based on agricultural production, and thus particularly sensitive to climate events (World Bank, 2013). Therefore, our results suggest the evidence of an “agricultural pathway” through which climate variability impacts internal migration via changes in agricultural productivity (Nawrotzki & Bakhtsiyarava, 2017, p.1). Indeed, climate variations and extremes pose a threat to the financial resources needed to finance the cost of moving by affecting agricultural income. Ultimately, it is not unlikely that climate events can trap individuals that are the most vulnerable to climate change, further increasing socio-economic inequalities in Sub-Saharan countries (Gray & Mueller, 2012b; Nawrotzki & DeWaard, 2018). Nevertheless, we cannot rule out the possibility that individuals are likely to be able to find local ways to adapt to these climate events, by, for instance, sharing risk within their network (Adger, 2007). Indeed, migration tends to be a last resort strategy, and research shows that households are likely to adopt coping mechanisms or adaptation strategies to avoid a move (Warner et al., 2010).

Furthermore, the relationship between climate change and migration to urban areas is of particular relevance given the fact that Africa is the least urbanised continent, yet has the highest rate of urbanisation in the world (UN-Habitat & UNECA, 2015). Previous micro-level evidence on 29 countries in Sub-Saharan Africa had shown that agro-climatic conditions such as a decrease in moisture increase rural-urban migration, with an effect confined to industrialised districts (which is about 25 percent of their total sample) (Henderson, Storeygard & Deichmann, 2017). Our results nuance the climate change-urbanisation relationship as we find very little evidence that climate change contributes to migration to urban areas. While our results reveal that beneficial climate conditions encourage geographic adaptation by migrating to rural areas, climate change has an inhibitory effect for people wanting to migrate to urban areas. Nevertheless, our findings must be interpreted carefully as we are not able to identify rural-urban from urban-urban moves.

This research provides interesting insights on some of the most pressing issues experienced by Sub Saharan countries, such as a rising population putting pressure on natural resources, the rapid urbanisation of cities and the overarching issue of climate change, to only name a few. While the latest UN estimates predict more than 86 million internal climate migrants by 2050 in Sub-Saharan Africa, one must not overlook climate inhibitor effects affecting the most vulnerable individuals of the society (Rigaud et al., 2018). Furthermore, while this study did not aim to identify the exact mechanism driving the impact of climate change on internal migration, comprehending the set of challenges and opportunities linking climate change and urbanisation is necessary to build climate resilient cities and decrease the vulnerability of people living in rural areas.

6 Conclusion

6.1 Research Aims

This study exploits exogenous spatiotemporal climate data and the characteristics of individuals from six Sub-Saharan countries to determine whether climate variability increases the likelihood to migrate across provinces. Two complementary hypotheses were tested:

(1) *Climate variability has a positive impact on the likelihood to migrate across provinces.*

(2) *Climate variability is more likely to trigger inter-provincial migration to urban areas than to rural ones.*

Overall, we find little evidence supporting our hypotheses. While previous evidence had shown that human mobility could serve as an adaptation strategy facing climate change, our results indicate that the exposure to climate extremes act as a climate inhibitor reducing inter-province migration. Indeed, we find that prolonged exposure to droughts and cold snaps discourage migration and immobilise individuals. Furthermore, this study nuances the climate change-urbanisation relationship as the results do not consistently support climate variability as a driver of urban-bound migration. Indeed, while our results suggest that beneficial climate conditions encourage geographic adaptation by migrating to rural areas, most climate measures have an inhibitory effect of inter-province migration to urban areas. Indeed, we identify the exposure to cold snaps as being the only significant climate-related push factor to urban-bound migration. Notwithstanding the limitations of this study, this research provides the first evidence of the climate inhibitor mechanism of internal migration across a large geographical area of relatively poor Sub-Saharan countries.

