Mixed Method Study: Gender Differentiated Drivers of Violent Extremism in Central Sahel

(Sahel CVE Research)

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Perceptions of VE Drivers: A Quantitative Analysis

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Acronym List

ACLED	Armed Conflict Local Event Data Project's
CVE	Countering Violent Extremism
USAID	United States Agency for International Development
USAID/WA	USAID West Africa Mission in Accra, Ghana
VE	Violent Extremism
VEO	Violent Extremist Organizations

I. Introduction

Violent extremism (VE) in the Central Sahel region has been on the rise since the onset of the Malian crisis in 2012. As noted in the accompanying literature review conducted by FHI360 (2020), violent attacks linked to militant Islamic groups in the region have more than doubled on a yearly basis since 2017, leaving more than 2,600 fatalities in 2019 and more than 1.2 million people displaced (Powell, 2018; Le Roux, 2019; Ammour, 2020). More than 10 violent extremist organizations (VEOs), comprised of jihadist groups and community-based militias, have been identified as actively operating in the region; additionally, government forces are responsible for attacks on the civilian population as well (FHI360, 2020; MacLean, 2020). Violent extremism is thus a phenomenon that threatens the region's security, the stability and consolidation of democracy, and, ultimately, the quality of life of "ordinary" citizens throughout the Liptako-Gourma region.

Understanding the causes and conditions conducive to VE in the Sahel Region is a key concern for public officials, academics, and stakeholders. In the last couple of years, a growing body of research has delved into the roots and drivers of radicalization. Most of this research is qualitative, based on interviews with political or academic elites and/or on focus groups gauging the opinions of former militants. The few quantitative studies conducted on this topic suffer from various methodological limitations: i) they are eminently descriptive; ii) they fail to simultaneously account for individual and contextual factors; iii) they are typically confined to particular geographical areas or specific segments of the population (e.g., those already radicalized and/or accused of acts of terrorism); and iv) they assume – either implicitly or de facto – a "homogeneous" population, failing to consider the diversity of "pathways" toward radicalization. In particular, previous statistical work has neglected gender-specific differences in the determinants of VE, mostly assuming that the mechanisms of radicalization are virtually identical for men and women. These methodological flaws hamper the accuracy of the conclusions drawn from these studies, limit the generalizability of their findings, and inhibit their ability to provide a comprehensive picture of the causes of radicalization, ultimately undermining the relevance of the policy recommendations emerging from this work.

The remainder of the report is structured as follows. Section II briefly reviews the key determinants of radicalization highlighted in the literature, and Section III formulates the hypotheses to be tested in the empirical analysis. Sections IV and V then describe – in non-technical terms – the methodological approach implemented in this quantitative study and summarize the publicly available data sources and variables used to operationalize the determinants of VE for the purposes of hypothesis testing. Section VI discusses the main empirical findings about the fundamental drivers of radicalization, focusing primarily on the drivers of female radicalization in the three countries under study, namely Burkina Faso, Mali and Niger. The Methodological Appendix contains additional technical details and supplementary results complementing the information presented in the study.

Based on the results of this quantitative analysis, and following USAID's review, the final section of the quantitative study will identify opportunities for reform and formulate some policy recommendations aimed at undermining the threat of violent extremism in the region.

Altogether, the overarching goal of this quantitative study is twofold: i) to quantify the impact of alternative (potential) determinants of radicalization and estimate their relative importance; and ii) to identify and characterize different segments of the

population that vary in their propensity to become radicalized and/or in their susceptibility to different VE drivers. Although the results of this study will provide insights into the general causes of radicalization and shed light on the population at risk of engaging in violent extremism as a whole, particular emphasis will be placed on a gendered interpretation of the conclusions drawn from the data, as this is an under-researched area within the VE literature.

II. Determinants of Violent Extremism and Radicalization in the Central Sahel

Previous research has underscored the influence of several key risk factors for violent extremism in the Central Sahel region. However, most of the literature has only partially examined the issue of gender-specific determinants of VE in the Central Sahel or explored the gender dynamics of VE in the region. Drawing on the extensive literature review conducted by the FHI360 team (FHI360, 2020), we can distinguish four broad categories of factors that contribute to individual and collective grievances and may fuel extremist views:

1. Weak or absent governance combined with negative experiences of government corruption and injustice;
2. Abuses by the security sector (in combination with communities' need for protection);
3. A desire for social status and recognition, especially in contexts of high unemployment and underemployment;
4. Geographic factors: Regional variations — in economic development and prospects, in the proximity to conflict areas, and access to natural resources — have also been posited to explain differences in the prevalence of violent extremism between and within the three countries in the Central Sahel region.

Systematic analyses of the relative weight and significance of these various factors are extremely rare. In particular, empirical evidence on both the direct impact of gender on attitudes towards VE and on the moderating effect of gender on the influence of these individual and contextual factors is extremely scarce. However, to paraphrase Blaydes and Linzer (2008, p. 583), most current knowledge about support for VE deals with the preferences and beliefs of men, while women may face a very different set of constraints and incentives.

The empirical analysis presented below takes advantage of these valuable insights from previous work, incorporating them as inputs in order to conduct a systematic analysis of VE drivers. Specifically, the "independent variables" aimed at explaining radicalization will operationalize the different sets of factors reviewed above. As noted before, especial emphasis will be placed on analyzing the differential effect of potential VE drivers between women and men, on identifying different types of gender- (female-) specific profiles of extremists, and on formulating policy recommendations aimed at mitigating the risk of VE in the Central Sahel region through a gendered-lens.

III. Hypotheses to be tested in the quantitative analysis

As mentioned in the Introduction, the overarching goals of this quantitative study are to measure and compare the impact of alternative – individual and situational – potential determinants of radicalization, and to assess how such factors operate across different segments of the population in the Central Sahel region – in particular, within the female population, and in comparison with their male counterparts.

Beyond these general goals, the empirical analysis will also seek to test specific hypotheses derived from the literature reviewed above. More concretely, based on the summary literature reviewed in Section II, the following hypotheses will be examined:

Hypothesis 1: Perceptions of government discrimination towards their own ethnic group (e.g., access to natural resources) and economic deprivation relative to other groups exacerbates disillusionment and mistrust of government and traditional institutions, and renders individuals more sensitive to narratives that, like those of VEOs, challenge the status quo.

Hypothesis 2: Government failure to provide security for its citizens, coupled with experiences of abuse at the hands of the State's security apparatus (e.g., police and armed forces) undermines trust in government and state institutions. Such discontent fuels adherence to extremist groups promising to meet these needs, thereby building support for VE.

Hypothesis 3: More generally, high levels of corruption and lack of accountability from the political elite, coupled with the inability of politicians and state institutions to solve some of the most pressing citizen problems (e.g., provision of basic public services like healthcare, education and security) generate frustration with political leaders and democracy more generally, creating popular disenchantment that may be harnessed by extremist groups.

Because the drivers and mechanisms of radicalization are expected to operate differently for women than for men, these hypotheses will be tested not only for the population of the Central Sahel region as a whole, but also separately for the female and male sub-populations. For instance, while it has been documented that higher education levels tend to be negatively correlated with support for VE on average (because higher education levels are associated with better wages and employment opportunities and with less dogmatic/more cosmopolitan worldviews), anecdotal evidence suggests that some of the strongest support for VE extremism in the Islamic world comes from highly educated women (Moghadam, 1993). Hence, the impact of education on the likelihood of radicalization may vary – in sign, magnitude, and significance – by gender.

More generally, personal and environmental (e.g., geographic) factors may condition whether, and to what extent, socio-economic, ideological and political circumstances fuel VE sentiments among women and men, as well as within specific sub-segments of the female and male populations of each of the countries under study. This further suggests that, in addition to gender-specific tests of these hypotheses, the analysis needs to be disaggregated at the national and sub-national level in order to gain a more detailed understanding of the way in which VE drivers operate in the Central Sahel. The next section presents the empirical strategy proposed to account for these various sources of heterogeneity.

IV. Methodological Approach

In order to examine and compare the impact of alternative explanatory factors on the risk of radicalization, the empirical analysis utilizes a multi-level mixture analysis.

Multi-level modelling is a statistical tool aimed at assessing the joint impact of individual (e.g., gender or education) and contextual (national-, region- or province-level) variables on individuals' opinions or behaviors when dealing with hierarchical data structures, such as survey responses of individuals "nested" within sub-national (e.g., region) and/or national (e.g., country) units (Steenbergen and Jones, 2002). As is well known, simply pooling together individual and contextual variables in a conventional regression model would yield downward-biased standard errors, leading to inaccurate inferences and potentially misleading substantive conclusions (Gelman and Hill, 2007). Multi-level models allow for accurately estimating the simultaneous influence of micro-, meso- and macro-level covariates, as well as testing for cross-level interactions and assessing the moderating effect of context on individuals' opinions. For instance, the impact of gender on radicalization may vary across geographical areas: a woman living in Djibo, Burkina Faso, may be more likely to engage in VE than an otherwise 'equal' woman living in Arbinda, Burkina Faso, simply because VEOs are much more active in the former department than in the latter. Multi-level modelling allows us to explicitly account for this sort of conditioning contextual influence. Same-level interactions can also be included in the multi-level model to assess the moderating influence of a given personal characteristic on other individual-level traits. For instance, interacting gender with socio-economic measures would allow testing the assumption that the impact of unemployment or poverty on the likelihood of adhering to VE differs between women and men, while an interaction between a female indicator and marriage would help examine Blaydes and Linzer (2008)'s contention that married women should be more radicalized than single ones.

Moreover, multi-level models not only capture the impact of observed contextual factors, but also account for the influence of unobserved or unmeasurable (e.g., cultural) environmental variables.[1] This property of hierarchical models is especially convenient for our particular application, given that publicly available statistical data on Burkina Faso, Mali and Niger is relatively sparse at the sub-national level, and thus probably unable to reflect all the potential sources of cross-regional differences in attitudes towards VE. Therefore, it is crucial to take unobservable sources of heterogeneity between regions into consideration as well.

Multi-level models thus exhibit several properties that make them suitable for our analysis, allowing us to estimate the "average" impact of the alternative determinants of radicalization, to explore potential gender-related differences in the drivers of VE perceptions, and to test whether the hypotheses presented in the previous section hold among the population as a whole and/or among the female sub-population.

As discussed in Section II, however, some authors have proposed alternative typologies of individuals that differ both in their susceptibility to different drivers and in their "pathways" towards radicalization. The existence of distinct types of individuals has so far been assumed but has not been empirically tested. Doing so would not only contribute to our understanding of the drivers and mechanisms of VE, but also help formulate more targeted or precise policy recommendations. That is, if the causes and conditions conducive to VE vary between different segments of the (female)

[1] From a technical perspective, the impact of these unobserved or unmeasured contextual factors is captured through the inclusion of hierarchical (e.g., country, region, province-level) random effects. See Gelman and Hill (2007).

population of the three countries under study, the appropriate measures to counter radicalization are likely to vary as well.

Unlike standard multi-level models, multi-level mixture analysis (Vermunt, 2010) allows testing for the existence of distinct types or categories of individuals that differ in their propensity to become radicalized and in the causes explaining their radicalization, accounting again for both individual and contextual factors. Hence, multi-level mixture models can be seen as a refinement of standard multi-level models that account for the existence of distinct sub-groups or segments within a population of interest. If distinct types or sub-groups actually do exist, multi-level mixture models will enable us to identify them, quantify their size, uncover their main characteristics, and estimate the differential impact of the drivers of radicalization on each category of individuals. The number, group and characteristics of the different "types" of individuals may or may not differ for women and for men, but this is an empirical matter that needs to be established based on the analysis of the data, rather than postulated a priori.

The Methodological Appendix provides more technical details about the modelling and estimation approach implemented in this study.

V. Data Sources and Variables

To fit the multi-level and mixture models, we use individual-level data taken from the Afrobarometer public opinion project as well as macro-level or contextual data (at the national and sub-national levels) taken from national statistical offices and inter-governmental organizations.

V.1 Survey Data from Afrobarometer

Survey responses from nationally representative samples of citizens from Burkina Faso, Mali and Niger were collected in four Afrobarometer waves: Wave 4 (2008), Wave 5 (2012-2013), Wave 6 (2014-2015) and Wave 7 (2018-2019). This is the longest and most comprehensive high-quality public opinion time-series data available for the countries in the Central Sahel region, allowing us to gather individual-level data from 1,200 respondents in each of the three countries every year with a reasonably good level of geographical sub-national coverage (see Table 1, next page).[2] Examining survey data for over a decade allows us to track the evolution and dynamics of public attitudes toward VE in the region.[3]

[2] Niger is only included in the last three Afrobarometer waves (5-7). Hence, cross-national comparisons with Niger must be restricted to the 2012-2019 period.

