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Interrelated drivers of migration intentions in Africa: Evidence from Afrobarometer surveys

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A B S T R A C T

Migration is influenced by various factors, including economic, political, social, and environmental drivers. While the multicausal nature of migration has been recognized, there are considerable gaps in understanding how different drivers interact with each other and jointly influence human mobility. This is particularly relevant in the African context, where local communities are faced with multiple, often interlinked challenges that affect their livelihoods, security, and health and well-being. Using detailed data from Afrobarometer surveys for 36 countries, this study analyzes the interconnected nature of 23 potential drivers of migration intentions that span across various domains. Our results show that previous migration experiences at the household level, political conditions and instabilities, the personal economic situation, as well as issues related to personal safety are particularly strongly related to respondents' intentions to migrate. The drivers are not independent of each other, but closely interconnected, jointly shaping and reinforcing migration intentions in non-linear ways. We also find strong evidence for heterogeneous effects of the drivers across sociodemographic groups, further contributing to diverse patterns in the relationships. Our study emphasizes the need to move beyond analyzing average linear effects and advocates for approaches that consider the interdependencies of various systems of drivers and their interconnected roles in shaping both intended and actual migration behavior.

1. Introduction

Migration is a multifaceted phenomenon influenced by the complex interplay of various factors. Contrary to what is often emphasized in public discourse, while economic motivations can play an important role, they are neither the sole driver nor equally relevant for all individuals. People migrate for various reasons, including to get an education, to follow family, a partner, or friends, or to flee from conflict or environmental hardships (Czaika and Reinprecht, 2022; de Haas et al., 2019; Piguet, 2012). Personal motives, individual circumstances, and contextual factors play a crucial role in shaping a person's migration intentions and behaviors (Carling and Collins, 2018; Carling and Schewel, 2018; de Haas, 2021).

Importantly, different sets of migration drivers are not independent of each other, but may be related. While the multicausal nature of migration has been recognized in the literature, there is a limited understanding and evidence of how different drivers are empirically connected and interact in jointly influencing migration intentions and behaviors. For example, different types of risks and

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stressors households are exposed to can influence and exacerbate each other and affect households' livelihoods and well-being in the form of compound effects (Buhaug et al., 2015; Lawrence et al., 2020; Mubaya et al., 2012; Thalheimer et al., 2023; Weber et al., 2020). Some drivers may only have an effect on migration if a household experiences influences from other drivers as well.

Specific migration drivers may also not affect all population groups and their mobility equally (Muttarak and Lutz, 2014; Thomas et al., 2019). While some groups may be willing and able to leave, others may prefer or be forced to stay, resulting in differential mobility patterns within a larger population (Adams, 2016; Upadhyay et al., 2015, 2021). In this context the co-occurrence of multiple stressors can also undermine a household's resources and abilities to migrate, ultimately leading to a reduction in mobility and potentially trapping populations in vulnerable and high-risk environments (Adams, 2016; Carling, 2002; Zickgraf, 2018). To comprehensively understand the role of different drivers and their impacts on migration, a holistic perspective is needed that considers the intricate interplay of different factors shaping migration decisions and outcomes.

This study contributes to the literature by comprehensively analyzing the interrelated nature of drivers of migration intentions in Africa and by exploring interactions between drivers in shaping the intentions of various population groups. Using large-scale Afrobarometer survey data from 34 countries (n = 45,823 respondents), we derive information on 23 distinct migration drivers related to political, economic, social, environmental, and infrastructural factors at the household and community level. We combine these data with information on the survey respondent's migration intentions, allowing us to analyze the influence of the interplay of different drivers on the willingness to migrate across different contexts. Our methodology is data-driven and enables us to determine the relevant importance of different drivers while accounting for their interconnectedness and joint influences on migration outcomes.

Through our approach, we aim to address the following four research questions: First, which set of drivers are robustly correlated with migration intentions in Africa, after accounting for the presence of other drivers and considering model uncertainty? Second, how are drivers interrelated with each other and which population groups are exposed to which set of drivers? Third, how do different drivers interact with each other in influencing migration intentions? And fourth, how do the estimated effects vary by population characteristics? By addressing these questions, our study provides insights into the complex and non-linear mechanisms underlying migration decisions of different population groups, offering guidance for researchers and policy-making working on the topic of migration.

Our results show that migration intentions are influenced by multiple factors simultaneously, including political conditions, the personal economic situation, safety concerns, and previous migration experiences at the household level. There is strong evidence of a non-linear relationship between the considered drivers and intentions to migrate. Exploring two potential underlying mechanisms, we find that interactions between drivers play a crucial role in shaping migration tendencies and that the effects of these drivers vary significantly across specific subpopulations and contexts. Additionally, we document that drivers are strongly interconnected and tend to manifest in clusters, showing variations across demographic groups with similar migration inclinations. These insights emphasize the complexity of migration dynamics and highlight the importance of considering the interdependencies among drivers for a comprehensive understanding of migration patterns. They also suggest the need for more nuanced methodological approaches in future research that take into account relevant inter-dependencies and non-linear relationships to comprehensively model the formation of migration decisions.

2. Conceptual framework and previous literature

Migration drivers refer to factors that can compel individuals or households to move from one place to another within a country (internal migration) or across a national border (international migration). These drivers can be diverse and vary significantly depending on individual circumstances, societal factors, and trends (Van Hear et al., 2018). Drivers can be related to conditions at the macro-level or pertain to conditions experienced by individuals and their households. Commonly, migration drivers can be distinguished in economic, social, political, environmental, infrastructural, and demographic factors. Aside from objective drivers, also subjective factors and individual perceptions can play an important role in influencing migration outcomes. Previous research has shown that it is primarily the perceptions of people that shape their intentions to migrate, and not so much the objective conditions in their country (Helbling and Morgenstern, 2023).

Economic factors and lacking access to adequate infrastructure can motivate people to migrate in search of a better livelihood and higher living standards. However, the relationships between economic drivers and migration are not deterministic and characterized by non-linearities which cannot be easily explained with conventional push–pull and neoclassical migration theories (Harris and Todaro, 1970; Lee, 1966; Todaro, 1969). For example, low-income countries typically have lower emigration rates as people face economic constraints in their mobility. Advancing development and improving economic conditions in these countries can lead to more instead of less migration because it increases people's capabilities and aspirations to move (de Haas, 2018, 2021). Accordingly, using global Gallup World Poll Data, Migali and Scipioni (2019) show that while the satisfaction with one's own standard of living is positively associated with the desire to move, the relation with the actual preparation to migrate is not as clear (see also Milasi, 2020). Docquier et al. (2014) confirm with actual migration data that it is particularly existing migration networks and the average income per person at destination as opposed to the income at origin that influences the size of migration flows between countries.

Social and political factors have been shown to play an important role in influencing migration intentions and behaviors. Political instability, persecution, conflict, or human rights violations can force people to flee their home countries in search of safety and asylum (Manuel Giménez-Gómez et al., 2019). At the same time, the experience of corruption (Bernini et al., 2024) or discrimination (Ruyssen and Salomone, 2018) in origin countries as well as a general dissatisfaction with the political system (Etling et al., 2020) have been shown to be relevant drivers in the migration process. Also, feeling insecure and the experiencing of violence and crime can exert a strong influence on an individual's desire to move (Morales-Muñoz et al., 2020). Even if a person is not directly affected by violent events, experiences in the close social and geographic proximity can change the perception of threats and be consequential for migration decisions (Helbling and Morgenstern, 2023).

In recent years, an increasing literature has considered the role of environmental factors as migration drivers (Hoffmann et al., 2020). Studies have shown that environmental hazards can result in displacement and contribute to increased migration in different parts of the world (Blocher et al., 2024; Bohra-Mishra et al., 2017; Chen and Mueller, 2018; Gray and Mueller, 2012; Koubi et al., 2016; Warner and Afifi, 2014). At the same time, there is no automatism at play: The occurrence of an adverse environmental event in an area does not always lead to increases in human mobility. Instead, the occurrence of distressing events can undermine household's capabilities to migrate and lead to entrapment, causing heightened vulnerability and a potential exacerbation of encountered losses and damages (Carling, 2002; Zickgraf, 2018).