6.2 Practical Implications

These findings suggest several courses of action for climate-related migration. *First*, rather than attempting to define and quantify climate migrants, greater efforts should be made at identifying the most affected by climate change, that are likely to be trapped due to a lack of resources. By identifying those in need of assistance, policymakers can implement social protection programs alleviating some of the barriers to migration. Targeting could be done empirically by interacting diverse measures of climate change with individual characteristics or spatially with the use of geographical hotspots. Altogether, such targeted programs should aim to facilitate migration and reduce climate vulnerability. *Second*, resilience to climate events can be enhanced by better dissemination of climate information. Building upon the widespread use of mobile phones in the region, forecast information on climate shocks could help prevent adverse consequences on individuals' livelihood. *Third*, a key policy priority should be to improve current urban planning policies to build climate resilient and migrant-friendly cities.

6.3 Future Research

Although we cannot completely rule out that the results of this study might be driven by the nature of the data and the construction of the migratory and climate variables, further research could build on our findings in several ways.

First, several questions remain regarding the heterogeneous impact of climate change. A greater focus on the impact of climate change per individual characteristic would provide evidence on the potential socio-economic divide in terms between the people affected and those able to migrate (McLeman et al., 2016). Besides, this study could be repeated to assess whether the overall effect mask country-specific heterogeneities, as found in the literature.

Second, our findings could be cross-checked by taking into account the seasonal patterns of precipitation and temperature when constructing the climate measures for each country. Besides, another climate data source such as MERRA could be used to assess the robustness of the results. Similarly, other measures such as moisture index could be considered to capture other potential migratory responses.

Third, while the need for large-scale micro-level evidence has generally been acknowledged in the literature, this strand of the research should not replace country-specific national studies which can evaluate the channels linking climate change and migration. That is to say, future research should attempt to detail the agricultural pathway through which climate variation impact internal migration, by, for instance, taking into account the wealth and occupation of individuals before migration.