[3] Missing data is not a particularly relevant concern in Afrobarometer surveys (compared to other commonly used survey instruments). That said, all the empirical analyses reported in this document have been conducted twice: once examining only complete cases (i.e., excluding respondents with missing values), and once using model-based imputation (Honaker and King, 2010) for the missing values. The main substantive findings presented below remain similar under both approaches, reinforcing our confidence in the robustness of the results and the validity of our conclusions.

Table 1: Afrobarometer's geographical coverage and sample sizes (average per wave)

Country	Geographical coverage	Total number of respondents	Areas of interest	Number of respondents in the areas of interest
Niger	Agadez, Diffa, Dosso, Maradi, Niamey, Tahoua, Tillabéri, Zinder	1,200	Tahoua	235
			Tilaberri	195
Burkina Faso	Boucle du Mouhoun, Cascades, Centre, Centre Est, Centre Nord, Centre Ouest, Centre Sud, Est, Hauts Bassins, Nord, Plateau Central, Sahel, Sud-Ouest	1,200	Oualam	20
			Soum	50
			Djibo	10
			Dory	20
Mali	Bamako, Gao, Kayes, Kidal, Koulikoro, Mopti, Ségou, Sikasso, Tombouctou	1,200	Gao	50
			Kidal	20

V.1.1. Explanatory variables

Our individual-level explanatory variables were built from a series of questions included in the Afrobarometer surveys that tap into attitudes and behaviors towards VE that are closely linked to the "push factors" identified by USAID (2009) as potential drivers of VE. Specifically, these independent variables were coded based on survey participants' responses to the following items:

Variables measuring opinions about the evolution of economic conditions:

- How would you evaluate the current economic conditions in your country, compared to twelve months ago?
- How would you evaluate your current household economic conditions, compared to twelve months ago?

Variables measuring relative deprivation and grievances:

- How would you evaluate your current household economic situation, compared to those of your con-nationals?
- How often is your ethnic group treated unfairly by the authorities?

Variables measuring attitudes about government/political institutions:

- How much trust do you have in the President?
- How much trust do you have in the National Assembly?
- How much trust do you have in the police?
- How much trust do you have in the armed forces/army?
- How prevalent is government corruption?
- How do you rate government's ability to provide public services like electricity?

<u>Variables measuring respondents' socio-demographic characteristics:</u>

- Age
- Education
- Employment status
- Marital Status
- Religiosity
- Income
- Urban/Rural
- Region/Province
- Country

We included the aforementioned explanatory variables in the model specification, fitting it first to the pooled sample of men and women and testing whether the female indicator was a key predictor of heterogeneity in the propensity to become radicalized. This provided us with a first indication of the number of distinct types or classes of individuals based on their propensity to become involved VE, and whether women belong to a distinct "type" than men. Based on these preliminary findings, we then divided the sample by gender and ran separate models on the female and male sub-samples. This yielded additional insights on the existence of relevant differences in the number, composition and characteristics of "types" of survey respondents within and between genders.[4] We estimated a general hierarchical model for data from Burkina Faso, Mali and Niger, as well as separate models fitted to data from each of the three countries in order to explore the geographic differences within each country in greater detail.

V.1.2 Dependent variables

While the operationalization of the explanatory variables is directly informed by the literature reviewed in Section II, selecting the outcome variable(s) is not straightforward. Although Afrobarometer surveys include a few questions that directly ask respondents about their effective involvement in VE (see below), radicalization and adherence to extremist violence are arguably – like many other political and sociological concepts – multifaceted latent constructs (Treier and Jackman, 2008; Katz and Levin, 2018). Hence, it is very difficult to accurately gauge attitudes towards VE through any single indicator. Several different variables might capture particular aspects of the latent construct of interest, but none of them is likely to provide a complete depiction of VE perceptions by itself. However, jointly examining and combining the information from these various measures can provide a better approximation to underlying attitudes towards VE and help us accurately identify "radical profiles" and their determinants (Treier and Jackman, 2008; Vermunt, 2010). The mixture modelling strategy used for this quantitative study is, thus, specifically designed to concomitantly examine multiple dependent variables that, together, are able to capture an underlying construct of interest.

[4] Nuanced differences in attitudes towards VE may not be fully captured by a simple "female indicator", and thus separately running the analysis on the sample of women and men can help gain more fine-grained information within- and between-gender differences in the VE drivers.

Hence, we examined individual responses to a series of questions tapping into Afrobarometer participants' experience with political violence, preferences about gender roles, the role of religion in government and politics, and support for fundamentalist movements. It is important to stress that none of these questions per se allows classifying an individual as being prone to engage in VE or not. However, prior research has shown that overall attitudinal patterns emerging from the joint responses to these questions can capture relevant aspects of radicalism or fundamentalism that, together, correlate strongly with support for religiously-oriented authoritarian regimes and extremist violence (e.g. Fish, 2002; Blayes and Linzer, 2008). Specifically, the dependent variables are built from the following Afrobarometer survey items:

<u>Questions about respondents' involvement in political violence</u>:

- Have you ever used/would you use violence to support a political cause?
- Do you agree that the use of violence is sometimes justifiable?

<u>Questions tapping into attitudes towards democracy and politics</u>:

- Do you agree that military solutions - including a military dictatorship - could help the country overcome its problems?
- To what extent do you agree that democracy is always the best form of government?
- Are you satisfied with the way democracy is working in your country?
- To what extent do you agree that elections are not necessarily the best way of choosing political leaders, and that other methods may be better suited for the country?
- To what extent do you agree that political parties should thus be dismantled?
- Do you believe that only one (your preferred) party should be allowed to take part in elections/government?
- Do you agree that whoever is in power has the right to ban movements or organizations he does not agree with?
- Do you believe that the National Assembly should be dismantled?
- Do you think that you should not abide by laws introduced by a government you did not vote for?
- Do you agree that the country should be ruled according to religious precepts?

<u>Questions measuring attitudes towards (own/other) religious and ethnic groups:</u>

- To what extent do you sympathize with/hate/mistrust other ethnic groups?
- To what extent do you sympathize with/hate/mistrust other religious groups?
- To what extent do you sympathize with/mistrust/hate Islam?

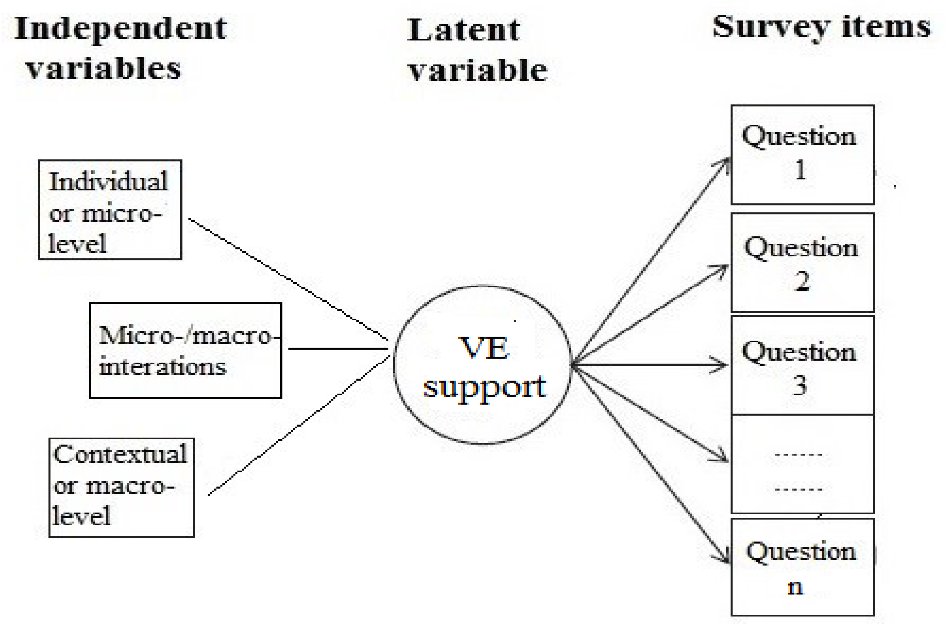
<u>Questions measuring preferences about gender roles and gender-related attitudes:</u>

- To what extent do you agree that men make for better politicians than women, and thus only men should participate in politics?
- To what extent do you agree that women should be subject to traditional values and customs, rather than having the same rights and receiving the same treatment as men?
- To what extent do you agree that men have the right to exert physical violence against their female partners?

- To what extent do you agree with the following statement: "Women and men should have equal rights to property/inheritance"?

The mixture modelling approach allows simultaneously examining the individual responses of every survey participant to each of these items, rather than having to combine them into composite indices.[5] In other words, instead of aggregating responses to all these question – which would discard relevant statistical information and lump together opinions on several potentially related but distinct issues– we can identify profiles or types of VE-perceptions and assign every survey participant to each type based on their joint responses to the full set of survey items (see Figure 1 below).[6]

Figure 1 - Relationship between survey questions, VE support, and independent variables



The mixture modelling approach also allows us to identify "bad" items that do not provide relevant information about the underlying latent construct of interest — propensity to engage in VE — either

[5] Standard multi-level analysis can also simultaneously handle multiple dependent variables without the need to combine them into an index or composite measure – e.g., relating these various individual outcomes through the specification of a covariance matrix (see for instance Lynch, 2007, ch. 10). However, conventional multi-level estimates would only allow us to estimate the impact of each explanatory factor on each outcome. By contrast, multi-level mixture models yield not only item-specific estimates, but also a summary measure of the overall impact of each explanatory factor on the underlying latent construct of interest.

[6] That said, we also conducted a principal component analysis (PCA) to verify the robustness of our findings regarding the latent "support for VA" variable. As latent class or mixture modelling analysis, PCA aims at summarizing the information contained in a large set of measured variables (in our application, the Afrobarometer survey items). Unlike mixture modelling, however, PCA aims at producing one or more (latent) index variables from this larger set of observed indicators (Joliffe, 2002). Also in contrast to multi-level modelling, standard PCA is not based on an associated probabilistic model for the observed data, which entails some drawbacks (Tipping and Bishop, 1999; Alvarez et al., 2020). Nonetheless, the two data reduction methods – i.e., multi-level modelling and PCA – have different strengths and weaknesses (e.g., Wetzel et al., 2015). As we show in the Methodological Appendix, which reports the results from a principal component analysis applied to our data, the main results regarding the information that the survey items provide about VE-related attitudes are similar under the two approaches.

because these questions do a poor job discriminating between types of individuals or because the items do not contain much variation to begin with (Blaydes and Linzer, 2008; Kreuter, Yan and Tourangeau, 2008).[7] This allows us to assess the validity of each of the dependent variables and to select a subset of relevant items for the final analysis. The empirical findings reported below are based on the subset of items that were found to effectively distinguish between individuals prone to engage in VE and the rest.

V.2 Official Statistical Data

In addition to individual-level survey data, our analysis uses meso- and macro-level data to account for the influence that contextual factors exert on the probability or risk that individuals become prone to engage in VE. Specifically, these contextual variables enable us to account for the impact that factors which figure prominently among the VE drivers in the theoretical literature — such as the competition for access to natural resources between herders, nomadic herders and sedentary farmers; the proportion of internally displaced persons (IDPs); and the geographical proximity to areas where political and ethnic violence is more prevalent — exert on individuals' propensity to become "radicalized" (Finkel et al. 2016; Guéret 2017; Raineri 2018).

Table 2 lists the contextual variables, their source and their level of aggregation. The results reported below are based only on the subset of contextual indicators that turned out to have a systematic influence on the probability that survey respondents belong to the "High VE-risk" group.

Table 2: Measures, data sources and coverage for the contextual explanatory variables

Variables	Source	Level of aggregation and coverage
Development and deprivation (Multidimensional) Poverty Inequality (Gini) Socio-economic vulnerability Disease prevalence (cholera, measles) (Infant) mortality Immunization rate (Infant) Malnutrition Literacy rate Governance	INFORM Sahel: Inter-Agency Standing Committee and European Commission (http://www.inform-index.org/Subnational/Sahel)	Region. Covers all the regions of the countries under study (including those identified as potentially relevant).

