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A Multi-Scale Investigation of Causal Pathways
in Different Institutional Contexts (CC2C)

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Does corruption trigger political violence? Evidence from Sub-Saharan Africa (1970-2020)

Raul Caruso[a], Emma Galli[b], Giulia Tringali[a,b]

[a] International Peace Science Center (IPSC), Università Cattolica del Sacro Cuore
[b] Sapienza University of Rome, Italy

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Raul Caruso, Department of Economic Policy & International Peace Science Center (IPSC), Università Cattolica del Sacro Cuore, Milano, Italy

🖂 raul.caruso@unicatt.it

Emma Galli, Department of Social and Economic Science, Sapienza University of Rome, Italy

🖂 emma.galli@uniroma1.it

Giulia Tringali, Sapienza University of Rome & International Peace Science Center (IPSC), Università Cattolica del Sacro Cuore, Milano, Italy

🖂 giulia.tringali@uniroma1.it

Dipartimento di Politica Economica
Università Cattolica del Sacro Cuore – Largo A. Gemelli 1 – 20123 Milano
Tel. 02-7234.2921

🖂 dip.politicaeconomica@unicatt.it

https://dipartimenti.unicatt.it/politica_economica

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Abstract

This paper empirically investigates the relationship between corruption and political violence in 49 Sub-Saharan African countries over the period 1970-2020. Specifically, it examines whether corruption influences both the incidence and the brutality of political violence. To address this question, the study employs an articulated estimation strategy: first, we analyze the impact of corruption on political violence incidence and brutality by using count data models (Negbin and ZINB) and a LPM; then we also employ an IV estimation for the OLS model and a Two-stage Residual inclusion (2SRI) estimation. Across the different specifications, our findings highlight a strong and positive relation between political corruption and both the incidence and brutality of political violence. Control variables present the expected relations with the dependent variable and in particular, we also focus on climate change. By employing also interaction terms between SPEI and corruption, the results suggest that an increase in precipitations in corrupted countries leads to and increase of violence. In addition, our main results show that past corruption level has a great impact on today violence, while past extreme weather events do not.
JEL classification: D73, D74, P00.

Keywords: corruption, political violence, terrorism, climate change, count models, ZINB, 2SRI

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1 *Introduction*

This paper analyzes the impact of corruption on political violence from 1970 to 2020 in 49 Sub-Saharian countries with a particular attention to the role of climate change. It starts from two streams of literature: corruption and political violence. Our analysis investigates how corruption affect the incidence and brutality of political violence, controlling for economic growth, population, institutional factor and climate change. For corruption we intent, as in Jain (2001), the practice whereby public officials, legislators, and politicians exploit powers delegated to them by the public to advance their own economic interests at the expense of the common good. For political violence, instead, we use the definition of terrorism of Sandler et al. (1983, p.37) where it is "the premeditated, threatened or actual use of force or violence to attain a political goal through fear, coercion, or intimidation". The results shows that there is a strong impact of corruption on political violence, in particular looking at its incidence. Our empirical strategy models corruption and the control variables as a function of political violence and analyzes this with three different estimators. The first is a Negative Binomial with fixed effects that accounts for overdispersion in the count data. To improve this model taking into account also the excess of zero in our count data we use a Zero Inflated Negative Binomial. Then, we run a linear regression with OLS and fixed effects to further investigates the entity of the impact of corruption on attacks and victims rate per 100,000 inhabitants. Finally, as robustness checks we develop other three steps. First, we take our general model and measure it with a 5 years lagged version of our independent variable. Secondly, to better study the impact of climate change, we measure the impact on political violence of the interaction of climate change with corruption. Thirdly, we improve our linear model instrumenting our independent variable and running and IV regression for panel data with fixed effects. All the results confirms the hypothesis that corruption has an impact on political violence and that climate change, measured with the Standardized Precipitation and Evapotranspiration Index, has not a significant impact on incidence and brutality of violence while doing a looking at country level analysis focused on institutional weaknesses.