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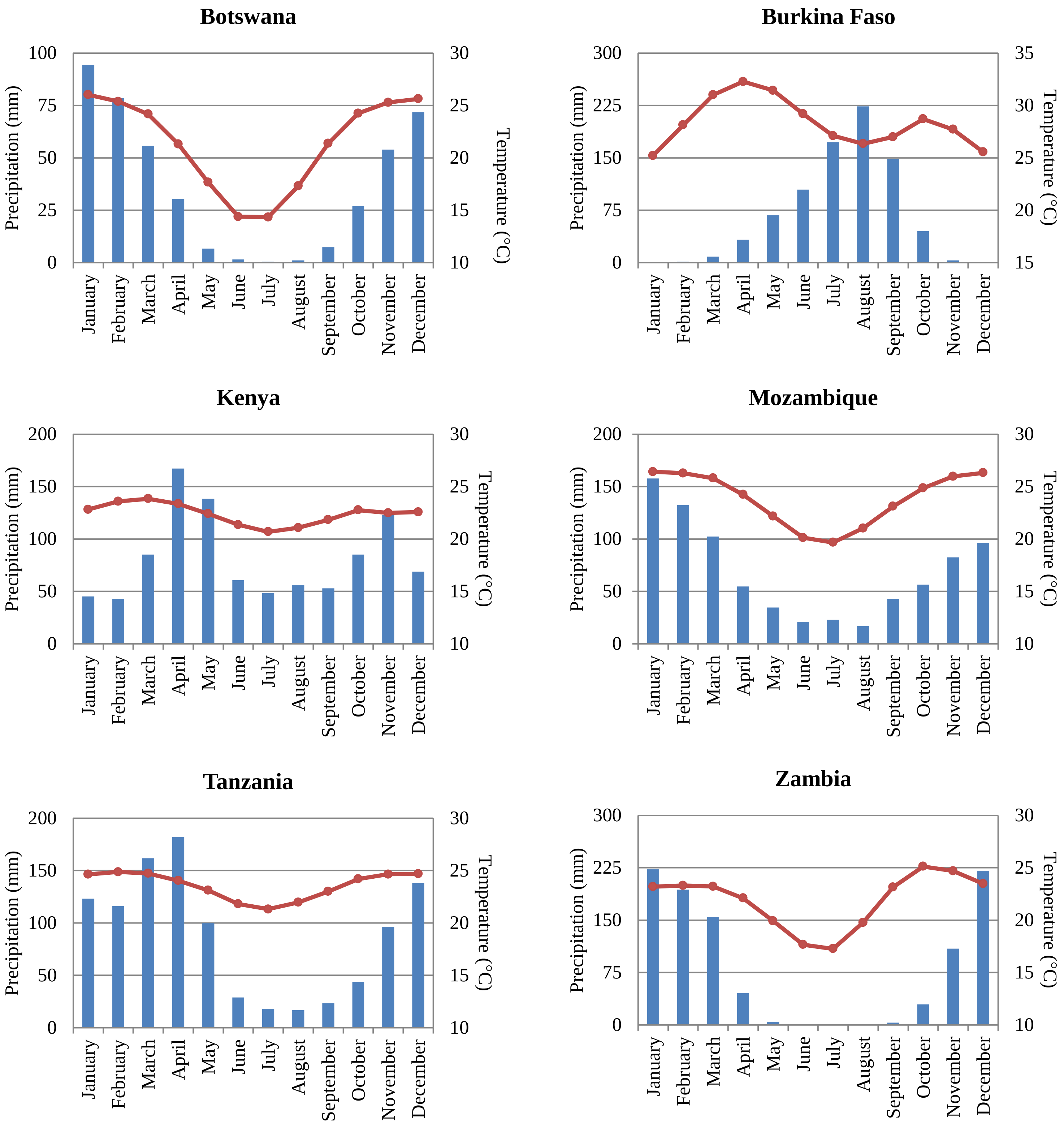