[7] Ideally, we would like to determine the validity of the items by comparing them against some external, "gold-standard" measure. In the case of VE, however, the only possible source of external data on the drivers of radicalization would be a survey conducted among individuals directly involved in VE, as official records or archival information would not typically provide detailed information beyond basic socio-demographic traits. Unfortunately, while the IMRAP/Interpeace (2017) participatory research study interviewed some women involved in VE, its sample size is too small to allow the findings to be generalizable; similar considerations apply to studies like Inks, Veldmeijer and Fomba (2017) and SIPRI (2017). More generally, this kind of studies can only capture the opinions of a very small and unrepresentative segment of the population (Bueno de Mesquita, 2005), and are in all likelihood subject to social desirability bias and misreporting (Katz and Katz, 2010). Fortunately, Kreuter, Yan and Tourangeau (2008) demonstrate that mixture models do a good job assessing the validity and quality of survey questions and discriminating between "good" and "bad" items based on the estimated item-specific response probabilities (also Blaydes and Linzer, 2008, p. 590). Furthermore, these authors also show that, in those rare instances in which external measures of the latent construct of interest are actually available, mixture models yield similar conclusions as analyses conducted on the gold-standard data.

State Infrastructure Access to public services (electricity, sanitation, clean water) Uprooted people Internally displaced persons Refugees Returned refugees Food insecurity Land degradation Agriculture droughts Prevalence of political violence		
Life expectancy Per capita income Years of schooling	Subnational Human Development Database (https://globaldatalab.org/shdi/)	Region. Covers all the regions of the countries under study (including those identified as potentially relevant).
School enrollment rates Number of hospital/clinics Medical personnel	INSTAT (www.stat-niger.org) INSD (http://www.insd.bf), INS (www.malikunnafoni.com)	Department. Covers all the regions of the countries under study (including those identified as potentially relevant)
Nomadic and sedentary population	UNICEF, Multiple Indicator Cluster Surveys, http://mics.unicef.org/	Region. Covers all the regions of the countries under study (including those identified as potentially relevant)
Event-based conflict data	ACLED (https://www.acleddata.com)	Community. Covers all the communities in which episodes of armed/violence took place.

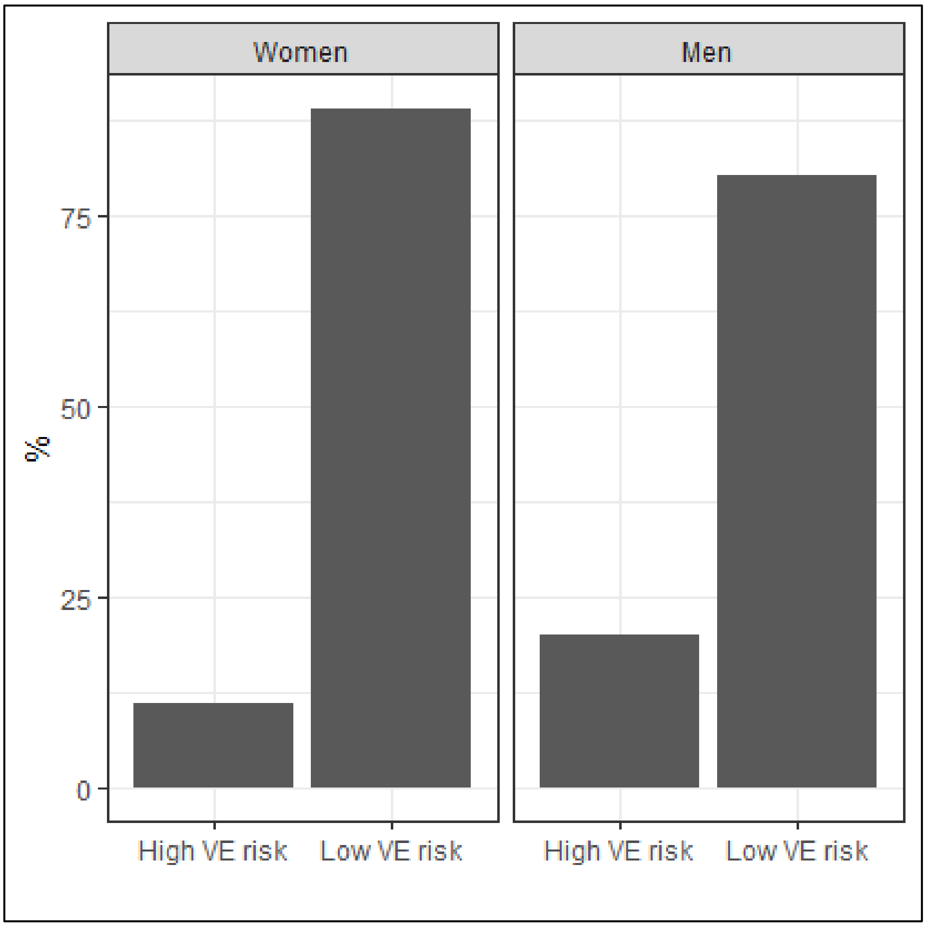
VI. Empirical Findings

This section presents (preliminary) empirical results emerging from the statistical analysis. The discussion focuses first on the whole sample of respondents from the three countries under study (Burkina Faso, Mali and Niger), comparing the drivers of radicalization by gender. We then compare the results between Burkina Faso, Mali and Niger, and track the evolution of the group of women at risk of supporting VE in the three countries over time.

VI.1 General patterns across countries throughout the period considered

Based on the broad definition of radicalization proposed by Blaydes and Linzer (2008), which considers participants' preferences about gender roles, attitudes toward the role of religion in government and politics, and support for fundamentalist Islamic movements, the multi-level mixture analysis distinguishes two sub-groups of female respondents in the Central Sahel. As seen in the left panel of Figure 2 below, the vast majority of women in the sample (almost 90%) exhibit little risk of radicalization. However, 10.93% of the women in Burkina Faso, Mali and Niger are classified as belonging to the "high VE risk" group.[8] The right panel of the figure shows a similar distinction among men in terms of VE perceptions, although the proportion of male respondents at risk of radicalization (19.87%) is higher than for women.

Figure 2 – Classification of women (left panel) and men (right panel) in the three countries under study, according to their "risk of radicalization"



Note: Classification of survey respondents into "High" and "Low" VE risk groups based on the results of the multilevel mixture model.

It is important to emphasize that the individuals – women or men – classified as belonging to the "High VE risk" group are not necessarily engaged in violent activities or involved with extremist groups. As noted in Section V.1.2, the classification of respondents into the two "risk groups" is based on a broad battery of question gauging their opinions and attitudes political violence, preferences about gender roles, the role of religion in government and politics, and support for fundamentalist movements. Women and men assigned to the "High VE risk" group (based on the mixture model

[8] This two-group partition of women and men is favored by both information-based (AIC, BIC) and goodness-of-fit (Pearson's χ^2, likelihood ratio chi-square G2) criteria over single-group models ignoring unobserved heterogeneity in survey participants' responses (Linzer and Lewis, 2011). These two-class models also outperform specifications with larger number of groups for either women or men, indicating that two gender-specific sub-populations are enough to capture variations in attitudes within survey respondents. See Tables A.1 and A.2 in the Methodological Appendix for details.

estimates) manifest opinions and attitudes that render them potentially more likely to become radicalized and more vulnerable to VEOs.

It is also worth noting that the proportion of individuals at risk of radicalization becomes smaller if, instead of relying on the more encompassing definition proposed by Blaydes and Linzer (2008), a more restrictive operationalization of VE-related attitudes is adopted. For instance, if only survey items measuring whether individuals resorted to violence to defend political positions in the past and whether they would consider ever doing so are considered, the proportion of women at risk of radicalization drops from 11% to less than 5% (4.76%). Similarly, the fraction of "VE-prone" men drops from 19.87% to 10.42%.

Table 3 summarizes the pattern of responses to different survey questions among the individuals assigned to the "high" and "low" VE risk groups. More specifically, the table displays the proportion of women and men in each group who agree with the statements included in the different items found to validly capture underlying attitudes towards VE and to effectively discriminate between the two sub-populations of women and men identified in the data (see footnote 6). These are the only items retained for the final empirical analysis.[9]

Table 3 – Responses to relevant survey items among women and men in the three countries under study, according to their "risk of radicalization"

Survey item	Women		Men	
	High VE risk	Low VE risk	High VE risk	Low VE risk
It is justifiable to use political violence to address the country's problems	30.02%	3.01%	47.16%	7.18%
I have used political violence in the past	1.47%	0.00%	4.01%	0.00%
A military dictatorship can be the best form of government	26.32%	5.01%	37.49%	7.01%
Democracy is always the best form of government	58.00%	83.20%	41.44%	82.13%
Whoever is in power has the right to ban movements or organization he does not agree with	42.22%	8.13%	45.34%	7.43%

Notes: The table reports the proportion of women and men in Burkina Faso, Mali and Niger agreeing with each statement, discriminating between individuals classified as belonging to the "high VE risk" and "low VE risk" groups. The vast majority of these responses are coded on a four-point scale (strongly agree/disagree/ agree/strongly agree). For ease of presentation, the table aggregates responses in the upper two (agree/ strongly agree) categories. Disaggregated response patterns are available from the author upon request.

Individuals in the "High VE risk" differ considerably in their endorsement of political violence and their attitudes towards democracy from those in the "Low VE risk". For instance, women in the "High VE risk" are 10 times more likely to justify the use of political violence to address the country's

[9] Responses to all the outcome variables (survey items) listed in Section V.1.2 – which were included in preliminary analyses – are available from the author upon request.

problems than those in the "Low VE risk". Moreover, 1.5% of the women in this category have in fact engaged in political violence in the past. On the other hand, none of the women in the "Low VE risk" category have been involved in political violence.

Women in the "High VE risk" group also have very different views about democracy than those less prone to engage in VE. More than a quarter of the female respondents allocated to the former group agree that a military dictatorship would be a desirable form of political regime, while only slightly more than half of them agree that democracy is always the best form of government. The corresponding figures for women in the "Low VE risk" category are 5.01% and 83.20%, respectively. Women "at risk of radicalization" are also more than 5 times as likely as those in the "Low VE risk" group to agree that whoever is in power has the right to ban organizations or movement he does not agree with.

Responses to the items gauging underlying attitudes towards VE are generally similar for men, although patterns for men in the "High VE risk" group are somewhat more "extreme" than for their female counterparts. For instance, men in the "High VE risk" group are more likely to have been involved in political violence, more prone to justify its use, more inclined to accept military regimes and less likely to unconditionally support democracy.

Interestingly, the key determinants of "radicalization" differ considerably by gender. As we noted above, this is a finding that has been largely ignored in the literature on VE in the Central Sahel. To illustrate this point, we discuss the effect of the most important demographic, socio-economic, political and contextual factors on the probability that the average woman becomes radicalized, and contrast these against the main determinants of high VE perceptions among men.[10] For ease of exposition, we only present results for those explanatory variables that have a significant effect on the risk of female and/or male radicalization – i.e., for those factors that systematically raise or reduce the probability that the average woman/man becomes radicalized. Other explanatory variables that were considered potential determinants of VE perceptions based on the theoretical literature, but that turned out not to have a systematic effect on radicalization in practice, are excluded from the discussion.[11]

Starting with the individual-level characteristics, Table 4 (next page) indicates that perceptions of ethnic discrimination, personal security concerns, religious beliefs and attitudes towards the military are the most important drivers of "female radicalization" in the three countries under study. We noted above that the average probability that a female respondent in Burkina Faso, Mali and Niger belongs to the "High VE risk" group is 10.93%. This probability jumps to 37.52% (that is, is almost 2.5 times higher) for women who feel that their ethnic group is systematically discriminated against by

[10] We define an "average" woman (man) as one that has the socio-economic, demographic, political and contextual characteristics of the majority of women (men) in the sample. The independent effect of each explanatory variable on the risk of radicalization is determined by conducting a "counterfactual exercise", computing how a change in the variable under consideration affects the probability of radicalization while holding all other individual and environmental characteristics constant at their typical (gender-specific) sample values. This sort of counterfactual analysis is commonly used in the social sciences to isolate the impact of particular explanatory variables in multi-variate statistical models. See Vowles, Katz and Stevens (2017) and Katz and Levin (2018) for technical details.