2 *Related literature and theoretical framework*

2.1 Institutions and political corruption

Political corruption is commonly defined as "the use of public office for private gains" (Bardhan, 1997, p. 1321). In this paper, corruption is specifically conceptualized as the practice whereby public officials, legislators, and politicians "exploit powers delegated to them by the public to advance their own economic interests at the expense of the common good" (Jain, 2001, p. 73).

This analysis recognizes the evolution of economic thought that directed, in the late '90s, the attention toward the quality of institutions and to the treatment of corruption as an economic issue looking at its determinants (Kaufmann, 1997; Rose-Ackerman, 1999; Andvig and Moene, 1990; Goel and Nelson, 2010; Sandholtz and Koetzle, 2000; Treisman, 2000; Tanzi, 1998; Jain 2001; Aidt, 2003; Lambsdorff, 2006; Dimant and Tosato, 2017).

In particular, the analytical framework adopted in this paper is consistent with the corruption theory proposed by Aidt (2008), which is grounded in the political economy approach. According to this perspective, corruption functions as "sand in the wheels of the economy" and arises when government officials, including both bureaucrats and politicians, act out of self-interest rather than benevolence. Consequently, as argued by Shleifer and Vishny (1993, 1998), these individuals are expected to extract rents from the private sector, with the extent of this behavior being constrained only by the prevailing economic and political institutions. In other words, the magnitude of corruption is shaped by institutional incentives. Building on Aidt's findings, which reveal a strong negative correlation between per capita wealth and corruption, we consider in this paper corruption as a significant obstacle to economic growth and development and a consequence of weak institutional frameworks (see Blackburn et al., 2006; Fiorino et al., 2012; Mauro, 1995; Tanzi, 1998).

Corruption, indeed, severely hampers economic growth and development in many different ways. First of all, corruption increases inequality, Gupta et al. (2002) provides evidence that high and rising corruption increases income inequality and poverty. Using OLS regression and instrumental variable techniques on cross-section of countries over the 1980–97 period, the authors find that an increase of one standard deviation in corruption increases the Gini coefficient of income inequality by about 11 points and income growth of the poor by about 5 percentage points per year. These findings are robust to use of different instruments for corruption and other sensitivity analyses. These results are confirmed also by da Silva et al. (2022) who finds causality between corruption and poverty. Corruption also affect growth hindering technological progress, creating barriers to business, inflating bureaucratic rents, and distorting the efficient allocation of resources, thereby slowing innovation. Murphy et al. (1993) shows how an increase in rent-seeking activity makes rent-seeking more attractive relative to productive activity and this lead to multiple "bad" equilibria that hurt innovative activities. Bureaucratic excess, indeed, is a core contributor to corruption, as the greater the number of regulations, the more frequent the interactions between public officials and private sector actors, increasing the likelihood of corrupt behavior (Goel and Nelson, 2010). Furthermore, corruption impedes growth by distorting the allocation of human capital (Ehrlich and Lui, 1999) and reducing the school enrollment. Dridi (2014) examines the effects of corruption on education both from a quantitative and qualitative point of view. The cross-country regression analysis shows a strong link between corruption and secondary school enrollment rates, the results suggest that high and rising corruption decreases significantly access to schooling. A unit increase in corruption reduces enrollment rates by almost 10 percentage points. These findings are robust to the use of alternative measure of corruption and other sensitivity analysis. Moreover, corruption negatively impact growth and development also discouraging foreign direct investment. Wei et al. (2000), show how corruption in capital-importing countries affects both the volume and the composition of their capital inflows. In particular, controlling for governments' policies toward FDI, it results clear that corruption in the host country exhibit a negative, statistically significant, and quantitatively large effect on inward FDI. In general, corruption distorts public expenditure priorities driving up the price and lower the level of government output and services (Shleifer and Vishny, 1993), reducing government revenue (Hindriks, Keen, and Muthoo 1999), which in turn can lower the quality of publicly provided services. The latter discourages some individuals from using these services and reduces their willingness to pay for them (through tax evasion), which shrinks the tax base and diminishes the government's ability to provide quality public services (Gupta et al., 2001).