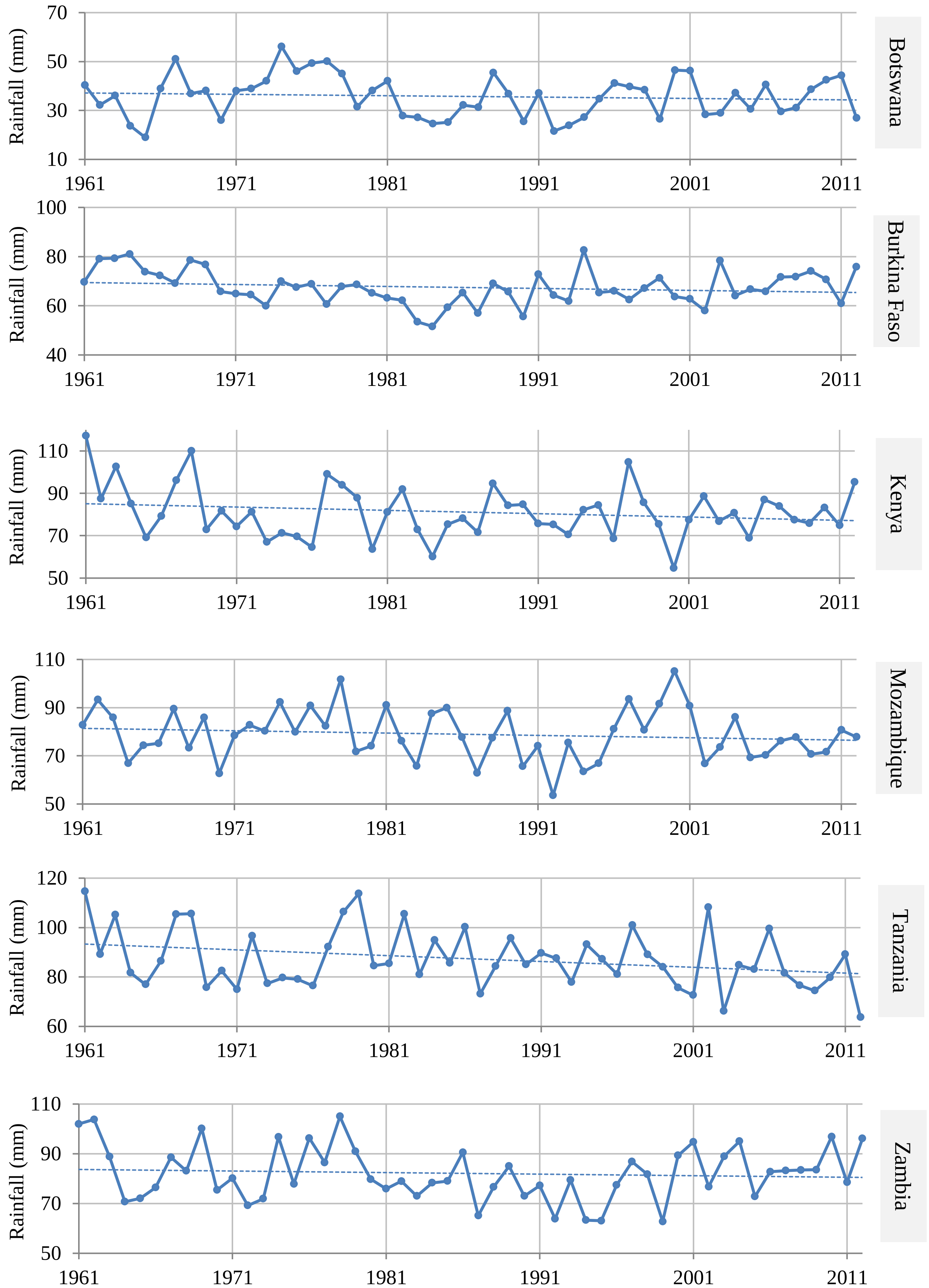
Appendix A