Importantly, different types of drivers are not independent of each other, but are closely interconnected, as illustrated in Fig. 1. For example, the political and demographic situation in a country can influence its economic conditions, and vice versa. Similarly, at the micro-level, challenges encountered by households can reinforce each other, often influenced by shifts at the macro-level. Moreover, migration effects of specific drivers can be exacerbated if there are compound effects from other drivers. In this regard, researchers have pointed to the importance of thresholds, non-linearities, and *social tipping points* that determine the stage at which the pressure on a household or social system becomes too large to sustain (Bardsley and Hugo, 2010; McLeman, 2017; Meze-Hausken, 2008; Nawrotzki et al., 2017).

3. Methods and research design

3.1. Data

In this study, we explore the interconnected nature of migration drivers, adopting an integrated perspective to examine their interrelations. Afrobarometer data are used as primary data source (Afrobarometer, 2024). Afrobarometer is a pan-African research network conducting surveys in most African countries since 1999 to inform research and policy-making. The surveys focus on various issues related to democracy, freedom, and citizen engagement; economy, poverty, and development; energy and infrastructure; environmental and climate issues; health, education, and social services; identity, society, and gender; institutions and governance; regional and global relations; as well as safety and security.

Data collection is carried out by national partner organizations in the form of face-to-face interviews with a nationally representative sample of the population of citizens aged 18 and older. All questionnaires are translated into local languages so respondents can be interviewed in their mother language. Sample sizes range from 1200 respondents in smaller countries up to 2400 in larger countries. Sampling is carried out in four or five stages, with secondary and primary sampling units being selected first, followed by the selection of a household sample, from which an eligible respondent is randomly drawn (Afrobarometer, 2024).

Our analysis is focused on the seventh Afrobarometer wave, which contains detailed information on respondent's desires and plans

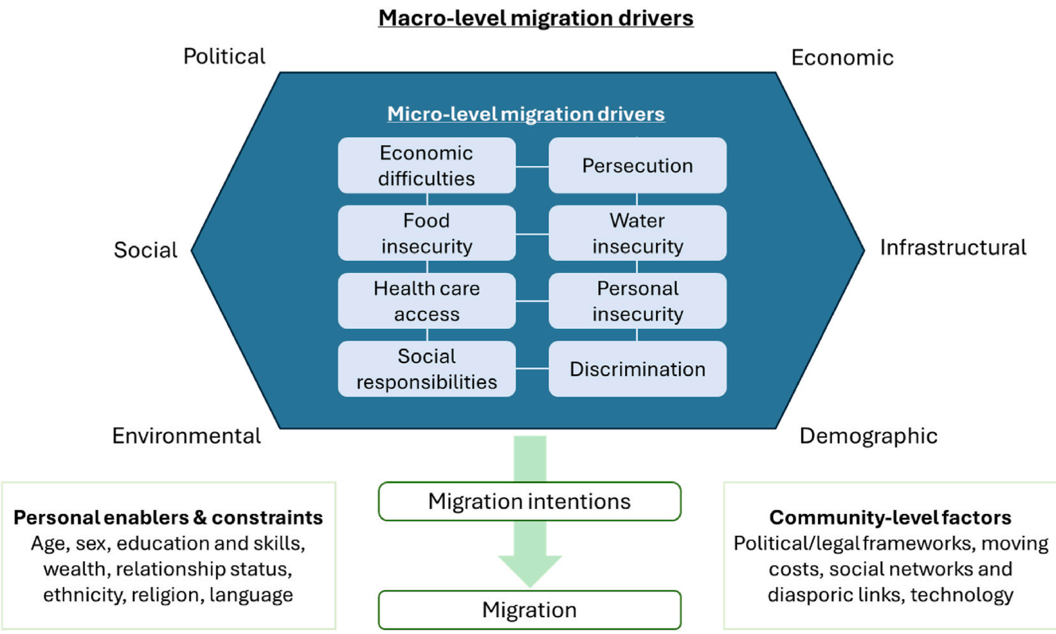

Fig. 1. Conceptual framework of main migration drivers at the macro- and micro-level. The drivers closely interact and reinforce each other. Whether or not changes in a driver translate into higher or lower mobility depends on enablers and constraints at the personal and community level. The figure represents an adaptation from the framework on drivers of migration of the *Foresight* report (Black et al., 2011a, 2011b).

to migrate to other countries as well as relevant migration drivers. No other Afrobarometer wave contains relevant data on migration, restricting the temporal scope of our analysis. The seventh wave was conducted among n = 45,823 respondents in 34 countries, providing a comprehensive picture on drivers of migration intentions for a large sample of the African population. Data collection was carried out between 2016 and 2018. In Table A1 of the Appendix, we provide sample sizes for each country and survey year based on the reported interview dates.

3.2. Measurement

To capture migration intentions, we rely on the survey question on how much respondents have considered moving to another country. If respondents indicated that they had 'somewhat' or 'a lot' considered moving as opposed to 'not at all' or 'a little', they are considered to have migration intentions. The resulting binary variable hence takes the value of one for those respondents with intentions, and zero otherwise.

The Afrobarometer data also provides rich information on a variety of potential migration drivers both at the personal and contextual level. Like the main migration intention outcome, we have coded all driver variables in a binary way for easier comparability across variables. All driver variables take the value of one if the respondent had encountered difficulties or made negative experiences in one area, and zero otherwise. Table 1 provides an overview of the key variables considered. Table A2 in the Appendix shows further details about the questions underlying each variable and our operationalization approach.

At the personal or household level, we consider as potential drivers whether (1) the respondent or another household member had migrated in the past 3 years; whether the respondent (2) faced economic difficulties or (3) undesired unemployment; (4) was affected by food or (5) water insecurity; (6) had insufficient access to medical treatments and healthcare; (7) experienced crime or felt unsafe; (8) had no social responsibilities, e.g., in the form of membership in community organizations; (9) had low levels of trust in others; and (10) experienced discrimination because of gender, religion, ethnicity, or a disability.

At the contextual level, we consider whether the respondent (11) thought that it was easy for people from his country to migrate elsewhere in the region; (12) perceived the economic conditions as challenging and (13) thought that the conditions overall were worsening; (14) believed that there was limited political freedom in the country, (15) reported challenges with democracy, (16) political oppression, and (17) corruption; (18) was unsatisfied with governmental policies and (19) had low trust in institutions; (20) was afraid of or has been affected by different forms of political violence; (21) had experienced impacts of climate change in the form of more severe droughts, flooding, or worsening agricultural conditions; and (22) reported heightened levels of gender inequality in the country. In addition, we consider whether (23) the respondent's community had access to basic infrastructures and services including a school, a health clinic, and a market.

For some of our analyses, we aggregate the different drivers into broader categories, based on theoretical considerations, distinguishing between migration-related, economic, food and water, political, violence and crime, environmental, sociocultural, and infrastructural categories of drivers (see second column in Table 1). This categorization allows us to perform analyses that would otherwise be difficult to conduct due to the large number of drivers considered, including latent class modeling and interaction analyses. Aggregating the data also facilitates interpretation when exploring the interconnected nature of different categories and how effects of sets of drivers change depending on the specific driver profile of respondents.

In addition, information on various sociodemographic controls was collected to account for potentially confounding factors and ensure a more accurate analysis of the drivers of migration intentions. At the time of data collection, 55.23% of the Afrobarometer sample resided in rural areas. On average, respondents lived in households with 3.9 adult members in rural areas and 3.5 adult members in urban areas. Education levels were significantly lower in rural settlements, with 27% of respondents having no formal education compared to 11% in urban areas. In both rural and urban areas, the largest share of respondents fell into the middle-age category, with 55% of rural and 52% of urban respondents being between 30 and 60 years old. The sample was well-balanced in terms of the sex of the respondents.

3.3. Analytical strategy

To analyze the factors influencing migration intentions and their interrelationships in the case study countries, our approach is divided into several methodological steps, which closely follow our research questions.

3.3.1. Determining robust correlates of migration intentions

To determine the relationship of migration drivers and migration intentions at various levels, we proceed in three steps, all of which are based on linear probability models[1] of the form

$$y_i = \alpha + x_i'\beta + w_i'\gamma + \epsilon_i \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2), \tag{1}$$

where y_i is a binary variable taking the value of one when respondent *i* has intentions to migrate and zero otherwise. α is an intercept, x_i

[1] While probit or logit models are typically more suitable for binary outcomes, computational constraints due to the large sample size make these models impractical for some of the modeling techniques we employ. However, selected checks indicate that the linear probability model and probit models yield comparable results for our data.

Table 1
Summary statistics of migration intention outcome and migration driver variables.