We also acknowledge the literature on natural resources and corruption that has an impact on economic growth and development. Leite and Weidmann (1999) present evidence that higher levels of corruption are associated with greater resource intensity. Using a system of three equations, their paper shows that corruption and resource intensity are mutually reinforcing and affect per-capita GDP through multiple channels. In this context, a weakening in the control of corruption is particularly harmful for economic development. At the same time, Bhattacharyya and Hodler (2010) further explore this dynamic, demonstrating how natural resource wealth can foster corruption, with the extent of this relationship depending on the quality of democratic institutions. Their study, based on panel data from 124 countries between 1980 and 2004, highlights that the relationship between resource rents and corruption is contingent upon the strength of democratic institutions. Indeed, we agree with Sachs and Warner (1997, 2001) who find in their quantitative analysis, poor policies and institutions explain a large share of the slow growth in Sub-Saharan Africa during the period 1965-1990, and that better policies would contribute to stronger economic performance. Africa's physical geography, difficult as it is, does not pose an insurmountable challenge to faster growth, even if it will tend to diminish growth rates compared to some other parts of the developing world.

While our paper focuses on corruption from a political economy perspective, it also takes into account other important key drivers. Ethnic diversity, for instance, can serve as a trigger for in-group favoritism. When members of a particular ethnic group hold public office, they may be more likely to retain their positions despite engaging in corrupt practices, as they tend to allocate resources in ways that benefit members of their own ethnic group, who, in turn, may offer reciprocal support (Treisman, 2007).

The structure and size of government also play a significant role in corruption. In democratic systems, regular and fair elections foster greater accountability and reduce corruption (Sandholtz and Koetzle, 2000; Jetter et al., 2015). Further, as suggested by Alexeev and Song (2013), increased market and political competition diminishes the likelihood that a small group of individuals will monopolize public goods, thus reducing the prevalence of corruption.

Moreover, the paper acknowledges mixed evidence regarding the influence of historical and colonial drivers, legal systems, property rights, and religion on corruption and its diffusion. Religion can increase demand for strong legal institutions and the rule of law, which may reduce corrupt practices within a society (North et al., 2013). In particular, countries with Protestant traditions, a history of British rule, more developed economies, and higher import levels tend to exhibit lower levels of corruption (Treisman, 2000), while less developed economies with weaker property rights enforcement tend to experience higher corruption levels (Acemoglu and Verdier, 1998).

2.2 Terrorism and political violence

In the literature terrorism is defined as "the premeditated, threatened or actual use of force or violence to attain a political goal through fear, coercion, or intimidation" (Sandler et al., 1983, p. 37). This definition incorporates the four key characteristics of terrorist activity identified by Weinberg et al., 2004; Schmid, 2004 and Shughart (2006): (i) the use or threat of violence for political purposes; (ii) a deliberate and planned course of action; (iii) operations conducted outside the boundaries of legitimate warfare; and (iv) the objective of generating widespread fear and insecurity, especially among civilians.

The determinants of terrorism are explored in the comprehensive reviews provided by Krieger and Meierrieks (2011) and Caruso and Schneider (2011) and in recent works by Schneider et al. (2010) and Enders and Sandler (2006). First, the economic deprivation hypothesis, rooted in the relative deprivation theory introduced by Gurr (1968), suggests that poor economic conditions and lack of opportunity foster terrorism and political violence. In situations of widespread poverty, the opportunity cost of joining terrorist organizations is low, making recruitment easier. Second, the immiserizing modernization hypothesis, based on the work of Olson Jr (1963), posits that economic growth and structural transformation can generate distributional shifts that fuel social grievances. In this view, modernization may marginalize certain social groups, whose resulting discontent can be exploited by terrorist organizations. Thus, paradoxically, terrorism can emerge in tandem with economic growth and development when such transitions exacerbate inequality or exclusion.