[11] A complete set of results, including estimates for all the explanatory variables listed in Section V.1.1 – many of which were found to have no systematic effect on VE perceptions in preliminary statistical analyses – is available from the author upon request.

government authorities, holding everything else constant. By contrast, the probability that women who do not believe to be discriminated against because of their ethnic origin belong to the high-risk group is only slightly above 5 percent. This finding provides partial support for **Hypothesis 1**. Interestingly, while perceived **ethnic** discrimination has a significant impact on the probability that women belong to the "High VE-risk" group, relative **economic** deprivation does not.

Personal security concerns – more specifically, fears of being victims of physical violence – also figure prominently among the determinants of support for VE among women. Women who are very afraid of being victims of physical violence are almost 15 percentage points more likely to belong to the "High VE risk" groups than otherwise equal women who do not. This lends credence to the argument that the quest for personal security and protection is a powerful driver of "female radicalization", in line with **Hypothesis 2.**

Religiosity is another important correlate of "female radicalization". Holding all other variables fixed, women who engage in religious practice more than once a day are almost 10 percentage points more likely to belong to the "High VE risk" than those who have no religious affiliation or do not engage in religious practices at all.

Table 4 – Individual determinants of VE perceptions among women

Indicator	Comparison	Probability of belonging to the "High VE risk" group
Ethnic group is discriminated against	Yes	37.52%
	No	5.21%
Fear of victimization	Yes	21.05%
	No	6.23%
Religiosity	Very religious	15.39%
	Not religious at all	6.46%
Trust in the armed forces	Not at all	27.61%
	A lot	4.23%
Unemployed	Yes	18.92%
	No	6.93%
Education	No formal education	13.75%
	Post-secondary education	8.10%

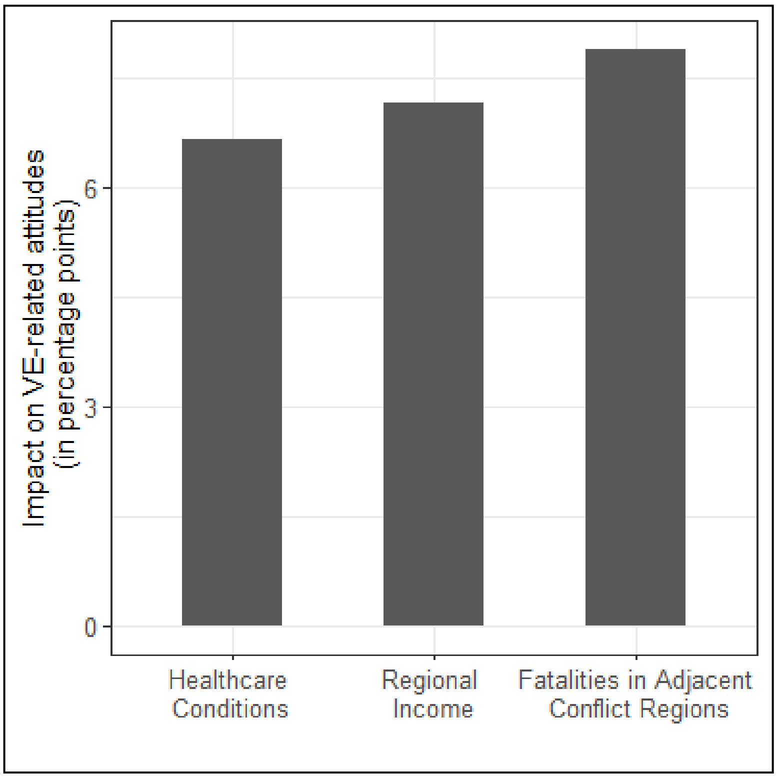
Note: The table compares average probabilities of belonging to the "high VE risk" group across selected categories of the individual-level explanatory variables found to have a significant effect on VE perceptions among women in Burkina Faso, Mali and Niger.

Trust in the armed forces is also an important determinant of female VE-related attitudes; among women who have no trust whatsoever in the armed forces, the probability of belonging to the "High VE-risk" group is 27.61%, which is 2.5 times as high as the average. The probability of belonging to this group drops to 4.23% among women who have a lot of confidence in the military. This again is consistent with the findings of the literature review (FHI360, 2020), in the sense that abuse from the armed forces – which in all likelihood undermines women's confidence in the security forces – render people more likely to support VEOs. Interestingly, while our model also included trust in elected officials (the president, members of Congress) and in the police as explanatory variables, none of them has a significant impact on the probability of group membership.

Among the socio-demographic characteristics, only unemployment and education have a significant influence on the probability of female radicalization. Unemployed female respondents are 12 percentage points more likely to belong to the "High VE-risk" group than employed (either full or part-time) and non-economically active women. Similarly, women with no formal education – who arguably enjoy fewer opportunities for economic and social recognition and thus find themselves in a more vulnerable situation – are more than 5 percentage points more likely to belong to the "High VE risk" group than those with post-secondary education.

Besides these individual or micro-level determinants, contextual factors also influence VE perceptions among women. In particular, access to/quality of healthcare in the region in which female respondents live, regional wealth and proximity to episodes of violence, are all powerful predictor of VE-related attitudes. This is illustrated in Figure 3, below, which plots the impact of a one-standard deviation increase in selected regional variables on the probability that women belong to the "High VE" or "Low VE-risk" groups.

Figure 3 – Impact of contextual variables on the probability of belonging to the "High VE-risk" group among female respondents



Note: The figure plots the impact of a standard deviation increase in regional factors on the probability that the average woman in Burkina Faso, Mali and Niger belongs to the "high VE risk" group. Only variables with a statistically significant influence on the probability of class allocation are plotted.

Holding everything else constant, the probability of being in the "high VE risk" group rises (drops) by 6.6 percentage points for women living in governorates with each standard deviation decrease (increase) in the healthcare indicators. In other words, consider two identical for a woman in Burkina Faso, one living in a region where healthcare conditions are similar to those prevailing in the Sahel and another living in a region with healthcare facilities like those in the Centre-East region. If we keep all other individual and contextual factors constant, the probability that the former belongs to the "High VE-risk" group is roughly 20 percentage points higher than for the latter. This provides some support for **Hypothesis 3**.

As illustrated in Figure 3, regional income levels are also important drivers of "female radicalization". Each standard deviation decrease in the region's per capita household income is also associated with a 7.16 percentage point increase in the probability that a woman living in that region belongs to the "High VE-risk" group. Interestingly, Table 4 did not indicate that women's personal income is a relevant determinant of radicalization (although unemployment did have a statistically significant impact on female group membership). This suggest that, other things equal, women living in more economically depressed regions are more prone to engage in VE, even after accounting for her household's own financial situation.

Finally, as expected, the prevalence of violence in women's environment affect their likelihood to engaging in VE as well. Each standard increase in the number of fatalities produced by VEOs in the proximity of a female respondent's region during the year prior to the survey is associated with a 7.90 percentage point increase in her probability of belonging to the "High VE-risk" group. That is, each additional fatality in the region in which the average woman lives is correlated with a 0.03% increase in her risk of adhering to VE.

Table 5, which summarizes the key individual and contextual factors shaping the probability that male respondents are allocated to the "high VE risk" group, highlights some commonalities but also some differences in the drivers of radicalization among men and women.

Table 5 – Main determinants of VE perceptions among men

Indicator	**Comparison**	**Probability of belonging to the "high VE risk" group**
Age	18-25	33.51%
	26-35	28.36%
	36-50	19.07%
	51-65	5.03%
	66 and older	2.22%
Ethnic group is discriminated against	Yes	47.13%
	No	8.16%
Religiosity	Very religious	60.39%
	Not religious at all	12.55%
Unemployed	Yes	23.53%
	No	14.41%

Education	No formal education	47.46%
	Post-secondary education	12.20%
Government's ability to fight crime	Government does a bad job	24.56%
	Government does a good job	15.34%
Government's ability to provide public services	Government is unable to provide services	29.67%
	Government does a good job providing services	11.45%
Corruption in the police	Corruption is widespread	31.05%
	Corruption is not prevalent	10.23%

Note: The table compares average probabilities of belonging to the "high VE risk" group across selected categories of the individual-level explanatory variables found to have a significant effect on VE perceptions among men in Burkina Faso, Mali and Niger.

Unlike for women, age is a key predictor of "radicalization" among male respondents. The probability of being in the segment of men vulnerable to VE jumps to 31% among male respondents between the ages of 18 and 25, and remains significantly above average also for men between the ages of 26 and 35. Similarly, evaluations of government performance (i.e., opinions about government's failure to provide basic public services like security and electricity) as well as perceived corruption in state institutions – the police, in particular – are important drivers of "male radicalization"; none of these factors exerted a significant influence on the probability that women belong to the "High VE-risk".

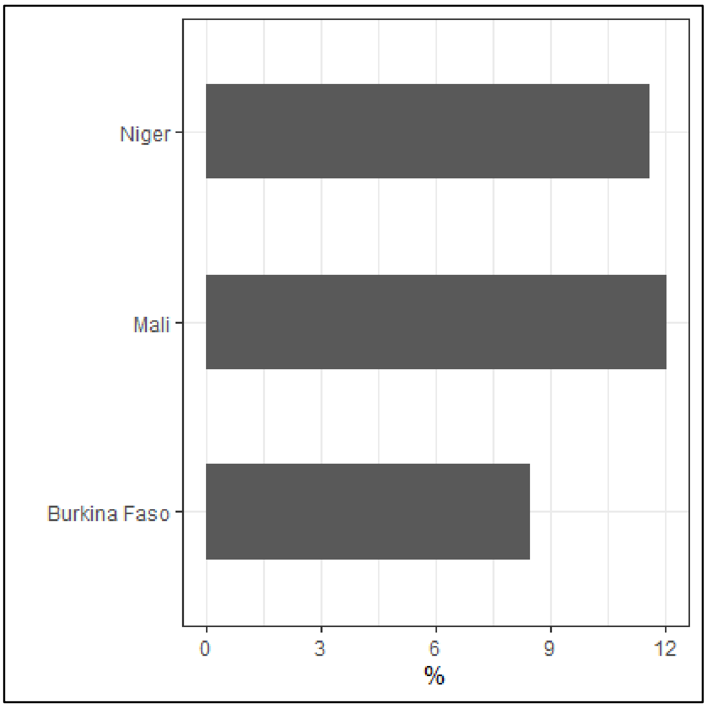
By contrast, variables that exerted a strong influence on the likelihood of female radicalization, such as personal security concerns, play no significant role on the probability that male respondents belong to the "High VE-risk" group.

Other variables that shape female radicalization, like (perceived) ethnic discrimination, religiosity, education and unemployment, at the individual level, along with regional income and proximity to conflict areas, at the contextual level, are significant predictors of the probability that male respondents belong to the "High VE-risk group".

VI.2 Country-specific patterns

Figure 4, below, plots the proportion of women belonging to the "High VE-risk" group in Burkina Faso, Mali and Niger, averaged across the whole period. The proportion of women "at risk of radicalization" is somewhat higher in Mali (12%) and Niger (11.60%) than in in Burkina Faso (8.46%).