Variable	Category	N	Rural		Urban	
			Mean	SD	Mean	SD
Outcome						
Migration intentions	Outcome	45668	0.21	0.41	0.31	0.46
Personal drivers						
Previous migration experiences	Migration	45677	0.23	0.42	0.28	0.45
Economic difficulties	Economic	45687	0.50	0.50	0.42	0.49
Unemployment	Economic	45690	0.27	0.44	0.28	0.45
Food insecurity	Food and Water	45753	0.37	0.48	0.26	0.44
Water insecurity	Food and Water	45750	0.43	0.49	0.31	0.46
Inadequate access to health care	Infrastructure	45637	0.44	0.50	0.29	0.45
Experienced crime	Violence and Crime	45702	0.37	0.48	0.44	0.50
No social responsibility	Sociocultural	45572	0.84	0.37	0.89	0.31
Low levels of trust in others	Sociocultural	45759	0.30	0.46	0.31	0.46
Experienced discrimination	Sociocultural	45718	0.12	0.33	0.14	0.34
Contextual drivers						
Low perceived migration barriers	Migration	45681	0.20	0.40	0.24	0.43
Challenging economic conditions	Economic	45796	0.56	0.50	0.56	0.50
Worsening conditions	Economic	45595	0.69	0.46	0.72	0.45
Limited political freedom	Political	45764	0.30	0.46	0.31	0.46
Challenges with democracy	Political	44792	0.58	0.49	0.64	0.48
Political oppression	Political	45723	0.78	0.41	0.81	0.39
Corruption	Political	45725	0.74	0.44	0.82	0.38
Low satisfaction with policies	Political	45387	0.75	0.44	0.75	0.43
Low trust in institutions	Political	45504	0.21	0.41	0.31	0.46
Political violence	Violence and Crime	45751	0.43	0.50	0.50	0.50
Climate change impacts	Environmental	44905	0.73	0.44	0.64	0.48
Gender inequality	Sociocultural	45512	0.29	0.45	0.26	0.44
Limited infrastructure	Infrastructure	45210	0.63	0.48	0.41	0.49
Control variables						
HH Size	Control	45815	3.87	2.78	3.52	2.46
No Education	Control	45544	0.27	0.44	0.11	0.31
Primary Education.	Control	45544	0.34	0.47	0.21	0.41
Sec. or Tert. Education	Control	45544	0.39	0.49	0.68	0.47
Age 30-	Control	45777	0.36	0.48	0.41	0.49
Age 30-60	Control	45777	0.55	0.50	0.52	0.50
Age 60+	Control	45777	0.10	0.29	0.08	0.26
Male	Control	45816	0.50	0.50	0.50	0.50

is a $K \times 1$ vector of binary migration drivers of respondent i with corresponding $K \times 1$ coefficient vector β, w_i is a $R\times 1$ vector of control variables and fixed effects with corresponding $R \times 1$ coefficient vector γ, including indicators for three age groups and three educational groups, household size, an indicator for urban/rural location of the household[2] as well as an indicator variable for the sex of the respondent and country, survey year and interview month fixed-effects. Finally, ϵ_i is a homoskedastic Gaussian error term with zero mean and variance σ^2. .

In the first step, we consider 23 'univariate' models, each including only a single driver alongside fixed effects and control variables (i.e., $K = 1$). This serves as a baseline analysis and allows us to determine the strength of the correlation between migration intentions and a given driver within similar socioeconomic groups within countries, without accounting for the partial effects of other drivers. In the second step, we use a single model that includes all 23 drivers (i.e., $K = 23$) to control for the effects of all other drivers. This approach helps determine the within-country and within-socioeconomic-group correlation of migration intentions with each driver while accounting for the partial effects of other drivers. This analysis provides deeper insights into the partial effects of migration drivers when considered as part of a larger system that may jointly influence individuals.

However, it is unlikely that a single model can fully capture the complexities of migration intentions. Relying solely on one chosen model for inference (or, similarly for forecasting, and drawing policy conclusions) poses significant risks. For instance, migration driver A may appear as a significant predictor of migration intentions when drivers B and C are included in the model, but not when drivers C and D are included and B is omitted. Without strong theoretical guidance on which migration drivers should be included together in the model, it is essential to account for this model uncertainty.

We address such model uncertainty via Bayesian model averaging (BMA). This statistical method explicitly accounts for model uncertainty by integrating outcomes from a collection of potential regression models, rather than relying on a single model. Each model is defined by a distinct set of migration drivers, including some and excluding others. BMA calculates a weighted average of parameter estimates, with weights reflecting the posterior probability of each model given the data. This approach is particularly

[2] The interviewer classifies household location into rural and several urban stages (e.g., urban, semi-urban), which are collectively recoded as urban.

beneficial in scenarios where the true model is unknown or where multiple competing theories exist. BMA ensures that the identified drivers are robustly connected to migration intentions and that the estimated effects are not dependent on a specific model choice, thereby providing more reliable insights into the factors influencing migration intentions. For a more formal introduction to BMA methodology, see Hoeting et al. (1999) or Steel (2020).

Posterior simulation is based on a birth-death Markov chain Monte Carlo algorithm implemented in R package *BMS* (Zeugner and Feldkircher, 2015). For each estimated BMA model, inference is based on 500,000 posterior draws after an initial burn-in period of 500,000 iterations. We rely on standard prior choices, with improper priors on the error variance σ^2 and the intercept term α, a g-prior with $g = N$ on the remaining regression coefficients and a uniform prior on model size (Ley and Steel, 2009).

3.3.2. *Exploring the interconnected nature and distribution of drivers*

Drivers may not be independent of each other but may be correlated and be of different relevance for different subgroups in a population, which can have implications for the estimation of the impacts of specific drivers. For basic insights into the dependency structure of various migration drivers, pair-wise correlations are analyzed as a baseline analysis. To explore the interconnections and correlations among various migration drivers in more detail, we then employ network analysis. Specifically, we estimate and visualize a partial correlation network of migration drivers (Epskamp and Fried, 2018). In this network, each variable is represented by a node, and the connections between nodes, or edges, reflect the strength of the relationship between variable pairs, adjusted for all other drivers, control variables and fixed effects (see Section 3.3.1). The edge values are derived from 23 separate regression models—one for each migration driver—where each driver is regressed on all others, along with control variables and fixed effects. An edge between two nodes V_i and V_j represents the average of the regression coefficients when driver i is regressed on driver j and when driver j is regressed on driver i. The edges between nodes therefore reflect the conditional dependence structure and strength of the links between the migration drivers.

To examine variations in how interrelated migration drivers are clustered and distributed among the survey respondent population, we implement a latent class model (Clogg, 1995). This model aims to categorize survey participants into distinct groups that share similar levels of exposure to various risk factors and drivers. For clarity and ease of interpretation, we create a binary outcome vector for each respondent. This vector indicates whether any driver within each of the six broader driver categories listed in Table 1 is 'active' or not. These binary vectors are then used as the basis for the clustering process. We employ the R package *BayesLCA* (White and Murphy, 2014) to estimate models ranging from 2 to 10 clusters using an expectation-maximization algorithm. Each model is estimated 500 times using random starting positions. After evaluating the Bayesian Information Criterion (BIC), a model with five clusters is selected and results for this specification are discussed in detail below.

3.3.3. *Non-linearities and potential channels*

To assess the functional form of the relationship between migration drivers and migration intentions, we conduct regression analysis using the following model:

$$y_i = \alpha + f(C_i) + w_i'\gamma + \epsilon_i \quad \epsilon_i \sim \mathcal{N}\left(0, \sigma^2\right) \tag{2}$$

Here, $f(C_i)$ represents a function of the total active migration drivers for respondent i, denoted as C_i and calculated as the sum of binary indicators for the 23 drivers. The remainder of the regression specification follows the model in Eq. (1). Estimation is based on ordinary least squares. We compare four basic specifications for $f(u)$, namely a linear one $f(u) = a_1 u$, a quadratic one $f(u) = b_1 u + b_1 u^2$, a cubic one $f(u) = c_1 u + c_2 u^2 + c_3 u^3$ and a threshold regression model with unknown threshold z where $f(u) = d_1 u$ if $u > z$ and $f(u) = d_2 u$ otherwise. For the threshold regression model, we estimate separate intercepts below and above the threshold, and the optimal threshold z in the number of active drivers is estimated by minimizing the BIC of threshold models over all possible threshold values.