Beyond these economic factors, the literature also emphasizes the role of political and institutional characteristics. Government structure (e.g., centralized vs. decentralized), regime type, policy orientation, state capacity (e.g., military or police power), and ideological alignment (e.g., left-wing vs. Right-wing) shape the strategic calculus of terrorist actors. For example, large, centralized states may limit rent-seeking opportunities, thereby increasing the incentive for violence as a means of rent extraction (Kirk, 1983). At the same time, political instability and weak or failed states may function as breeding grounds for international terrorism, where periods of civil war or disorder provide individuals with experience and networks that fuel transnational campaigns (Campos and Gassebner, 2009). Identity-based grievances also play a critical role. Terrorist groups may mobilize support more easily when targeting rival identity groups, often defined along ethnic or religious lines. As noted by Bernholz (2006), ideologies emphasizing identity supremacy, such as claims to religious or ethnic purity, can reduce moral constraints on violence and enhance internal cohesion, thereby increasing the effectiveness and appeal of terrorism. Furthermore, the global political and economic order, particularly the dynamics of globalization, may influence terrorism. International grievances, often related to perceptions of Western dominance or economic marginalization, can provoke violent resistance. In this context, variables such as trade openness, political alignment with Western powers, and membership in international alliances are shown to influence terrorist activity (Bergesen and Lizardo, 2004). Marginalized or traditionalist groups may view globalization as a cultural and economic threat, turning to violence as a means of preserving identity and autonomy. Another important dimension is the contagion effect. Terrorism tends to exhibit self-reinforcing dynamics over time and space. As shown by Midlarsky et al. (1980), temporal contagion implies that past terrorist acts increase the likelihood of future attacks within the same country, while spatial contagion suggests that terrorism can spread across borders through imitation, inspiration, or organizational networks. It is also worth recalling the game-theoretical approach to terrorism, particularly the model proposed by Bapat (2006), which explores how host state incentives and constraints affect the ability of terrorist groups to form credible commitments. Related studies have emphasized bargaining dynamics in suicide terrorism and strategic violence (Jacobson and Kaplan, 2007; Sandler and Enders, 2007) and the contest theory (Caruso and Schneider, 2013) which examines how terrorism's intensity and brutality can be modeled as outcomes of strategic contests over power and visibility.

3 Methodology and Data

3.1 Dependent variable

Our main dependent variable for assessing the incidence of terrorism is the number of terrorist attacks per country-year, following Meierrieks and Auer (2025). In an alternative specification aimed at capturing the brutality of terrorism, we use the number of victims per country-year, defined as the total number of individuals killed or wounded, as in Caruso and Schneider (2013) and Prieto-Rodríguez et al. (2009). Data on terrorism are drawn from the Global Terrorism Database (GTD), as described in LaFree and Dugan (2007). The GTD compiles information on terrorist events from reputable media sources. To be included in the database, an event must be reported by at least one high-quality source and meet all three of the following criteria: (1) it must be intentional, (2) it must involve violence or the threat of violence, and (3) it must be perpetrated by non-state actors, thereby excluding violence committed by state actors. Additionally, the event must meet at least two of the following three conditions: (1) it must be carried out with the aim of achieving a political, economic, religious, or social objective; (2) there must be evidence of an intent to coerce, intimidate, or communicate a message to a broader audience beyond the immediate victims; and (3) the act must occur outside the context of conventional warfare (LaFree and Dugan, 2007).