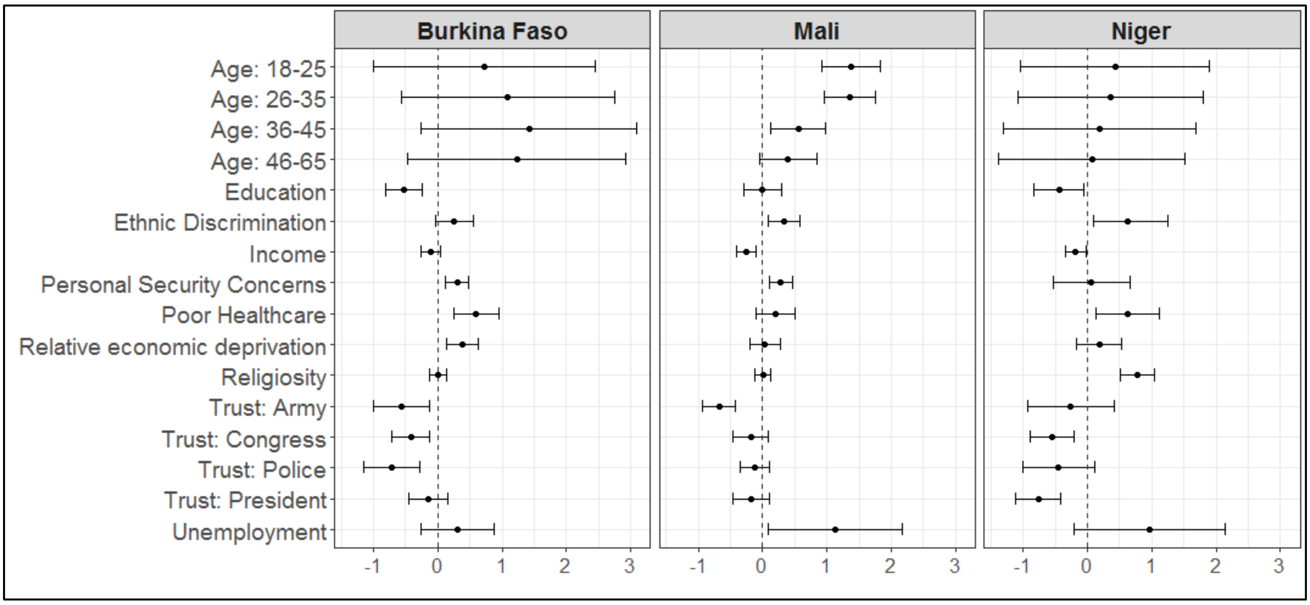
Figure 4 – Comparison of the share of women in the "high VE risk" group in Burkina Faso, Mali and Niger



In order to contrast the main determinants of female radicalization across the three countries, Figure 5 displays the impact of individual characteristics on the probability that women in Burkina Faso, Mali and Niger women belong to the "high VE risk" category. Specifically, the figure plots the effect of a one percentage point increase in various sub-national level variables on the probability that an average woman is assigned to the "high VE risk" group, along with 95% confidence intervals. Variables for which the estimated effects (represented as solid circles) and confidence intervals (represented as solid horizontal lines) all lie above (below) zero have a positive (negative) impact on the probability that a women is classified as exhibiting "high VE risk". Variables whose 95% confidence intervals overlap (cross) zero have no significant effect on women's VE perceptions.

The figure reveals some commonalities but also some differences in the drivers of "female radicalization" between Burkina Faso, Mali and Niger. Lack of trust in state institutions significantly increases the likelihood that women in all the countries belong to the "high VE risk group". However, socio-economic characteristics (e.g., age, income, employment status) are generally more important in Mali than in the other two nations, although **relative** economic deprivation does play a role in VE-related attitudes among women in Burkina Faso. Personal security concerns (i.e., the fear of being victims of physical attacks), in turn, are important determinants of "female radicalization" in Burkina Faso and Mali, but do not seem to exert a systematic influence on the probability of belonging to the "high VE-risk" group in Niger. Perception of ethnic discrimination are positively correlated with the probability of female radicalization in all countries, although the impact of this variable is marginally insignificant in Burkina Faso.

Figure 5 – Impact of individual-level variables on the on the share of women classified as having "High VE risk" in Burkina Faso, Mali and Niger



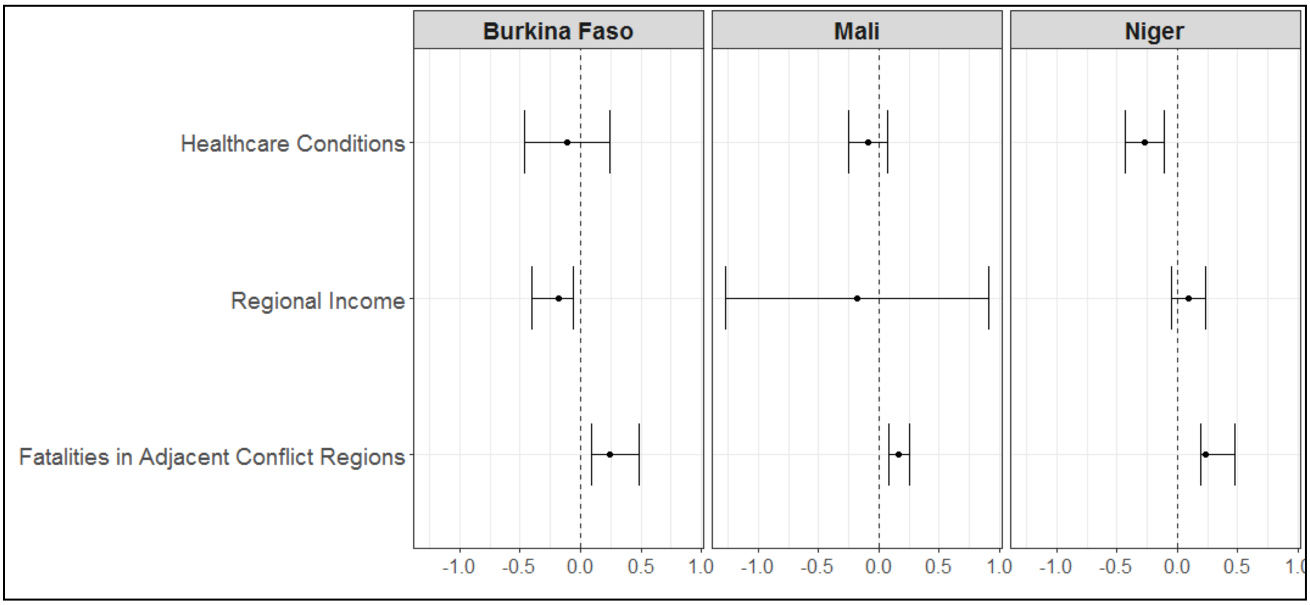
Notes: Effect of individual-level determinants on the probability that women in Burkina Faso (left panel), Mali (center panel) and Niger (right panel) belong to the "high VE risk" group. Circles represent point estimates, and solid horizontal lines give the 95% confidence (credible). Dashed vertical lines mark the "no significant effect" (zero) value.

In general, assessments of government's performance are less relevant as a determinant of VE-related attitudes among female respondents than among their male counterparts. An exception in this respect refers to evaluations of governments' health-care provision: women in Burkina Faso and Niger who believe that the government is failing to provide them with adequate healthcare are significantly more likely to belong to the "high VE-risk" group than otherwise identical female respondents who are less critical of public health services. Perceptions of poor healthcare provision are also positively correlated with the likelihood of holding "pro-VE" attitudes in Mali, although in this country this relationship is marginally insignificant after controlling for other VE drivers.

There are also differences in the relevance that the contextual factors play in Burkina Faso, Mali and Niger, as illustrated in Figure 6. [12] While proximity to conflict zones is positively correlated with the likelihood of engaging in VE in the three countries, the impact of other contextual factors differs across them. In particular, the lack of access to healthcare is an important driver of female radicalization in Mali, but not in the other two countries.

[12] As was the case for Figure 5, regions for which the estimated contextual effects (represented as solid circles) **and** confidence intervals (represented as solid horizontal lines) all lie above (below) zero have a positive (negative) impact on the probability that a women is classified as exhibiting "high VE risk". Variables whose 95% confidence intervals overlap (cross) zero have no significant effect on women's VE perceptions.

Figure 6 – Impact of contextual variables on the on the share of women classified as having "High VE risk" in Burkina Faso, Mali and Niger



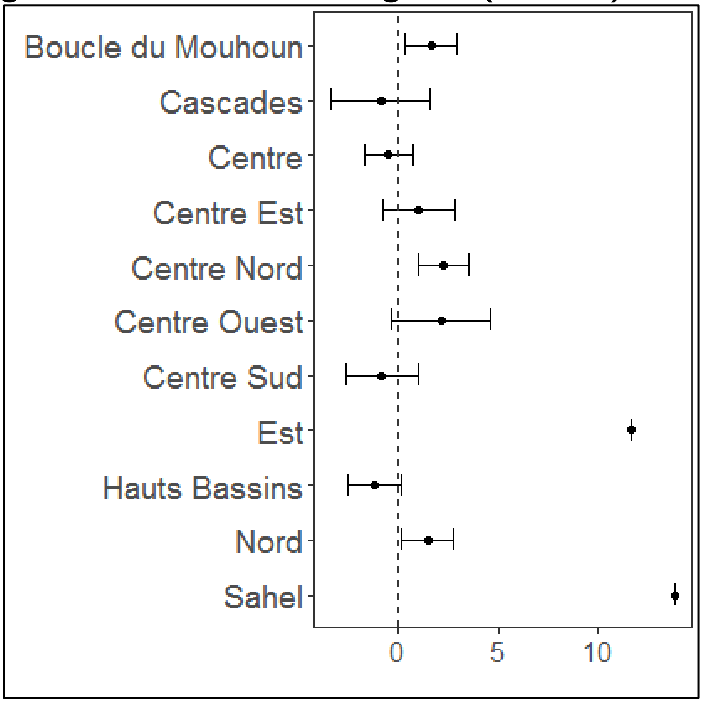
Notes: Effect of regional determinants on the probability that women in Burkina Faso (left panel), Mali (center panel) and Niger (right panel) belong to the "high VE risk" group. Circles represent point estimates, and solid horizontal lines give the 95% confidence (credible). Dashed vertical lines mark the "no significant effect" (zero) value.

Besides these cross-national variations in the prevalence and determinants of female radicalization, we observe variations within each country as well. This is illustrated in Figures 5-7, which plots regional effects on the probability that women in Burkina Faso, Mali and Niger, respectively, belong to the "High VE-risk" group.[13]

As seen in Figure 7, the likelihood of belonging to the "high VE-risk" group increases strongly and significantly in the Sahel and East regions and, to a lower extent, in the Centre-North and North regions as well. For instance, holding all other variables constant, a woman in the Sahel is 13 times more vulnerable to radicalization than an **otherwise identical** woman living in the Central Plateau.

[13] As was the case for Figure 4, regions for which the estimated effects (represented as solid circles) **and** confidence intervals (represented as solid horizontal lines) all lie above (below) zero have a positive (negative) impact on the probability that a women is classified as exhibiting "high VE risk". Variables whose 95% confidence intervals overlap (cross) zero have no significant effect on women's VE perceptions.

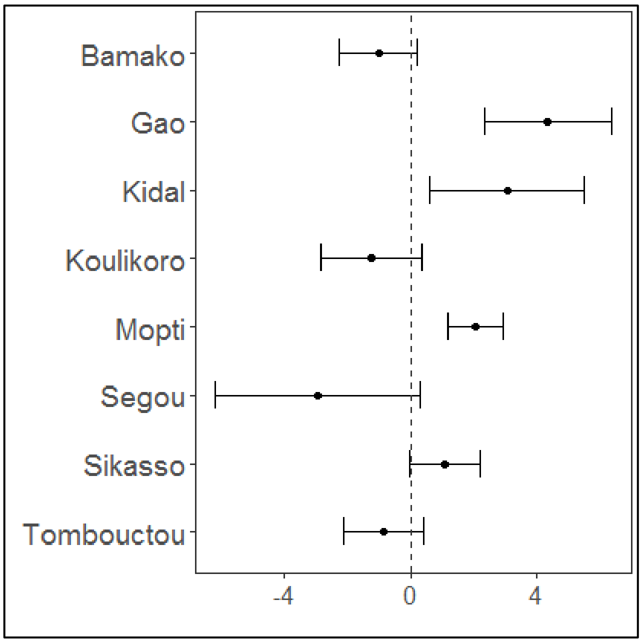
Figure 7 - Burkina Faso's regional (random) effects



Note: The figure reports estimates and 95% credible intervals for Burkina Faso's region-specific random effects. These random effects capture the influence of unobserved (unmeasured) region-level contextual factors on the risk of female radicalization.