To determine whether migration drivers operate independently or have compounding effects (where drivers might reinforce each other), we implement an interaction model. This helps identify specific groups of drivers that potentially contribute to compounding effects and nonlinearities. The interaction model takes the following form:

$$y_i = \alpha + v_i'\beta + \sum_{j=1}^{8} \sum_{k=j+1}^{8} \beta_{jk} v_{ij} v_{ik} + w_i'\gamma + \epsilon_i \quad \epsilon_i \sim \mathcal{N}\left(0, \sigma^2\right) \tag{3}$$

In this model, $\mathbf{v}_i$ is a 8×1 vector indicating the count of active drivers in each of the eight summary categories listed in Table 1, Column 2. The model also includes all first order interaction terms between the driver variables to evaluate how different driver categories may interact to influence migration intentions. The remaining regression specification follows the model in Eq. (1), and estimation is based on ordinary least squares.

4. Results

4.1. *Descriptive statistics*

Across the entire sample, 25.5% of respondents said they considered migrating to another country in the survey period. This value varies substantially across countries, with more than 30% of respondents considering migrating in some areas, as shown in Fig. 2A. The highest values are observed for the island states of Cape Verde (49.7%) and São Tomé and Príncipe (47.3%) as well as the western African states of Sierra Leone (41.9%) and Togo (40.4%). The share of respondents with migration intentions is considerably higher in urban (31%) as opposed to rural areas (21%), as shown in Table 1.

Among the driver variables considered, we find the highest prevalence among variables referring to the political situation in the countries (Table 1). 74.9% of the respondents reported a low or very low satisfaction with policies in their countries, and 79.5% and 77.7% of respondents named political oppression and corruption as challenges. A large share of respondents (68.9%), especially in rural areas, reported also issues related to climate change impacts in form of worsening droughts and flooding and more unfavorable conditions for agriculture. Typically, higher levels were observed for driver variables that pertain to conditions in the community or country (contextual drivers) and lower levels for those that are directly related to the respondents' livelihoods, security, and well-being (personal drivers). This suggests that many respondents perceive potential stressors that go beyond their personal experiences and that might indirectly shape their migration intentions.

As part of the Afrobarometer surveys, respondents with migration intentions were asked to state the primary reason why they would like to migrate, which is depicted in Fig. 2B. Economic factors are by far the most dominant motive in the perception of the respondents. The reasons for having a desire to move away vary substantially across countries, reflecting different aspirations and abilities to migrate in different contexts. Table A4 in the Appendix illustrates these differences across countries. For example, while in Namibia and Gabon, a relatively large share of respondents mentioned education (21.9% and 17.9%) as well as traveling and tourism (5.7% and 10.5%) as important reasons, economic motives are more relevant in countries in Central Africa, such as Malawi (94.2%), Niger (90.7%), or Mali (90.2%). In Mauritius, on the other hand, political reasons and persecution (9.4%) and social reasons (8.7%) are named as important factors.

However, these answers have to be taken with caution. The survey question about the primary reasons for migrating blinds out secondary motives and the fact that migration reasons may not be independent of each other, but closely related. Environmental factors, for example, are rarely mentioned by respondents (0.15%), despite their relevance for the region and potential impacts on respondents' lives and economic livelihoods, which may lead respondents to list them under economic reasons (Hoffmann et al., 2021). The goal of our statistical analysis is to simultaneously assess the relevance of multiple drivers measured through different variables and to show the mutual interdependence between them.

Major diversity also exists in terms of the preferred migration destinations of the survey respondents, as illustrated in Fig. 2C and Table A5 in the Appendix. The majority of respondents with migration intentions wishes to migrate to another country in Africa, followed by destinations in Europe and North America. Again, differences across countries are visible: While in Morocco and Tunisia, 70.4% and 61.4% of respondents stated that they would wish to move to Europe, this share was with 2.8% considerably smaller in Niger. These differences are driven by geographical factors (e.g., proximity between migration origin and destination) and migration barriers and challenges encountered.

Across the sample of respondents, only 22% said that it was easy for someone from their country to move to another country either within or beyond Africa. While overall intentions to migrate in the future are highly correlated with past migration experiences as well as perceived migration barriers, some notable differences are visible across countries, which are illustrated in Figure A1 in the Appendix. For example, while many respondents in Sierra Leone were considering migrating, few had actual experiences with migration either personally or in their family. This might be due to historical reasons or constraints the respondents face in translating their intentions into actions. Indeed, respondents from Sierra Leone reported high migration challenges with only 11% perceiving it as easy or very easy for people in West Africa to cross international borders to work or trade in other countries. Typically, across countries, we find that past migration experiences at the household level have a stronger association with the intention to migrate compared to the perceived difficulty of migrating.

4.2. Identifying robust predictors of migration intentions

Table 2 shows the results of the regression analyses to determine robust correlations of the considered migration drivers and migration intentions. The first two columns are results from 'univariate' regression models including controls (1). The second column pair shows the results of a multivariate linear model (2). The final three columns show the results of the Bayesian model averaging exercise (3). Coefficient point estimates as well as estimated standard errors are provided for all models.

For the BMA exercise, we also report estimated posterior inclusion probabilities (PIPs) of the migration drivers. PIPs quantify the importance of each predictor, calculated as the weighted average of its inclusion across all considered models, with weights based on each model's posterior probability given the data. PIPs range from 0 (never included) to 1 (always included) and are a typical measure of variable importance in BMA exercises. PIPs indicate how often each driver is considered important across many different models, accounting for the model fit of each model. Control variables are included in all models, so we do not report estimated PIPs for them since they are equal to one by definition.

Comparing the univariate (1) and multivariate models (2), we find that the number of significant correlates is relatively large in the univariate setting and decreases when controlling for the partial effects of other migration drivers. This underscores the importance of considering multiple drivers simultaneously when examining their effects on migration intentions, as these drivers may be correlated, potentially leading to the misattribution of the effect of one driver to another. The number of robustly correlated drivers decreases further when accounting for model uncertainty via BMA (3).

In the BMA models (3), we find that previous migration experiences at the household level are the most important predictor of migration intentions by a large margin. Having previous migration experiences increases the probability of intending to migrate by an average of 16.3% (SE 0.5%). Unemployment as an economic driver follows as the second most impactful factor. Being unemployed