3.2 Independent variables

Our measure of corruption is the political corruption index from the Varieties of Democracy Dataset (VDEM; Coppedge et al., 2019). Higher values of this index correspond to higher levels of political corruption. This political corruption index is the arithmetic mean of four variables measuring corruption in the (1) executive, (2) legislature, (3) judiciary, and (4) public sector. The authors are aware of the different measures of corruption, the subjective measures as the Corruption Perception Index, the judicial and economic measures. But for this specific analysis the best index we can chose is the VDEM, as in Meierricks and Auer (2025), because it covers corruption in the various branches of government and at various levels of government. This corruption index accounts for corruption aimed at influencing policy and law-making as well as the implementation of these policies and laws. Finally, it covers different forms of corruption, accounting for both "passive" corruption (such as taking bribes) and "active" corruption, for example, in the form of the embezzlement of public resources by public officials and politicians. VDEM relies on country and subject-based expert opinion. For instance, to evaluate the extent of legislative corruption, experts are asked to assess to what extent members of the legislature abuse their position for financial gain. To arrive at representative values of political corruption per country-year observation that can also be compared between countries, VDEM then applies item response theory and subjects the individual expert opinion data to other forms of statistical scrutiny to minimize uncertainty and bias (Coppedge et al., 2019).

3.3 Control variables

The choice of the control variables follows the above-mentioned literature on the determinants of corruption and terrorism. In particular, we take into account the literature on the relation between violence and climate change (Hendrix et al., 2012; Raleigh and Kniveton, 2012; Gleditsch 2012; Harari and La Ferrara, 2013; Nordås and Gleditsch 2014; Burke et al., 2015; Buhaug 2016; De Juan and Hänze, 2021; Balestri and Caruso, 2024). This let us control for the vicious cycle driven by the interconnections between vulnerability, conflict, and climate-related impacts (Buhaug and Von Uexkull, 2021). In our case, it is important to control for climate change also because in Sub-Saharan Africa economies are heavily dependent on natural resources and a large share of the population is employed in the primary sector (e.g. Creti et al., 2021). We measure climate change with the annual Standardized Precipitation-Evapotranspiration Index (SPEI), a drought index that incorporates both precipitation and potential evapotranspiration (PET) to assess anomalies in the climatic water balance (Beguerìa and Vicente-Serrano, 2014). The annual SPEI, calculated over a 12-month timescale (SPEI), captures long-term drought conditions affecting hydrological and agricultural systems. It compares the current 12-month cumulative climatic water balance to historical records to identify whether a given period is unusually dry or wet. This index is widely used to study the impacts of climate change and, in particular, allows us to engage with the literature on extreme weather events and the rise of violence (Maystadt et al. 2014; Couttenier and Soubeyran, 2014; Jenkins and Warren, 2015; Breckner, 2019). We include, also, controls for GDP per capita growth and for population growth, taking them from the World Bank Indicator Database. Then we control also for identity-based grievances with the the exclusion by social group index where lower scores indicate a normatively better situation and higher scores a normatively worse situation (Pemstein et al., 2025). We account also for political regime type classified considering the competitiveness of access to power (polyarchy) as well as liberal principles. This index goes from closed autocracy to liberal democracies taking into account the ambiguity of some regime type and we interact it with the regime type end, because we know that regime change has a destabilizing effect especially in less-democratic countries. (Lührmann et al., 2018). Finally, we want to take into account also the military expenditure as in the literature is know that there is a negative relationship between level of democracy and military burden and that social democratic regimes have a tendency to spend less on armaments (Töngür et al., 2015). We also know that military regimes have the highest military spending, whereas personalist dictatorships have the lowest level (Bove and Brauner, 2016) and that high military spending in post-conflict significantly increases the risk of renewed conflict (Collier and Hoeffler, 2006).