Source: IPUMS Terra (Minnesota Population Center, 2016).

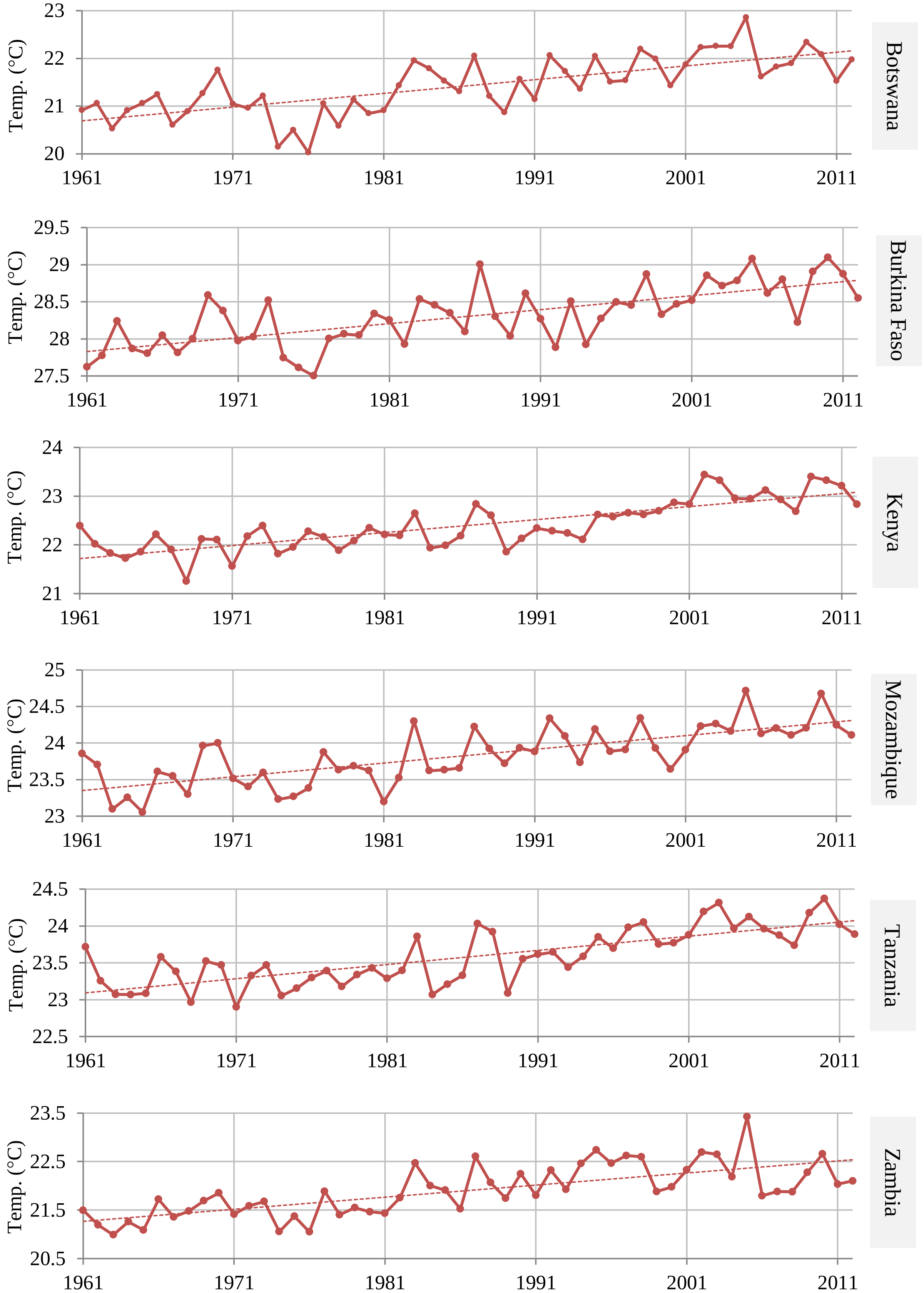
Figure 7: Average monthly temperature and rainfall, 1961-2012