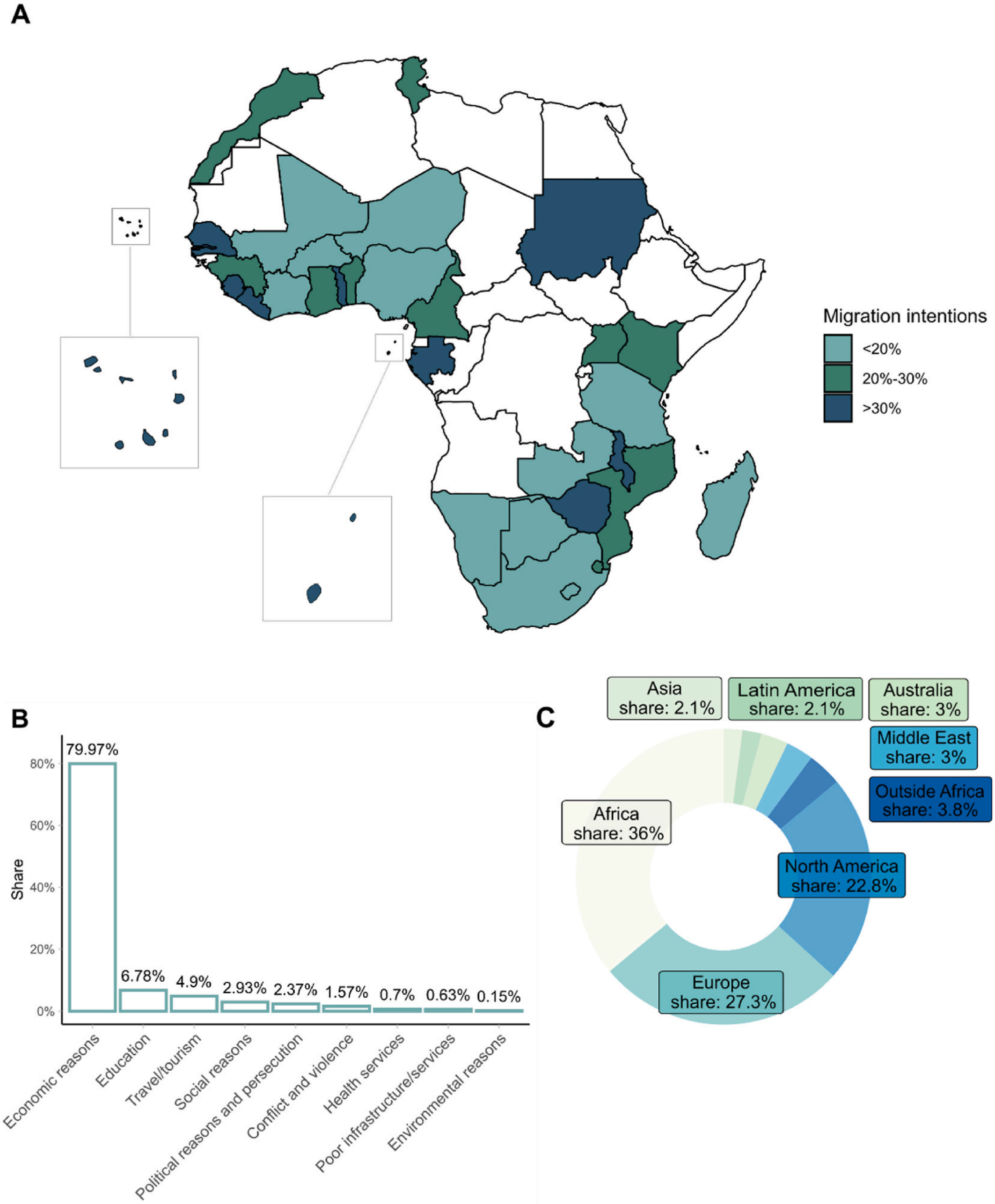

Fig. 2. Distribution of migration variables in the Afrobarometer data. Panel A shows the distribution of migration intentions across countries in Africa with darker colors indicating higher levels of intentions to migrate in the country. Panel B shows the primary reasons of survey respondents for having migration intentions. Panel C shows the preferred migration destination of respondents with migration intentions. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

raises the probability for having migration intentions by 5.5% (SE 0.5%). Likewise, the general evaluation of the economic situation in a country is found to play a role, but to a lesser extent (+2.0%, SE 0.6%). Food security is found to be an important factor as well, increasing migration intentions by 2.3% (SE 0.5%) on average.

Aside from economic and health related factors, various political and sociocultural factors, including discrimination, oppression, or political violence, show a meaningful positive effect on the migration outcome considered. For example, experiences with discrimination or forms of political violence are associated with a 5.0% (SE 0.6%) and 4.3% (SE 0.4%) higher probability of having migration intentions.

Concerning the interpretation of the control variable coefficients, urban households and male respondents express a higher level of intentions to migrate. In terms of age, after adjusting for other factors, the strongest migration intentions are seen in individuals below

Table 2
Results of univariate linear models (left column pair), a multivariate linear model (middle column pair) and a Bayesian model averaging exercise (right column triplet).

	Outcome: Migration Intentions (1/0)						
	(1)		(2)		(3)		
Model	Univariate Linear		Multivariate Linear		Multivariate Linear BMA		
Estimation	OLS		OLS		MCMC		
	Coef.	SE	Coef.	SE	Coef.	SE	PIP
Migration Drivers							
Migration Experience	**0.188**	**0.005**	**0.163**	**0.005**	**0.163**	**0.005**	**1.000**
Unemployment	**0.089**	**0.005**	**0.054**	**0.005**	**0.055**	**0.005**	**1.000**
Discrimination	**0.091**	**0.006**	**0.050**	**0.006**	**0.050**	**0.006**	**1.000**
Pol. Violence	**0.089**	**0.004**	**0.043**	**0.004**	**0.043**	**0.004**	**1.000**
Democracy	**0.086**	**0.005**	**0.038**	**0.005**	**0.039**	**0.005**	**1.000**
Oppression	**0.079**	**0.005**	**0.031**	**0.005**	**0.032**	**0.005**	**1.000**
Trust in Institutions	**0.069**	**0.005**	**0.025**	**0.005**	**0.026**	**0.005**	**1.000**
Food	**0.015**	**0.005**	**0.022**	**0.005**	**0.023**	**0.005**	**0.998**
Crime	**0.057**	**0.004**	**0.019**	**0.004**	**0.019**	**0.005**	**0.983**
Econ. Situation	**0.045**	**0.004**	**0.016**	**0.005**	**0.020**	**0.006**	**0.976**
Corruption	**0.062**	**0.005**	**0.018**	**0.005**	**0.016**	**0.008**	**0.827**
Climate Impacts	**0.017**	**0.005**	**0.014**	**0.005**	0.006	0.008	0.435
Livelihood	**0.019**	**0.004**	**0.011**	**0.005**	0.001	0.004	0.093
Difficult to Migrate	**0.010**	**0.005**	**0.010**	**0.005**	0.000	0.002	0.042
Worsening Conditions	**0.042**	**0.005**	0.008	0.005	0.000	0.002	0.040
Policy Satisfaction	**0.043**	**0.005**	0.006	0.005	0.000	0.001	0.019
Soc. Responsibility	−0.004	0.006	−0.008	0.006	0.000	0.001	0.013
Interpersonal Trust	0.001	0.005	−0.006	0.004	0.000	0.001	0.013
Political Freedom	**0.028**	**0.005**	−0.006	0.005	0.000	0.001	0.010
Gender Inequality	**0.012**	**0.005**	−0.005	0.005	0.000	0.001	0.008
Infrastructure	**−0.032**	**0.004**	−0.004	0.004	0.000	0.000	0.007
Health	0.001	0.005	−0.002	0.005	0.000	0.000	0.006
Water	0.007	0.005	0.000	0.005	0.000	0.000	0.006
Control Variables							
HH Size	0.001	0.001	0.000	0.001	0.000	0.001	–
Urban	**0.078**	**0.004**	**0.037**	**0.005**	**0.037**	**0.004**	–
Primary Educ.	**−0.068**	**0.005**	**0.024**	**0.007**	**0.024**	**0.007**	–
Sec. or Tert. Educ.	**0.132**	**0.004**	**0.080**	**0.007**	**0.080**	**0.007**	–
Age 60+	**−0.168**	**0.007**	**−0.104**	**0.007**	**−0.104**	**0.007**	–
Age 30-	**0.117**	**0.004**	**0.073**	**0.004**	**0.072**	**0.004**	–
Male	**0.060**	**0.004**	**0.056**	**0.004**	**0.057**	**0.004**	–

Note: 'Coef.' refers to OLS coefficient estimates for frequentist models and estimated posterior mean for Bayesian model averaging (BMA). 'SE' denotes the standard error estimate for frequentist models and posterior standard deviation for BMA. 'PIP' is the estimated posterior inclusion probability for each variable. All models include control variables, year, month, and country-specific fixed effects. Bold estimates are significant at a 95% confidence interval for frequentist models or part of the 'median probability model' for BMA (PIP >0.5). The reference category for age is 30–60, for sex is 'female', for urban/rural is 'rural', and for education is 'no education'.

thirty, with a decline observed in the 30–60 age group and a substantial decrease for those over 60. Regarding education, a clear positive gradient is visible, where migration intentions increase from individuals with no education to those with primary education, and further to those with education beyond the primary level.

4.3. Analyzing the interconnected nature of migration drivers

In the next step, we analyze how the different drivers are related, acknowledging that these do not operate in isolation but may depend on each other. Fig. 3 displays the full sample correlation matrix (Panel A) as well as the estimated partial correlation network among all migration drivers (Panel B). The size of the nodes in the network indicates the relative importance of each driver relative to all others, reflecting the overall connectedness to all other nodes.

The strong connections between nodes suggest significant partial correlations between specific drivers. Both the correlation matrix and the network structure highlight that migration drivers do not operate independently but often in conjunctions or groups. For example, issues related to water, food security, and health are closely correlated as are drivers related to the economic situation in the country and respondents' livelihoods.

Based on the correlation structure of the different drivers, the network also shows clusters of drivers that are commonly found together. These align closely with the theoretically guided categorization of drivers provided in Table 1. For example, one clear cluster of variables includes drivers like political freedom, government satisfaction, trust in institutions, democracy, oppression, corruption, and political violence. A key insight of this analysis is that drivers should not be viewed as isolated factors but as components of a system generating correlated impacts, where multiple drivers are likely to be active simultaneously.