Table 1: Variables Summary Statistics

Type / Variable	**Description**	**Source**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
			Dependent Variable				
Sum of attacks	Aggregated number of attacks per country-year	GTD Dataset	2458	9.598	51.237	0	872
Victims (killed + wounded)	Sum of killed and wounded per country-year	GTD Dataset	2458	66.092	374.173	0	10058
			Independent Variable				
Political corruption index	Arithmetic mean of corruption measures in executive, legislature, judiciary, public sector	V-Dem	2458	0.614	0.232	0.076	0.965
			Control Variable				
GDP per capita growth	Annual GDP per capita growth (%)	World Bank	2458	2.294	7.339	-48.428	140.490
Population growth	Annual population growth (%)	World Bank	2458	2.587	1.473	-17.988	16.749
SPEI (annual)	Standardized Precipitation Evapotranspiration Index (12 months)	SPEI Database	2356	-0.195	0.702	-2.705	2.691
Exclusion by social group	Social exclusion by group index	V-Dem	2458	0.583	0.239	0.102	0.994
Regime type	Regime type from less to more democratic	V-Dem	2458	2.686	2.363	0	9
Regime end type	Regime end type from violent to less violent change	V-Dem	2458	8.107	5.135	0	13
Military expenditure (log)	Log of military expenditure in USD	SIPRI	1840	0.396	1.233	-10.974	3.537
State ownership of the economy	State ownerwhip of the economy	V-Dem	2458	-0.002	1.132	-3.379	2.274
Government censorship on media	Press freedom	V-Dem	2458	-.34790	1.251	-2.951	2.577

Table 2: Correlation Table with Significance Stars - Attacks

	Attacks	Corr.	GDPpc gr.	Pop. gr.	SPEI	Excl. group	Regime type	Regime end type	Mil. exp.	Gov. censor.	State own. econ.
Sum of the Attacks	1.000	0.149***	-0.008	0.017	0.004	0.078***	-0.006	0.083***	-0.026	0.082***	0.142***
Political corruption index	0.149***	1.000	-0.046**	0.083***	-0.079***	0.412***	-0.261***	-0.211***	-0.064***	-0.132***	0.101***
GDP per capita growth	-0.008	-0.046**	1.000	0.004	0.042*	-0.058**	0.102***	0.085***	-0.069***	0.082***	0.040
Population growth	0.017	0.083***	0.004	1.000	0.056***	0.128***	-0.104***	-0.072***	0.041*	-0.089***	-0.059***
SPEI	0.004	-0.079***	0.042*	0.056***	1.000	0.019	-0.108***	0.038*	0.040	-0.097***	-0.071***
Exclusion by Social Group	0.078***	0.412***	-0.058**	0.128***	0.019	1.000	-0.540***	-0.205***	0.160***	-0.600***	-0.322***
Regime type	-0.006	-0.261***	0.102***	-0.104***	-0.108***	-0.540***	1.000	0.261***	-0.179***	0.667***	0.477***
Regime end type	0.083***	-0.211***	0.085***	-0.072***	0.038*	-0.205***	0.261***	1.000	-0.048**	0.198***	0.093***
Military expenditure (log)	-0.026	-0.064***	-0.069***	0.041*	0.040	0.160***	-0.179***	-0.048**	1.000	-0.145***	-0.207***
Gov. censorship of media	0.082***	-0.132***	0.082***	-0.089***	-0.097***	-0.600***	0.667***	0.198***	-0.145***	1.000	0.606***
State ownership of economy	0.142***	0.101***	0.040	-0.059***	-0.071***	-0.322***	0.477***	0.093***	-0.207***	0.606***	1.000