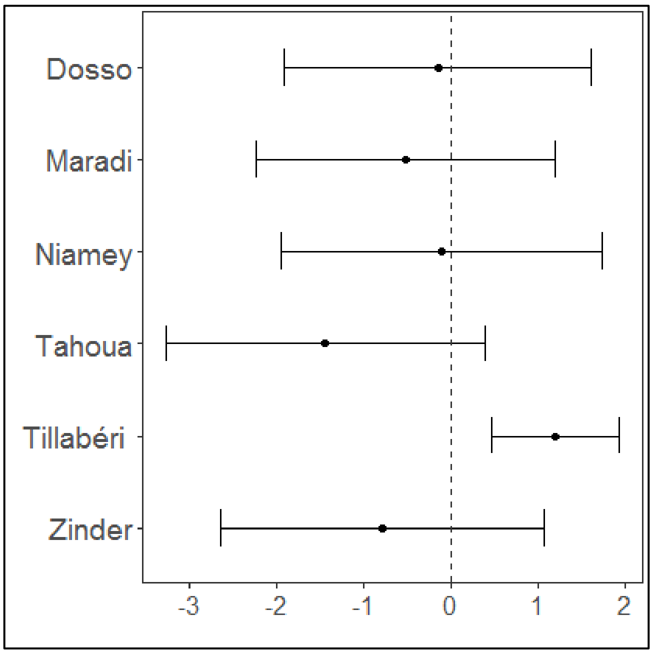
Region-specific variations in the propensity to engage in VE are also observed in Mali and Niger, although less marked than in Burkina Faso. For instance, keeping all other factors constant, a woman living in Mopti, Kidal or Gao is between 2 and 4 times more likely to belong to the "high VE risk" group than an **analogous woman** living in Kayes (Figure 8). In the case of Niger, living in Tillabéri is associated with a 1.2 percentage point increase in the risk of pro-VE attitudes, after accounting for other VE-drivers (Figure 9). Note that these regional differences hold even after accounting for the influence of measured regional-level factors such as access to healthcare, income or proximity to conflict areas – i.e., they reflect cultural or other environmental factors that shape attitudes towards VE beyond those for which we have observable indicators. The next step of the quantitative analysis will be to delve into these regional differences, looking at a lower (province, department, location) level of aggregation.

Figure 8 - Mali's regional (random) effects



Note: The figure reports estimates and 95% credible intervals for Mali's region-specific random effects. These random effects capture the influence of unobserved (unmeasured) region-level contextual factors on the risk of female radicalization.

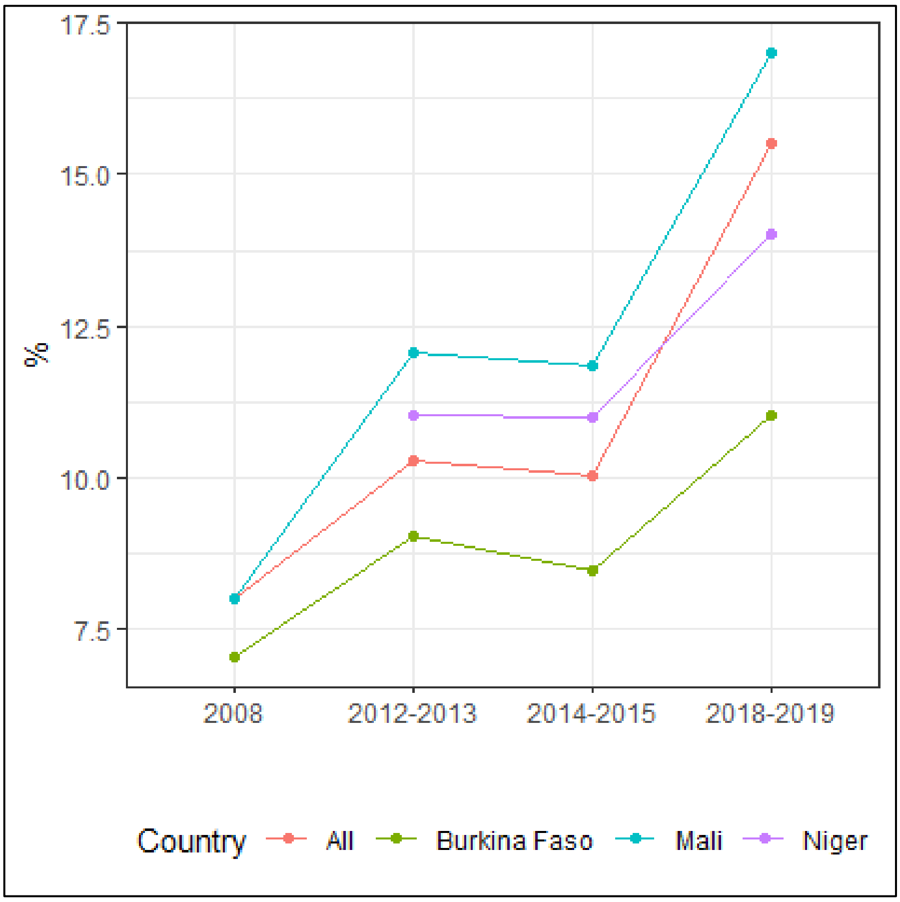
Figure 9 - Niger's regional (random) effects



Note: The figure reports estimates and 95% credible intervals for Niger's region-specific random effects. These random effects capture the influence of unobserved (unmeasured) region-level contextual factors on the risk of female radicalization.

Despite these differences, we observe an upward trend in the three countries over the last years, consistent with anecdotal evidence (FHI360 2020) and statistics on violent incidents in the region (ACLED, https://www.acleddata.com). In particular, as shown in Figure 10, we observe an increase in the proportion of women belonging to the "high VE-risk" group — in each of the countries as well as in the region as a whole — right after the 2012 crisis in Mali. The proportion of women "at risk of radicalization" stabilized, or even declined, between 2012 and 2015 but rose considerably afterwards. The fraction of female in the "high risk" category almost doubled over the last decade, rising in every one of the countries under study and, in the case of Mali, rising by 112%. This points to the need to adopt urgent policy measures to prevent the fraction of women prone to espouse pro-VE stances from spiraling.

Figure 10 – Evolution of women in the "High VE risk" category 2008 – 2019



Note: Evolution of female survey respondents assigned to the "High VE risk" group between 2011 (Wave 4 of the Afrobarometer survey) and 2018-2019 (Wave 7), by country.

VII. Methodological Appendix

VII.1. Multilevel Mixture Model - Estimation Details and Additional Results

Let $\boldsymbol{Y_{i,j,t}} = (Y^1_{i,j,t}, Y^2_{i,j,t}, \ldots, Y^K_{i,j,t})'$ denote the outcome variables - responses to the survey items used to build the latent VE variable (see Section V.1 above) - for individual i in country j at time t (wave) of our Afrobarometer sample. Denote by $X_{i,j,t}$ a vector of individual-specific characteristics (age, education, etc.) taken from Afrobarometer surveys; and $W_{j,t}$ a vector of contextual (e.g., country, region and province-level) variables.[14] Finally, let $C_{i,j,t}$ denote a latent categorical variable that takes

[14] See Sections V.1 and V.2 of the report for a detailed description of the individual and contextual variables included in covariates included in $X_{i,j,t}$ and $W_{j,t}$, respectively.

the value $k \in \{1, \ldots, K\}$ if subject i belongs to "type" or "class" k (e.g., "High VE Risk" and "Low VE Risk"), with $P\left(C_{i,j,t_i} = k\right) = \pi_{i,j,t,k}$.

Our multi-level mixture ordered-probit regression model can be written as:[15]

$$f(\boldsymbol{Y}_{i,j,t}; \boldsymbol{\pi}, \boldsymbol{p}) = \sum_{k=1}^{K} \pi_{i,j,t,k} \prod_{m=1}^{16} \Phi\left(\rho_{m,k,Y_{i,j,t}^m} - X'_{i,j,t}\alpha_k^m - W'_{j,t}\delta_k^m\right) - \Phi\left(\rho_{m,k,Y_{i,j,t}^m - 1} - X'_{i,j,t}\alpha_k^m - W'_{j,t}\delta_k^m\right) \quad (1)$$

where: Φ represents the standard normal cumulative distribution function; $\rho_{k,Y_{i,j,t}^m}$ are class- or type-specific thresholds for each of the ordinal response variables $Y_{i,j,t}^m$, $m = 1, \ldots, K$; and α_k^m, δ_k^m are type- and response-specific regression coefficients.

The probability that individual i belongs to "type" or "class" k is modelled as:

$$\pi_{i,j,t,k} = \frac{\exp\,(X'_{i,j,t}\beta_k + W'_{j,t}\gamma_k + \phi_{j,k} + \tau_{l(j),k} + \upsilon_{t,k})}{\sum_{h=1}^{K}(\exp\,(X'_{i,j,t}\beta_h + W'_{j,t}\gamma_h + \phi_{j,h} + \tau_{l(j),h} + \upsilon_{t,h})} \quad (2)$$

The country-, region- and time-specific random effects ϕ_j, $\tau_{l(j)}$ and υ_t, respectively - with $j = Burkina\ Faso, Mali, Niger$, l is a region (or sub-national unit) in country j, and t representing different Afrobarometer waves – account for unobservable or unmeasurable geographical or temporal factors (e.g., culture, aspects of the political environment that cannot be directly measured). To allow for "regional contagion" between geographically proximate regions, $\tau_{l(j)}$ are specified as spatial random effects $\tau_{l(j),k} \sim N\left(\frac{1}{m_l}\sum_{s\in\partial_l}\tau_{s(j),k}, \Delta_{l(j),k}\right)$, where ∂_l denotes the set of neighbours for region l, m_l is the number of neighbours sharing a geographical border with region l, and $\Delta_{l(j),k}$ is a component-specific scaled variance-covariance matrix (Besag et al., 1991; Neelon et al., 2014). The country- and year random effects follow normal $N(0, \sigma^2_{\phi,k})$ and $N(0, \sigma^2_{\upsilon,k})$ distributions.

Both the observable individual and contextual variables included in $X_{i,j,t}$ and $W_{j,t}$, as well as unobservable factors captured by the random effects, are allowed (but not forced) to affect the probability that individual i is of "type" k.

Given the small number of countries and Afrobarometer waves under consideration, and in view of the complexity of the model specification, asymptotic assumptions underlying frequentist approaches to estimating hierarchical models are highly unlikely to hold. Hence, the model was fitted through Markov chain Monte Carlo (MCMC) simulations. Starting with initial values for all the model

[15] All the items used to estimate the latent VE variables are ordinal. Hence, and since the use of a normal distribution allows taking advantage of conjugate priors to increase the number of Gibbs sampling – at the expense of the slower Metropolis-Hastings – steps in the Markov chain Monte Carlo (MCMC) algorithm (Gelman et al., 2004), we relied on an ordered probit specification for modelling responses to the survey items $\boldsymbol{Y}_{i,j,t}$. A detailed description of the MCMC algorithm is provided below.

parameters $\Theta = (\rho, \alpha, \beta, \gamma, \phi, \tau, \nu, C)$, the MCMC algorithm iterates through the following steps until convergence:

1. Updating the parameter relating individual- and contextual-variables to the probability of latent class membership, $\Upsilon_k = (\beta_k, \gamma_k)$, from their full conditional distribution:
$p(\Upsilon_k | \Theta_{-\beta_k,\gamma_k}) \propto$
$$\prod_{j=1}^{J} \prod_{i=1}^{N_j} \frac{\exp\left(X'_{i,j,t}\beta_k + W'_{j,t}\gamma_k + \phi_{j,k} + \tau_{l(j),k} + v_{t,k}\right)}{\sum_{h=1}^{K}\left(\exp\left(X'_{i,j,t}\beta_h + W'_{j,t}\gamma_h + \phi_{j,h} + \tau_{l(j),h} + v_{t,h}\right)\right)} N(\Upsilon, 0, \left(\tfrac{9}{4}\right) \mathrm{I})$$

   where the prior for $\Upsilon = (\beta, \gamma)$ is a multivariate normal distribution evaluated Υ. This conditional distribution does not have a closed form. However, Υ can be updated through a random-walk Metropolis step with a multivariate $Student - t_3(s, A)$ proposal, using the empirical covariance matrix of Υ from an extended burn-in period to tune A and improve mixing (Haario et al., 2005) and adjusting the scaling parameter s to achieve an acceptance rate of approximately 25% (Robert and Casella, 2010).

2. Updating the country-specific random effects $\phi_{j,k}$ from:
$p\left(\phi_{j,k} \middle| \Theta_{-\phi_{j,k}}\right) \propto$
$$\prod_{i=1}^{N_j} \frac{\exp\left(X'_{i,j,t}\beta_k + W'_{j,t}\gamma_k + \phi_{j,k} + \tau_{l(j),k} + v_{t,k}\right)}{\sum_{h=1}^{K}\left(\exp\left(X'_{i,j,t}\beta_h + W'_{j,t}\gamma_h + \phi_{j,h} + \tau_{l(j),h} + v_{t,h}\right)\right)} N(\phi_{j,k}, 0, \sigma^2_{\phi.k})$$

   As in Step 1, this full conditional does not have a closed form, so $\phi_{j,k}$ is updated using random-walk Metropolis steps. A similar approach is used to update the governorate- and time-specific random effects ($\tau_{l(j),k}$ and $v_{t,k}$, respectively).