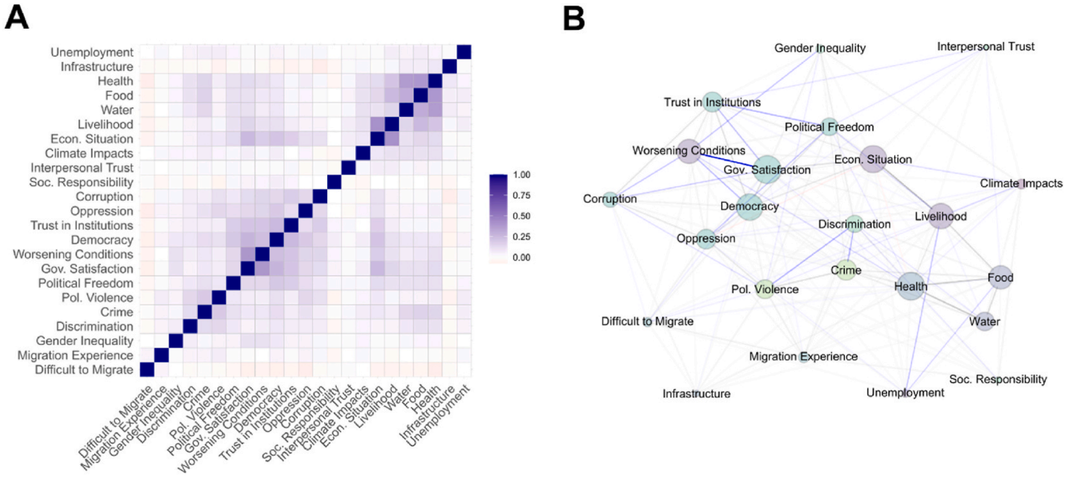

Fig. 3. The interrelated nature of drivers of migration intentions. Panel A shows the raw correlation matrix and Panel B the partial correlation network representing the dependence structure of the analyzed migration drivers. In the network plot, each node represents one driver. Edges represent partial correlations estimated using linear probability models including all drivers, socioeconomic controls, and country and time fixed effects. Edge color indicates positive (blue) or negative (red) conditional pair-wise relationship. Edge transparency is inversely proportional to edge weight. Node color is based on the broader categories in Table 1, Column 2. Node size is proportional to the strength centrality of a node, i.e., the sum of weights of all connecting edges. Nodes with stronger connections are positioned closer to each other.

4.4. *Clusters of migration drivers and their distribution*

Building on the observation that certain drivers tend to not occur in isolation, we explore whether different groups in the wider population are affected by different sets of drivers. For this, we consider how drivers form clusters which affect different population groups differently. The goal of this explorative analysis is to show that certain groups share patterns in the extent to which they are affected by certain drivers, and that these can be influential in shaping migration intentions.

Fig. 4 illustrates the outcomes of the latent class analysis, which yielded five distinct clusters of respondents affected by different combinations of drivers. Here, we consider the eight broader categories of drivers (Table 1) for tractability. Panel A shows the share of the population in each cluster (based on the maximum a posteriori classification of each respondent) for which each driver category is relevant; and Panel B shows the estimated probabilities of having migration intentions across all five clusters.

Cluster 1, representing 38.9% of respondents, is relatively more urban, young, and educated, after controlling for country and household size.[3] This cluster's driver profile emphasizes economic, political, and sociocultural factors. Cluster 2 (36.7%) is relatively more rural, middle-aged, male, and low-educated. This group is characterized by a poly-driver setting where most driver categories are active. Both clusters show strong intentions to migrate, with around 30% of individuals expressing such intentions.

Cluster 3 (13.9%) is relatively more rural, older, female, and of low education. This cluster is strongly influenced by drivers related to food/water, climate change, and infrastructure, with low influence from violence and crime drivers. Cluster 4 (4.6%) and Cluster 5 (5.9%) are rather small groups in the population with less distinctive socioeconomic features. Cluster 4 is slightly more female and has slightly higher primary education rates, while Cluster 5 is relatively older and has higher rates of lower-than-primary education. Cluster 4 has no significant drivers active beyond economic, political, and sociocultural factors, while Cluster 5 is the only group not characterized by significant activity of economic drivers. Clusters 3, 4, and 5 show lower migration intentions, with around 20% of respondents reporting intentions to migrate in each cluster.

In general, these findings highlight the complexity of forming migration intentions. For example, Cluster 2 has relatively higher intentions to migrate, whereas Cluster 3 has relatively lower intentions, even though both are affected by many potential migration drivers simultaneously. Two important insights are that various driver profiles can lead to similar migration intentions and that significant differences exist in driver profiles across demographic groups.

4.5. *Investigating nonlinearities and interactions*

Panel A of Fig. 5 displays changes in the predicted probability of a respondent having migration intentions (y-axis) based on the number of simultaneously active drivers (x-axis) for different linear and non-linear models. The linear probability model (grey background line) indicates that each additional active driver increases the probability of having migration intentions by approximately

[3] Socioeconomic differences across clusters are assessed based on five logistic regression models, where the outcome variable is maximum a posteriori cluster membership in a given cluster (1) versus membership in any other cluster (0), which is regressed on socioeconomic controls and country fixed effects.

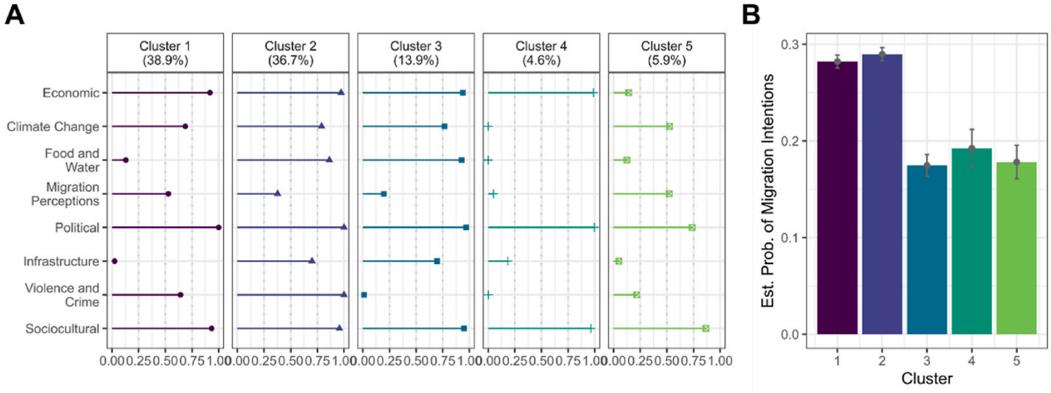

Fig. 4. Clusters of migration drivers and differences in migration intentions. Panel A shows the results of the clustering analysis. Bar lengths represent the estimated share of respondents in each cluster who report at least one of the migration drivers within a given category (x-axis). Panel B shows the estimated probability of intentions to migrate in each cluster, based on regressing migration intentions on the maximum a posteriori estimate of cluster membership. Grey error bars indicate 95% confidence intervals, which are based on the coefficient standard errors from these regressions.

2%, regardless of the number of already active drivers.

In contrast, across all non-linear models, a larger number of drivers is associated with a greater marginal effect of an additional driver on migration intentions. Across all non-linear models, the marginal effect of an additional driver becomes particularly pronounced when a person experiences more than 10 to 12 drivers simultaneously. This finding suggests that the effects of different drivers are not merely additive in influencing migration intentions. Notably, based on the BIC, the non-linear models provide a significantly better fit compared to the linear model.

One potential underlying channel for these non-linear patterns is that various drivers amplify the effects of other drivers, leading to a heightened impact on migration intentions as more drivers become active. To investigate this, we use a regression model that includes the sum of active drivers within each driver category (see Table 1), as well as first-order interactions between all driver categories. This approach allows us to determine whether the influence of one driver category on migration intentions depends on another driver category being active.

Panel B of Fig. 5 illustrates the outcomes from this model. The results suggest multiple (typically positive) interactions between the considered driver variables, suggesting that these can amplify each other's effects. For example, the effect of food and water-related issues is significantly exacerbated by various other factors, such as infrastructural issues (including access to healthcare facilities) and sociocultural issues. Similarly, we find that perceptions towards migration (including previous experiences with migration at the household level) positively interact with political drivers and issues related to food and water security.