Appendix B



Source: IPUMS Terra (Minnesota Population Center, 2016).

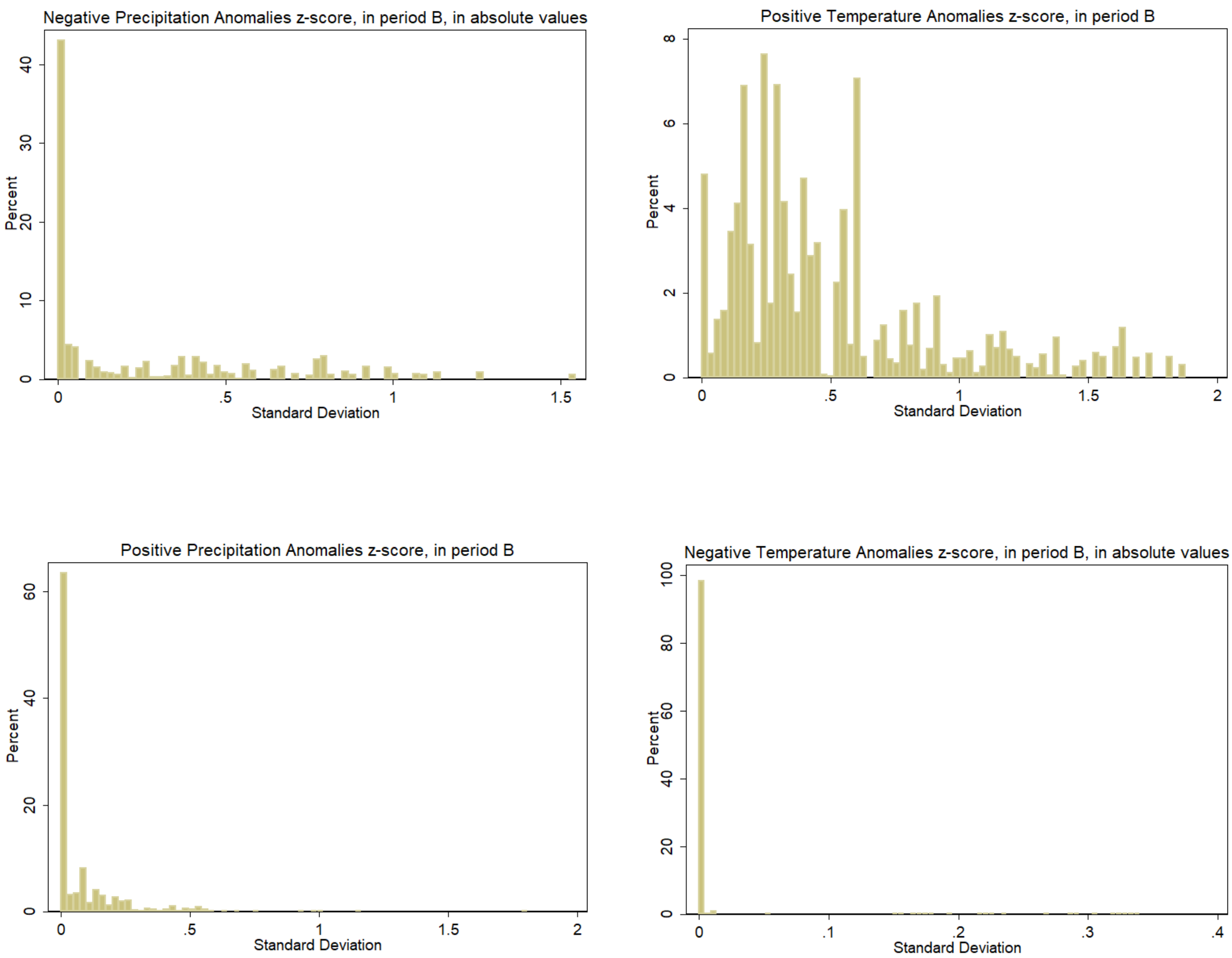
Figure 8: Average yearly precipitation



Source: IPUMS Terra (Minnesota Population Center, 2016).

Figure 9: Average yearly temperatures

Appendix C



Source: IPUMS Terra (Minnesota Population Center, 2016).

Figure 10: Distribution of climate anomalies z-scores over observation period B

Appendix D

Table 11: Robustness check of the likelihood of inter-province migration

	Model A	Model B	Model C	Model D
Climate shock intensity				
Neg. Precip anomalies z-score	0.961			
	(0.054)			
Pos. Precip anomalies z-score		1.015		
		(0.046)		
Pos. Temp. anomalies z-score	0.959			
	(0.097)			
Climate shock exposure				
Count, monthly rainfall < (-)2 SD			0.920**	
			(0.032)	
Count, monthly rainfall > 2 SD				1.039
				(0.059)
Count, monthly temperature > 2 SD			0.972	
			(0.047)	
Count, monthly temperature < (-)2 SD				0.909
				(0.084)
Control variables				
Male	0.937***	0.935***	0.936***	0.936***
	(0.022)	(0.022)	(0.022)	(0.022)
Age (years)	0.999	0.999	0.999	0.999
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Dependency ratio	0.183***	0.179***	0.183***	0.184***
	(0.053)	(0.052)	(0.053)	(0.054)
Primary education	1.133**	1.135**	1.128**	1.133**
	(0.062)	(0.062)	(0.062)	(0.062)
Secondary education	1.685***	1.691***	1.677***	1.683***
	(0.14)	(0.14)	(0.14)	(0.14)
N	7,075,381	7,075,381	7,075,381	7,075,381

Notes: Odds ratios and their standard errors clustered at the province of origin level are reported in parentheses. The regressions include census decade and province of origin fixed effects. Observations are weighted by the inverse probability of selection. The following six countries are included in the regressions: Botswana, Burkina Faso, Kenya, Mozambique, Tanzania and Zambia. The sample is restricted to adults aged between 15 and 30 years old. Climate measures are computed over observation A, that is 12 months before the census took place.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: IPUMS International combined with IPUMS Terra (Minnesota Population Center, 2015; 2016).