Table 3: Correlation Table with Significance Stars - Victims

	C Vict	Corr.	GDPpc gr.	Pop gr.	SPEI	Excl. group	Regime type	Regime type end	Mil. exp.	Gov. cens.	State own. econ.
Victims	1	0.136***	-0.015	-0.011	0.000	0.074***	0.002	0.075***	-0.015	0.079***	0.109***
Political corruption index	0.136***	1	-0.046**	0.083***	-0.079***	0.412***	-0.261***	-0.211***	-0.064**	-0.132***	0.101***
GDP per capita growth (annual %)	-0.015	-0.046**	1	0.004	0.042*	-0.058**	0.102***	0.085***	-0.069***	0.082***	0.040
Population growth (annual %)	-0.011	0.083***	0.004	1	0.056***	0.128***	-0.104***	-0.072***	0.041	-0.089***	-0.059***
Standardised Precipitation-Evapotranspiration Index (annual)	0.000	-0.079***	0.042*	0.056***	1	0.019	-0.108***	0.038	0.040	-0.097***	-0.071***
Exclusion by Social Group index	0.074***	0.412***	-0.058**	0.128***	0.019	1	-0.540***	-0.205***	0.160***	-0.600***	-0.322***
Regime type	0.002	-0.261***	0.102***	-0.104***	-0.108***	-0.540***	1	0.261***	-0.179***	0.667***	0.477***
Regime end type	0.075***	-0.211***	0.085***	-0.072***	0.038	-0.205***	0.261***	1	-0.048*	0.198***	0.093***
Military expenditure (log)	-0.015	-0.064**	-0.069***	0.041	0.040	0.160***	-0.179***	-0.048*	1	-0.145***	-0.207***
Government censorship effort - Media	0.079***	-0.132***	0.082***	-0.089***	-0.097***	-0.600***	0.667***	0.198***	-0.145***	1	0.606***
State ownership of economy	0.109***	0.101***	0.040	-0.059***	-0.071***	-0.322***	0.477***	0.093***	-0.207***	0.606***	1

3.4 The Model

This analysis explores the relationship between corruption and political violence through the following functional specification:

$$Y_{it} = f\big(\text{Corruption}_{it}, \text{Controls}_{it}, \text{SPEI}_{it},\big) \tag{1}$$

where Y_{it} represents the level of *political violence* (in terms of incidence and brutality) in country i at time t. The function $f(\cdot)$ captures how political violence responds to changes in institutional quality, other contextual factors and climate change. The main variable of interest is Corruption_{it}, which reflects the degree of institutional corruption. The control variables include GDP per capita, population growth, regime type interacted with regime end type, exclusion by social group, military expenditure, and the Standardized Precipitation-Evapotranspiration Index (SPEI_{it}). This functional form provides the conceptual foundation for the subsequent econometric specifications, where the marginal effects of each determinant on political violence are empirically estimated. To examine the effect of corruption on political violence, we propose three complementary empirical methods that differ in their functional assumptions and treatment of the dependent variable.

Negative Binomial Specification Model

Given that political violence (Y_{it}) is a count variable characterized by overdispersion, the first model adopts a negative binomial functional form:

$$Y_{it} = e\big(\text{Corruption}_{it}, \text{Controls}_{it}\big) \tag{2}$$

where the expected number of violent events is modeled as an exponential function of corruption and a set of control variables. Formally, the conditional mean can be expressed as

$$E(Y_{it} \mid X_{it}) = \exp(\beta_0 + \beta_1 \text{Corruption}_{it} + \beta_2 \text{Controls}_{it})$$

Zero-Inflated Negative Binomial Model (ZINB)

To account for the excess of zero observations, we estimate a zero-inflated negative binomial model, which assumes that observed outcomes arise from two distinct processes:

$$Y_{it} = \begin{cases} 0, & \text{with probability } \pi_{it} = g(Z_{it}) \\ e(X_{it}), & \text{with probability } 1 - \pi_{it} \end{cases} \tag{3}$$

where $e(X_{it})$ represents the negative binomial count process as in Model 1, and $g(Z_{it})$ is a logit function determining the probability of an excess zero, typically modeled as a function of GDP per capita or other structural characteristics.