The complex interaction structure is further reflected in Panel C of Fig. 5, which shows the distribution of marginal effects of an additional active driver within the eight categories we consider across the survey sample. These distributions indicate that certain driver categories, such as migration perceptions, are consistently positively correlated with migration intentions. However, several other categories exhibit large effect heterogeneity depending on the activity or inactivity of other driver categories. For example, the marginal effects of food and water security are mostly close to zero or even negative (suggesting reduced migration intentions), but certain driver combinations result in a long positive tail, indicating a significant positive marginal effect when specific drivers are active simultaneously. Overall, these findings highlight the importance of studying migration drivers in a systemic context, as different drivers can modulate each other, and compounding effects can significantly shape the collective influence of sets of drivers on migration intentions.

4.6. Differential impacts of drivers across population subgroups

A related setting that can potentially induce non-linearity is effect heterogeneity across subpopulations. For example, if the effects of migration drivers are particularly large among those with low education and this group experiences more drivers on average than other subpopulations, non-linear patterns, as seen in Fig. 5, could emerge. Apart from potentially inducing non-linear effects, it is in general interesting to explore how the effect of various drivers on migration intentions differs across sociodemographic subpopulations.

To investigate this, we repeat the BMA exercise from Section 4.2 separately for subgroups delineated by sex, age, urban/rural location, and educational levels. Sample sizes for each setting are reported in Table A3 in the supplementary materials. The dot-whisker plots displayed in Fig. 6 show the size of the coefficients and confidence intervals, measuring the change in the probability that a respondent intends to migrate if a specific driver is active. The transparency of the dots and whiskers is inversely proportional to the PIP. The more solid the color shading, the more relevant a driver is in influencing migration after accounting for model uncertainty.

The outcomes indicate that migration experiences, either personal or within the family, persist as the most robust and important predictor across all population groups. Yet, the magnitude of this effect differs significantly, with point estimates ranging from +20%

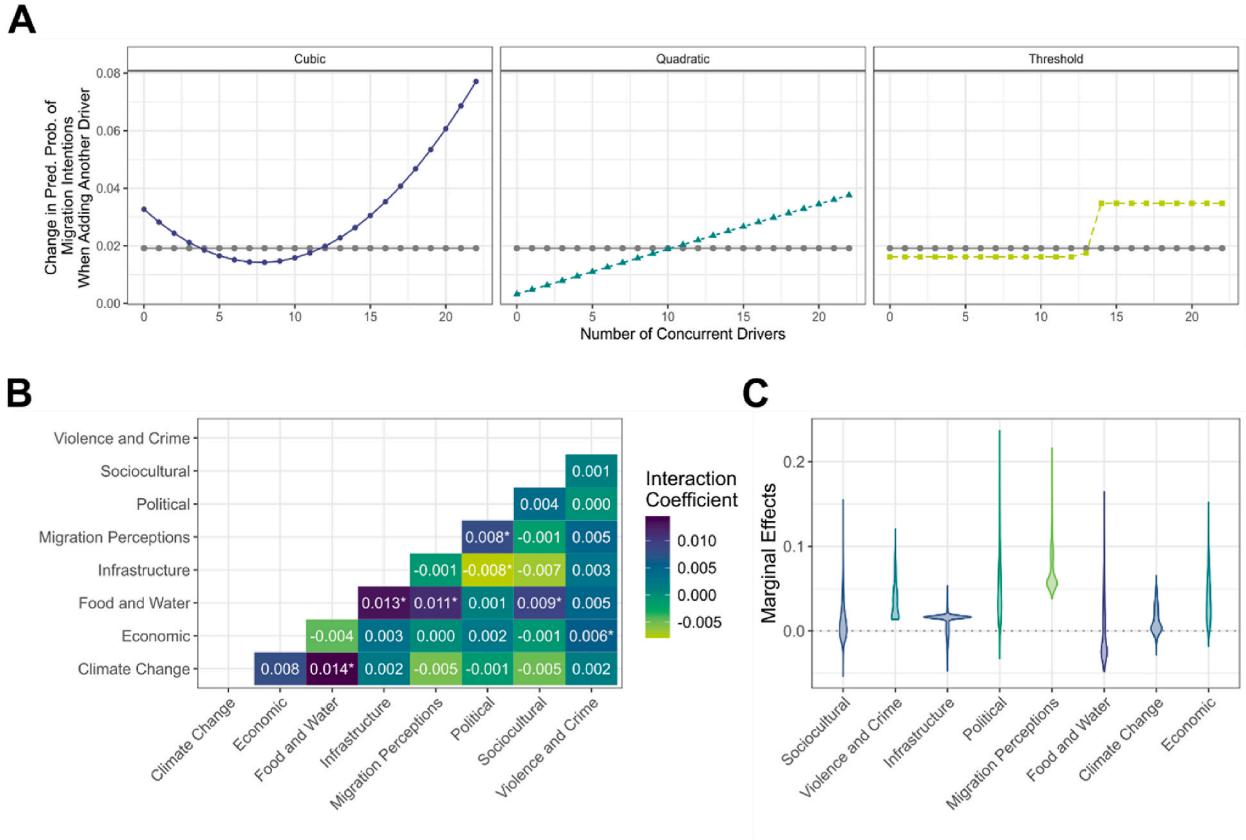

Fig. 5. Illustrating the role of non-linearities in the impacts of different drivers on migration intentions. Panel A illustrates the marginal effect of a single driver on the probability of having migration intentions (y-axis) versus the number of currently active drivers (x-axis). The three non-linear models include a cubic term (left; BIC: 44711.6) and a quadratic term (middle; BIC: 44713.7) in the number of active drivers. The threshold regression model (right; BIC: 44716.3) employs linear models before and after a threshold point, which is estimated by minimizing the BIC. The grey baseline effect is derived from a model that is linear in the number of active drivers (all panels; BIC: 44733.3). Panel B displays the estimated interaction coefficients for each combination of two migration driver categories. Numbers and tile colors represent the point estimates of these interaction terms, with stars indicating statistically significant interactions based on 95% confidence intervals. For brevity, the upper triangular part of the heatmap is omitted. Panel C presents the distribution of the marginal effects of an additional active driver for each category in the observed sample.

(among males with no education) to less than 10% (among females over 60). Unemployment consistently emerges as a strong predictor across most demographic subsets. In the older age category, unemployment appears as only relevant predictor next to previous exposure to migration experiences. While the significance of the sociocultural and political factors fluctuates slightly between educational groups, the general importance of these variables underscores their relevance in shaping migration intentions across all population groups considered.

5. Discussion and limitations

The formation of migration intentions is a complex phenomenon which is influenced by a multitude of interconnected drivers that can interact with each other. Our empirical analysis underscores the necessity of considering such interconnections and the potentially non-linear effects they produce. While leveraging detailed and large-scale data, our empirical approach has several limitations which are important for the interpretation of our findings. First, the use of cross-sectional data renders causal identification impossible and limits the interpretation of the coefficients as structural. Our analysis cannot account for the full chain of causal relations and inherent endogeneity between the different drivers considered which can influence each other over time. However, the primary objective of our empirical analysis is not to establish causal relationships but to delineate and examine the complex interplay and dependencies among various factors influencing migration intentions and behaviors in different contexts. This exploration aims to shed light on the multifaceted and interconnected nature of migration drivers, offering insights that could guide future research in this domain.