Table 12: Robustness check of the likelihood of inter-province migration to urban areas

	Model A	Model B	Model C	Model D
Climate shock intensity				
Neg. Precip anomalies z-score	1.012			
	(0.053)			
Pos. Precip anomalies z-score		0.971		
		(0.053)		
Pos. Temp. anomalies z-score	0.785**			
	(0.074)			
Climate shock exposure				
Count, monthly rainfall < (-)2 SD			0.955*	
			(0.025)	
Count, monthly rainfall > 2 SD				0.976
				(0.052)
Count, monthly temperature > 2 SD			0.927	
			(0.046)	
Count, monthly temperature < (-)2 SD				1.183**
				(0.085)
Control variables				
Male	0.840***	0.838***	0.839***	0.840***
	(0.028)	(0.028)	(0.028)	(0.028)
Age (years)	0.994**	0.994**	0.994**	0.994**
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Dependency ratio	0.079***	0.077***	0.079***	0.079***
	(0.018)	(0.018)	(0.019)	(0.019)
Primary education	1.211**	1.213**	1.204**	1.208**
	(0.10)	(0.10)	(0.10)	(0.10)
Secondary education	2.183***	2.186***	2.165***	2.178***
	(0.23)	(0.23)	(0.23)	(0.23)
N	7,075,381	7,075,381	7,075,381	7,075,381

Notes: Odds ratios and their standard errors clustered at the province of origin level are reported in parentheses. The regressions include census decade and province of origin fixed effects. Observations are weighted by the inverse probability of selection. The following six countries are included in the regressions: Botswana, Burkina Faso, Kenya, Mozambique, Tanzania and Zambia. The sample is restricted to adults aged between 15 and 30 years old. Climate measures are computed over observation A, that is 12 months before the census took place.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: IPUMS International combined with IPUMS Terra (Minnesota Population Center, 2015; 2016).

[i] Unlike the Intergovernmental Panel on Climate Change (IPCC), the UNFCCC makes an important distinction between climate change attributable to human activities and natural causes of climate variability (IPCC, 2014; UNFCCC, 1992).

[ii] However, the absence of international standing led the authors to modify their definition to ‘‘environmental emergency migrants’’ a few years later (Renaud et al., 2011).

[iii] Furthermore, the absence of internationally accepted definition contributes to the complexity of the phenomenon and prevents systemic responses from being implemented (McAdam, 2009). As Warner et al. (2010) point out: “Some level of conceptual clarity regarding who constitutes an environmentally displaced person/ community is needed. Numerous definitions exist at various levels of restriction, making arriving at universally applicable standards difficult, whether desirable or not” (Warner et al., 2010, p.710).

[iv] Future earnings, or expected earnings, are the product of the observed earnings corresponding to their skills and the probability of employment in the destination area (Massey et al., 1993).

[v] Similarly to McLeman and Smit (2006), yet a step further, Perch-Nielsen et al. (2008) developed two models in which vulnerability of households is both a function and an outcome of the choice of adaption mechanism. In other words, the adaptation mechanism chosen by the household will ultimately impact its response and vulnerability to future environmental stressors.

[vi] Assuming that rainfall improves agricultural outcome, young labour force is required which explains why the effect becomes insignificant as the age increases (Thiede, Gray & Mueller, 2016).

[vii] Botswana’s economic development stands as an exception due to its distinctive slave and colonial context which led to the establishment of stable institutions (Acemoglu, Johnson & Robinson, 2001; Nunn, 2008a, 2008b) coupled with the discovery of diamonds (Beaulier, 2015; Soest, 2009) in the late 1960s that fuelled its economic growth.

[viii] Figure 1 includes the the 6 SSA countries which are included in this study: Botswana, Burkina Faso, Kenya, Mozambique, Tanzania, and Zambia. The International Disaster Database only includes disasters that satisfy one of the following conditions: (1) the disaster caused at least 10 deaths; (2) At least 100 people are affected by it; (3) the country declared a state of emergency and/or required international assistance (Caruso, 2017).

[ix] However, when comparing Botswana to Senegal, Nawrotzki, Schlak & Kugler (2016) found that the effect of the dependency ratio on the likelihood to migrate differed between the two countries and is likely to be country-specific.

[x] In both observation windows the census year is not included.

[xi] Clustering the standard errors at the household level does not change the significance of the results. Yet, the mean difference between migrant and non-migrants for primary education becomes insignificant if the errors are clustered by province of origin.