3. Updating the variance of the country-specific random effects, $\sigma^2_{\phi.k}$, from the posterior $Inverse - Gamma(0.1 + \frac{n}{2}, 0.1 + \frac{{\phi_k}^T \phi_k}{2})$ distribution, were n is the number of countries. A similar approach is used to update the prior variance of the wave-specific prior variances, $\sigma^2_{v.k}$.
4. Updating the variance of the region-specific random effects $\Delta_{l(j),k}$ from its full conditional Invers Wishart distribution.

5. Updating individuals' types, C_{i,j,t_i}, from the full conditional or "categorical" distribution $C_{i,j,t} | \Theta_{-C_{i,j,t}} \sim Cat(p_{i,j,t,k})$, where

$$p_{i,j,t,k} = \frac{\pi_{i,j,t,k} \prod_{m=1}^{16} \Phi\left(\rho_{m,k,Y^m_{i,j,t}} - X'_{i,j,t}\alpha^m_k - W'_{j,t}\delta^m_k\right) - \Phi\left(\rho_{m,k,Y^m_{i,j,t}-1} - X'_{i,j,t}\alpha^m_k - W'_{j,t}\delta^m_k\right)}{\sum_{h=1}^{K} \pi_{i,j,t,h} \prod_{m=1}^{16}\left(\rho_{m,h,Y^m_{i,j,t}} - X'_{i,j,t}\alpha^m_h - W'_{j,t}\delta^m_h\right) - \Phi\left(\rho_{m,h,Y^m_{i,j,t}-1} - X'_{i,j,t}\alpha^m_h - W'_{j,t}\delta^m_h\right)}$$

   where $\pi_{i,j,t,k}$ is given by equation (2) above.

6. Updating the thresholds ρ and parameters α, δ of the ordered probit specifications (equation 1). To do so, I extend Albert and Chib (1993)'s Bayesian approach for estimation of ordered probit models to the latent class or mixture model framework. For each item $Y^{m}_{i,j,t,}$, $m = 1, \dots, K,$ with reponses coded on a G-level scale, let $z^{m}_{i,j,t,k}$ denote a continuous latent variable such that:

$$Y^{m}_{i,j,t} | C_{i,j,t} = k \text{ equals } g, g = 1, \dots, G \text{ if } z^{m}_{i,j,t,k} \in (\rho_{m,k,g-1,}\rho_{m,k,g}),$$

with $-\infty = \rho_{m,k,0} < \rho_{m,k,1} = 0 < \cdots .. < \rho_{m,k,G} = \infty$. Following Albert and Chib (1993) $z^{m}_{i,j,t,k}$ is assumed to follow a standard normal distribution:

$$z^{m}_{i,j,t,k} \sim N(X'_{i,j,t}\alpha^{m}_{k} + W'_{j,t}\delta^{m}_{k}, 1).$$

Adopting conjugate normal priors for the regression parameters, regression and threshold parameter of the ordered probit model can be updated from:

5.1. $\alpha^{m}_{k} \sim N(\alpha^{m}_{*}, \Sigma_{\alpha^{m}_{*}})$, with

$$\Sigma_{\alpha^{m}_{*}} = (\mathrm{I} + \textstyle\sum_{i:C_{i,j,t}=k} X_{i,j,t}\, X^{T}_{i,j,t})^{-1} \text{ , } \alpha^{m}_{*} = \Sigma_{\alpha^{m}_{*}} \ [\textstyle\sum_{i:C_{i,j,t}} X_{\,i,j,t} \left(z^{m}_{i,j,t,k} - W'_{j,t}\delta^{m}_{k}\right)]$$

5.2. $\delta^{m}_{k} \sim N(\delta^{m}_{*}, \Sigma_{\delta^{m}_{*}})$, with

$$\Sigma_{\delta^{m}_{*}} = (\mathrm{I} + \textstyle\sum_{i:C_{i,j,t}=k} W_{j,t}\, W^{T}_{j,t})^{-1} \text{ , } \alpha^{m}_{*} = \Sigma_{\alpha^{m}_{*}} \ [\textstyle\sum_{i:C_{i,j,t}} W_{\,i,j,t} \left(z^{m}_{i,j,t,k} - X'_{i,j,t}\delta\alpha^{m}_{k}\right)]$$

5.3. $\rho_{m,k,g} \sim Uniform(\max\{max\ (z^{m}_{i,j,t,k} | Y^{m}_{i,j,t} = g, C_{i,j,t} = k), \rho_{m,k,g-1}\},$

$$\min\{min\ (z^{m}_{i,j,t,k} | Y^{m}_{i,j,t} = g + 1, C_{i,j,t} = k), \rho_{m,k,g+1}\})$$

7. Finally, the continuous latent variable $z^{m}_{i,j,t,k}$ is updated from a truncated normal posterior: $N\left(X'_{i,j,t}\alpha^{m}_{k} + W'_{j,t}\delta^{m}_{k}, 1\right) 1_{[z^{m}_{i,j,t,k} \in (\rho_{m,k,g-1},\rho_{m,k,g})]}$

Models with different numbers of underlying classes K were estimated, running the corresponding MCMC algorithm for 3,000,000 cycles, with an initial burn-in period of 1,500,000 iterations and a thinning interval of 150 iterations to reduce sample autocorrelations. Convergence was assessed based on standard Bayesian diagnostics (e.g., Brooks and Gelman, 1998), and routine sensitivity checks were performed to check the robustness of the estimates to the prior distributions (Gelman et al., 2004). In order to speed up convergence, the MCMC algorithm was coded in C++ as called from R (Dirk, 2013), and estimation was performed in a high-performance computing environment (*via* Unix shell scripting).

To choose the "optimal" number of classes, we: i) relied on the Deviance Information Criterion (Spiegelhalter et al., 2002); ii) compared the prior and posterior distributions for the parameters governing the baseline class probabilities (β, γ, and random effects); and iii) used posterior predictive checks to assess the fit of models with different values of K (Elliott et al., 2005). A model with 2 classes ("High VE Risk" and "Low VE Risk") was favoured based on these criteria. The average overlap between the prior and posterior distributions of β, γ was quite small, indicating that the model is well identified and relatively insensitive to prior assumptions (Garrett and Zeger, 2000). We also used other information-based (AIC, BIC) and goodness-of-fit (Pearson's $\chi 2$, likelihood ratio chi-square G2) to compare the selected 2 class mixture model vis-à-vis a more parsimonious single-group multivariate ordered probit ignoring unobserved heterogeneity in response patterns (Linzer and Lewis, 2011). Again, the results of these comparisons favoured the chosen 2 class model.

In order to deal with potential "label switching", a well-known problem for MCMC estimation of latent class models, I applied the decision-theoretic post-processing algorithm proposed by Stephens (2000) to each (convergent) MCMC draw.

Table A.1. Model Selection: Comparing Models with Varying Number of Classes for women in Burkina Faso, Mali and Niger

	(1)	(2)	(3)	(4)
Number of classes, *K*	**Log-likelihood**	**Likelihood ratio chi-square test (p-value)**	**DIC**	**BIC**
1	-197,0134.3	0.00	331,314.2	422,313.6
2	-127,134.2		212,113.3	255,134.8
3	-133,813.8	1.00	255,134.7	268,139.3
4	-141,134.2	1.00	262,544.2	272,945.4
5	-142,341.4	1.00	263,134.9	299,314.1

Notes: The table reports values of various commonly used model selection criteria comparing specifications with varying number of categories for the latent VE variable fitted to the sub-sample of female respondents from Burkina Faso, Mali and Niger. Column (1) presents the log-likelihood for each model. Column (2) reports the p-value of the likelihood ratio test (in parenthesis) relative to our preferred specification ($\boldsymbol{K} = 2$); significant p-values (conventionally $p<0.05$) indicate that the more complex model fits the data significantly better than the more parsimonious one (Nylund et al., 2007). Column (3) reports the values of the Deviance Information Criterion (DIC) for each model. Differences of more than 10 rule out the model with the higher DIC; differences between 5 and 10 are substantial; if the difference in DIC is lower than 5, and the models make very different inferences (Spiegelhalter et al., 2002). Columns (4) reports the values of the Bayesian (BIC) information criterion for each model. As a "rule of thumb," BIC differences larger than 10 provide overwhelming evidence in favour of the model with the lower value (see Ntzoufras, 2011, and the references therein). All the criteria favour our preferred (2-class) specification.

Table A.2. Model Selection: Comparing Models with Varying Number of Classes for men in Burkina Faso, Mali and Niger

	(1)	(2)	(3)	(4)
Number of classes, K	Log-likelihood	Likelihood ratio chi-square test (p-value)	DIC	BIC
1	-257,937.6	0.00	372,586.3	374,386.1
2	-136,331.3		248,139.2	252,859.3
3	-146,334.3	1.00	263,958.2	261,570.3
4	-149,940.2	1.00	266,405,2	252,826.8
5	-157,796.4	1.00	289,489.3	301,569.4

Notes: The table reports values of various commonly used model selection criteria comparing specifications with varying number of categories for the latent VE variable fitted to the sub-sample of male respondents from Burkina Faso, Mali and Niger. Column (1) presents the log-likelihood for each model. Column (2) reports the p-value of the likelihood ratio test (in parenthesis) relative to our preferred specification ($K = 2$); significant p-values (conventionally p<0.05) indicate that the more complex model fits the data significantly better than the more parsimonious one (Nylund et al., 2007). Column (3) reports the values of the Deviance Information Criterion (DIC) for each model. Differences of more than 10 rule out the model with the higher DIC; differences between 5 and 10 are substantial; if the difference in DIC is lower than 5, and the models make very different inferences (Spiegelhalter et al., 2002). Column (4) reports the values of the Bayesian (BIC) information criterion for each model. As a "rule of thumb," BIC differences larger than 10 provide overwhelming evidence in favour of the model with the lower value (see Ntzoufras, 2011, and the references therein). All the criteria favour our preferred (2-class) specification.

VII.2. Principal Component Analysis

This section reports the results of a principal component analysis applied to our data. Principal component analysis (PCA) is a data reduction technique aimed at summarizing the information contained in multiple observed variables (in our application, responses to the set of Afrobarometer items listed in Section V.1.2 of the main text, tapping into survey respondents' experience with political violence, preferences about gender roles, the role of religion and government in politics and support for fundamentalist movements) into few latent variables known as principal components (PCs), which are a linear combination of the original data. The number of principal components, to incorporate in the empirical analysis is chosen by cross-validation.

Figure A.1 plots the proportion of the variance in the "dependent variables" accounted for by these first four principal components. Figure A.2, in turn, plots the eigenvalues of the first four principal components obtained from applying a PCA to the survey items taken as dependent variables in our multilevel mixture model. As seen in the first figure, the first four principal components account for more than 95% of the variability in the responses to the 19 survey items used to gauge Afrobarometer participants' attitudes towards VE. Moreover, the first principal component accounts for more than 70% of this variation. Additionally, as seen in Figure A.2, only the first eigenvalue is larger than one; the remaining eigenvalues become progressively smaller (and the additional eigenvalues – not plotted – are extremely low).