Also, while our study aims to capture a range of factors that may influence migration, we cannot comprehensively measure and account for all potential drivers. For example, information on the respondent's health condition was not collected as part of the Afrobarometer, hence restricting our ability to consider this factor in our analysis, even though previous studies have highlighted its

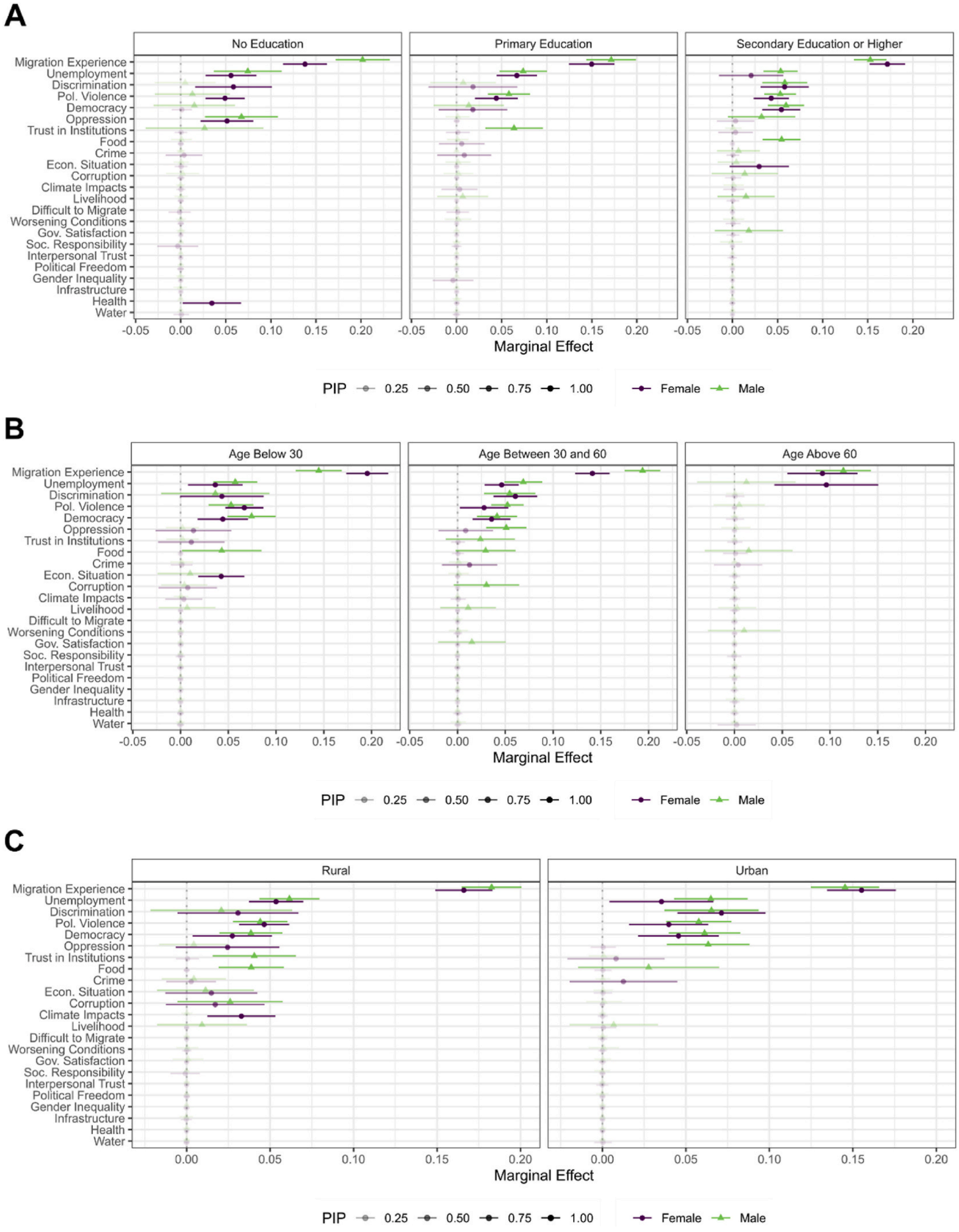

Fig. 6. Differential impacts of migration drivers across population subgroups. Results of subsample BMA Exercises in 16 subgroups, segmented by education (Panel A), age (Panel B), rural/urban status (Panel C) and sex (colors). Point estimates are estimated posterior means of the marginal effect of migration drivers on the probability of having migration intentions. Error bars indicate 95% credible intervals. Transparency of the estimate is inversely proportional to the posterior inclusion probability of the respective covariate. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

importance in shaping migration (Schwerdtle et al., 2020). It is not the goal of our analysis to comprehensively capture all possible drivers and to provide causal estimates of their impacts, but to explore the network of drivers that shape migration intentions in different contexts and the relevance of interactions between drivers. Furthermore, the dichotomization of the variables represents a simplification, which may blind out relevant aspects, such as the degree of relevance of a driver for a person or the intensity with which a person is affected. Despite this limitation, dichotomization allows us to ensure comparability across the different driver categories and facilitates the visualization and interpretation of the effects, especially those derived from more complex models.

Our analysis is based on subjective data regarding migration intentions, focusing exclusively on future intentions instead of actual migration behaviors. Although research has shown that intentions are predictive of migration (Tjaden et al., 2019), there may be systematic differences for certain groups, complicating the extrapolation of our findings to predict actual migration behavior. Likewise, measurement issues may further affect the accuracy of our outcome and explanatory variables. Despite these limitations, our study presents consistent findings as to how different subjectively perceived drivers are related to each other and jointly influence the specific migration measure considered.

In terms of data collection, we acknowledge that conducting household surveys in the African context presents unique challenges and can potentially lead to issues with representatives, particularly when it comes to accurately surveying remote populations (Seidler et al., 2024). In addition, while our analysis covers a substantial share of the African population, it does not encompass all countries or the entire population of the African continent. However, the data we use remain the most comprehensive available to date and are frequently utilized in empirical research. Its extensive coverage and methodological rigor provide a valuable foundation for our analysis, despite the inherent difficulties in data collection.

In terms of sample composition and survey design, we rely on unweighted inference. This approach is primarily due to the fact that several methods we employ do not naturally extend to using survey weights, and Afrobarometer Wave 7 only provides within-country survey weights. As a robustness check, we re-ran the multivariate OLS specification in Table 2 using survey stratification by country and within-country weights, which did not change the results or general insights derived from our analysis. However, it should be noted that our findings do not necessarily reflect the behavior of nationally representative populations but rather the specific population surveyed by Afrobarometer. Additionally, the sample is likely skewed towards individuals who were unable to migrate and does not capture those who have already migrated. Hence, our study reflects the effects of various contextual and personal drivers on the migration intentions of populations still residing in their countries of origin.

Finally, it is worth pointing out that we rely on statistical methodology to connect self-reported migration intentions and perceived drivers of migration. Future research could attempt to survey the relationship that we explore using statistical extrapolation by more directly by exploring how people respond to whether they would migrate if certain scenarios (such as food insecurity, unemployment or similar) realize.

6. Conclusion

This study explores the interconnected nature of migration drivers and analyzes how diverse drivers interact to jointly influence migration intentions. We find that drivers do not operate in isolation but in groups or clusters, which are not uniformly distributed across populations. Instead, different driver profiles can be observed among groups that share similar sociodemographic characteristics and a similar inclination toward migration.

Several factors simultaneously affect migration intentions in Africa, such as those related to political conditions in the countries, the personal economic situation of respondents, and issues related to personal security. Previous experiences with migration have a particularly strong influence, consistent with network theories of migration (Choquette-Levy et al., 2021; Haug, 2008; Munshi, 2020).

Our findings further support the notion of non-linear and compounding effects of different drivers (Bentley et al., 2014; Cappelli et al., 2023; McLeman, 2017), and open avenues for future research to explore interactions and inter-dependencies in greater detail. Depending on the specific population group and context, the influence of drivers can vary. In addition, our empirical results support the notion that migration drivers can exert a mutually reinforcing effect on migration intentions (Helbling and Morgenstern, 2023; Naudé, 2010). When studying the dynamics of migration and migration intentions, it is therefore essential to move beyond simplistic analyses that focus solely on average, linear effects of migration drivers.

Our findings also have important policy implications. For policies addressing the root causes of migration, it is not sufficient to focus on singular drivers only. Instead, policymakers need to adopt a holistic approach that considers the interplay among multiple factors and their joint influence on migration decision making. As we show in our analysis, the overlap and accumulation of multiple drivers can amplify migration responses in a given setting. At the same time, not everyone who wishes to migrate can do so and households may find themselves trapped despite difficult circumstances (Zickgraf, 2018). For immobile groups, it is essential to minimize livelihood stressors and safeguard well-being. Establishing robust protection schemes for both mobile and immobile groups can help to support vulnerable populations, ensuring equitable outcomes across different contexts and groups.

CRediT authorship contribution statement

Roman Hoffmann: Project administration, Methodology, Investigation, Formal analysis, Data curation. **Gregor Zens:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Code and data availability

The Afrobarometer (wave 7) data used in this study are publicly available on the Afrobarometer website. The code used to generate and visualize the results reported in this study are available upon request from the authors. The data analysis was carried out in R. All used packages are acknowledged and cited in the source code files.

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Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envdev.2024.101096.

Data availability

All data used for this study are freely available through Afrobarometer. Relevant code files are avaialble upon request (see data and code statement in manuscript)

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