Figure A.1 – Proportion of the total variance explained by the (first four) principal components

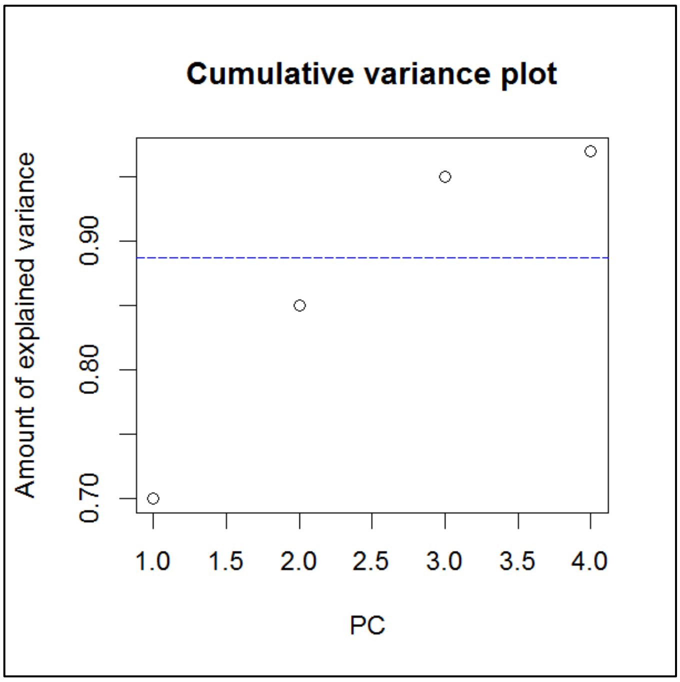
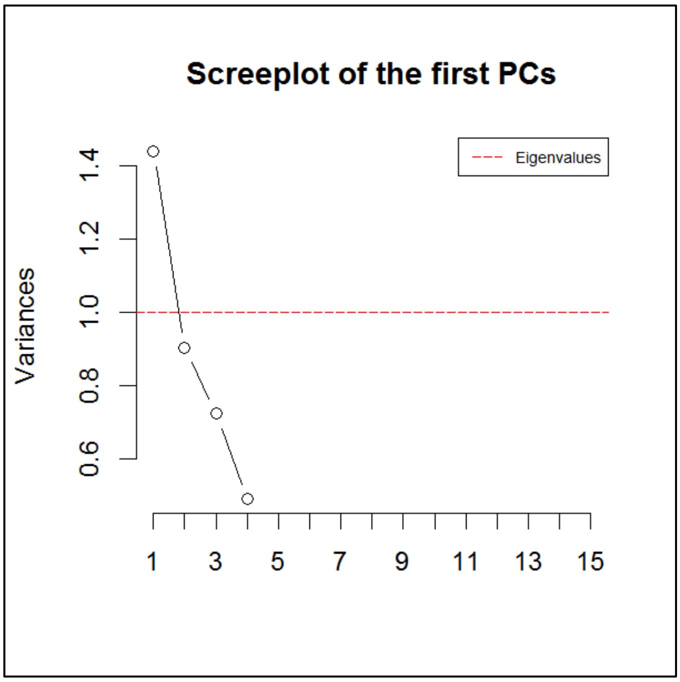


Figure A.2 – Proportion of the total variance explained by the (first four) principal components



As seen in Table A.3, the variables that contribute the most to this first principal component are those measuring respondents' past use or agreement with the use of political violence, their opinions about democracy as a form of government, their views regarding the justifiability of military dictatorships, and their beliefs about a ruler's right to ban movements or organizations he does not agree with. These are, precisely, the same survey items that exhibited clearly different patterns between the "high VE-risk" and "low VE-risk" groups of female and male respondents in the multilevel mixture model (Table 3 in the main text). In other words, the principal component analysis and the mixture model largely coincide with respect to what are the survey items that exert the strongest influence in shaping the latent VE support variable.

Table A.3 – Contribution of each of the survey items gauging VE-related attitudes to the first principal component (in percentage)

Survey item	Women	Men
Have you ever used/would you use violence to support a political cause?	**10.02**	**22.37**
Do you agree that the use of violence is sometimes justifiable?	**13.45**	**20.43**
Do you agree that military solutions - including a military dictatorship - could help the country overcome its problems?	**18.52**	**12.21**
To what extent do you agree that democracy is always the best form of government?	**16.43**	**11.97**
Are you satisfied with the way democracy is working in your country?	3.67	3.12
To what extent do you agree that elections are not necessarily the best way of choosing political leaders, and that other methods may be better suited for the country?	2.98	3.01
To what extent do you agree that political parties should thus be dismantled?	2.01	2.11
Do you believe that only one (your preferred) party should be allowed to take part in elections/government?	1.97	2.02
Do you agree that whoever is in power has the right to ban movements or organizations he does not agree with?	**13.42**	**9.66**
Do you believe that the National Assembly should be dismantled?	1.94	1.48
Do you think that you should not abide by laws introduced by a government you did not vote for?	1.32	1.09
Do you agree that the country should be ruled according to religious precepts?	3.07	2.02
To what extent do you hate/mistrust other ethnic groups?	2.87	4.02
To what extent do you hate/mistrust other religious groups?	2.31	2.75

To what extent do you mistrust/hate Islam?	0.84	0.98
To what extent do you agree that men make for better politicians than women, and thus only men should participate in politics?	1.60	0.31
To what extent do you agree that women should be subject to traditional values and customs, rather than having the same rights and receiving the same treatment as men?	0.65	0.37
To what extent do you agree that men have the right to exert physical violence against their female partners?	1.91	0.04
To what extent do you agree with the following statement: "Women and men should have equal rights to property/inheritance"?	1.02	0.04

VIII. References

Albert, J., and Chib, S. 1993. "Bayesian analysis of binary and polychotomous response data." *Journal of the American Statistical Association* 88(422): 669-679.

Ammour, L.-A. (2020, February 26). "How Violent Extremist Groups Exploit Intercommunal Conflicts in the Sahel. Africa Center for Strategic Studies." Available at https://africacenter.org/spotlight/how-violent-extremist-groups-exploit-intercommunal-conflictsin-the-sahel/.

Alvarez, R. Michael, Katz, Gabriel, Levin, Ines, and Lucas Nunez. 2020. "Conventional and Unconventional Participation in Latin America: A Hierarchical Latent Class Approach." *Political Science Research and Methods*, Online First, Available at https://doi.org/10.1017/psrm.2020.35.

Besag, J., J. York, and A. Mollie. 1991. "Bayesian image restoration, with two applications in spatial statistics." *Ann. Inst. Statist. Math* 43: 1-20.

Brooks, S.P., and Gelman, A. 1998. "General Methods for Monitoring Convergence of Iterative Simulations." *Journal of Computational and Graphical Statistics* 7(4): 434-455.

Bueno de Mesquita, Ethan. 2005. "The Quality of Terror." *American Journal of Political Science* 49(3): 515-530.

Dirk, E. 2013. *Seamless R and C++ Integration with Rcpp*. New York, NY: Springer.

Elliott, M., Gallo, J., Ten-Have, T., Bogner, H. and Katz, I. (2005) "Using a Bayesian Latent Growth Curve Model to Identify Trajectories of Positive Affect and Negative Events Following Myocardial Infarction." *Biostatistics* 6(1): 119-143.

FHI360. 2020. "Mixed Method Study: Gender Differentiated Drivers of Violent Extremism in Central Sahel – Literature Review." Cooperative Agreement No. 72062420CA00002, Submitted July 20, 2020.

Finkel, S. E., McCauley, J. F., Belasco, C. A., & Neureiter, M. 2016. "Contextual Violence and Support for Violent Extremism: Evidence from the Sahel". Report for the United States Agency for International Development (USAID)'s Peace through Development (PDEV II) initiative.

Fish, M. Steven. 2002. "Islam and Authoritarianism." *World Politics* 55(1): 4-37.

Garrett, E. and Zeger, S. 2000. "Latent Class Model Diagnosis." *Biometrics* 56 (4): 1055–1067.

Gelman, Andrew, and Jennifer Hill. 2007. *Data Analysis using Regression and Multilevel/Hierarchical Models*. New York: Cambridge University Press.

Gelman, Andrew, John Carlin, Hall Stern, and Donald Rubin. 2004. *Bayesian Data Analysis*. Boca Raton, FL: Chapman and Hall–CRC.

Guéret, Tristan. 2017. "Niger and the Fight Against Violent Extremism in the Sahel". Royal United Services Institute. Available at www.rusi.org.

Haario, H., Saksman, E., and Tamminen, J. 2005. "Markov chain Monte Carlo methods for high dimensional inversion in remote sensing." *Computational Statistics* 20: 265-273.

Hogberg, Torbjorn, Magnussen, Anabella, Lutzen, Kim, and Beatrice Ewalds-Kvist. 2012. "Swedish Attitudes Towards Persons with Mental Illness." *Nordic Journal of Psychiatry*, 66(2), 86-96.

Honaker, James, and Gary King. 2010. "What To Do About Missing Values in Time Series Cross-Section Data". *American Journal of Political Science* 54(2):561–81.

IMRAP/Interpeace. 2017. "Je marche avec les garçons." Trajectoires des jeunes vers la violence, miroir des dynamiques de genre à l'échelle de leur société ? IMRAP/Interpeace.

Inks, Lisa, Annalies Veldmeijer, and Abdoul Kassim Ibrahim Fomba. (2017). We Hope and We Fight-Youth, Communities, and Violence in Mali. Mercy Corps.

Jolliffe, Ian T. 2002. Principal component analysis, 2nd edn. New York, NY: Springer-Verlag.

Katz, Gabriel, and Ines Levin. 2018. "Varieties of Political Support in Emerging Democracies: a Cross-National Analysis." *Social Science Research 70*: 55-70.

Katz, Jonathan, and Gabriel Katz. 2010. "Correcting for survey misreports using auxiliary information with an application to estimating turnout." *American Journal of Political Science 54*(3): 815-835.

Kreuter, Frauke, Ting Yan, and Roger Tourangeau. 2008. "Good Item or Bad – Can Latent Class Analysis Tell?: The Utility of Latent Class Analysis for the Evaluation of Survey Questions." *Journal of the Royal Statistical Society A* 171(3): 723-738.

Le Roux, P. (2019a, June 10). "Exploiting Borders in the Sahel: The Islamic State in the Greater Sahara." Africa Center for Strategic Studies.

Linzer, Drew, and Jeffrey B. Lewis. 2011. "poLCA: An R Package for Polytomous Variable Latent Class Analysis." *Journal of Statistical Software* 42(10): 1-29.

Lynch, Scott. 2007. *Introduction to Applied Bayesian Statistics for Social Scientists*. New York, NY: Springer.

MacLean, R. (2020, July 7). "Over 180 Bodies Found Dumped In Burkina Faso Town, Report Says." New York Times. Available at https://nytimes.com/2020/07/07/world/africa/.

Neelon, B., A. Gelfland, and M. Miranda. 2014. "A multivariate spatial mixture model for aereal data: examining regional differences in standardized test scores." *Applied Statistics* 63(5), 737-761.

Nylund, K. L., Asparouhov, T., and Muthen, B. 0. (2007). "Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study". *Structural Equation Modeling: A Multidisciplinary Journal* 14(4): 535-569.

Ntzoufras, I. 2011. *Bayesian Modeling using WinBUGS*. Hoboken, NJ: John Wiley & Sons.

Powell, Nathaniel. (2018, February 8). "The Destabilizing Dangers of U.S. Counterterrorism in the Sahel." War on the Rocks. Available at https://warontherocks.com/2018/02/thedestabilizing-dangers-of-american-counterterrorism-in-the-sahel/

McGregor, A. 2017. “The Fulani Crisis: Communal Violence and Radicalization in the Sahel”. *CTC Sentinel* 10(2): 34-40;

Robert, C. P., and Casella, G. (2010). *Introducing Monte Carlo Methods with R*. New York, NY: Springer.

Spiegelhalter, D. J.; Best, N. G.; Carlin, B. P.; and van der Linde, A. (2002). "Bayesian measures of model complexity and fit (with discussion)." *Journal of the Royal Statistical Society, Series B*. 64 (4): 583–639.

Steenbergen, Marco R., and Bradford S. Jones. 2002. “Modelling Multi-level Structures”.

Stephens, Matthew (2000) “Dealing with Label Switching in Mixture Models”. *Journal of the Royal Statistical Society* Series B 62(4): 795–809.

Treier, Shawn, and Simon Jackman. 2008. “Democracy as a Latent Variable.” *American Journal of Political Science* 52(1): 201-217.

Tipping, Michael, and Christopher Bishop. 1999. “Probabilistic Principal Component Analysis”. Journal of the Royal Statistical Society B, 61(3), 611-622.

USAID. 2009. *Development Assistance and Counter-Extremism: A Guide to Programming*.

Vermunt, Jeroem K. 2010. “Mixture Models for Multilevel Data Sets”. In Joop J. Hox and J. Kyle Roberts (eds.), *Handbook of Advanced Multilevel Analysis*, pp. 59-84. New York: Routledge.

Vowles, Jack, Gabriel Katz, and Daniel Stevens. 2017. “Electoral Competitiveness and Turnout in British Elections, 1964-2010.” *Political Science Research and Methods*, *5*(4), 775-794

Wetzel, Eunike, Xu, Xueli Xu, and Matthias von Davier. 2015. “An Alternative Way to Model Population Ability Distributions in Large-Scale Educational Surveys”. *Educational and Psychological Measurement* 75(5), 739–763.