Linear OLS Specification Model

For comparison, we also estimate a linear model, treating political violence as a continuous variable:

$$Y_{it} = h\big(\text{Corruption}_{it}, \text{Controls}_{it}\big) \tag{4}$$

with the linear functional form:

$$E(Y_{it} \mid X_{it}) = \beta_0 + \beta_1 \text{Corruption}_{it} + \beta_2 \text{Controls}_{it} + \varepsilon_{it}$$

Each functional form, exponential, mixed (zero-inflated), and linear, provides a distinct way of testing the robustness and nature of the relationship between institutional corruption and political violence.

4 *Estimates and results*

4.1 Preliminary evidence with Negative Binomial model

At first stage[2] we estimate the impact of corruption on political violence incidence and brutality with a Negative Binomial model for panel count data, where y_{it} is the sum of attacks at time t in country i in the first specification, and the number of the victims, killed plus wounded, in the second specification. The model is specified as:

$$y_{it} \sim \text{NegBin}(\mu_{it}, \theta), \qquad \mu_{it} = \exp(\alpha + \beta_1 y_{i,t-1} + \beta_2 x_{it} + \gamma' Z_{it})$$

Where the μ_{it} is the expected count of events, θ is the overdispersion parameter, α the intercept, $\beta_1 y_{i,t-1}$ captures the effect of past political violence on the current period (Caruso, 2013). The main explanatory variable of interest is political corruption $\beta_2 x_{it}$, while $\gamma' Z_{it}$ is the vector of control variables with associated coefficients. We also run average marginal effects:

$$AME_{x_k} = \frac{1}{N}\sum_{i,t} \frac{\partial \mathbb{E}[y_{it} \mid X_{it}]}{\partial x_{k,it}} = \frac{1}{N}\sum_{i,t} \beta_k \, \mu_{it} = \frac{1}{N}\sum_{i,t} \beta_k \exp\left(\alpha + \beta_1 y_{i,t-1} + \beta_2 x_{it} + \gamma' Z_{it}\right).$$

The average marginal effect (AME) of variable $x_{k,it}$ represents the average change in the expected count of the outcome associated with a one-unit increase in $x_{k,it}$, holding all the rest constant. It is computed by first deriving the individual marginal effects $\beta_k \mu_{it}$ and then averaging them across all observations. Here, y_{it} denotes either the number of attacks or the number of victims in country i at time t, μ_{it} is the expected count, α is the intercept, $\beta_1 y_{i,t-1}$ captures the persistence of political violence, $\beta_2 x_{it}$ measures the effect of political corruption, and Z_{it} is the vector of control variables with associated coefficients γ. As robustness we also estimate a poisson regression with panel data, results in Appendix B.

4.1.1 Effects of corruption on incidence of political violence

The following section discusses the results of the negative binomial regression having as dependent variable the count of the attacks. We try to measure here the relation between corruption and the incidence of political violence and the main empirical findings presented in Table 4 and 5 can be summarized as follows. Political corruption is always positively related at the incidence of political violence. In all the specifications, indeed, an increase in corruption is associated with an increase in the number of attacks. In the specifications from 1 to 4, this relation is particularly significant, but when we add the regime type interacted with the regime end type and we add also the military expenditure as control variables, the significance of political corruption decreases. The average marginal effect shows that a one unit increase in the political corruption index increases the expected political violence by around 30 or more attacks, on average, across the sample. However the standard error is particularly high al leads to a loss of significance in the last specification, so the model should be improved.

[2]Firstly, we estimate a Poisson regression model to test for overdispersion (Appendix B), and to evaluate the fit of the model, we conducted a goodness-of-fit test based on the Pearson chi-square statistic. The result shows a Pearson chi-square value much higher than the degrees of freedom (Goodness-of-fit chi^2 = 223071.3 with df = 1753) and a p-value that is effectively zero. This leads to a strong rejection of the null hypothesis indicating the presence of significant overdispersion. Secondly, we try to figure out if fixed or random effects are preferred. The empirical results show a chi-square statistics of 8.91 with a p-value of 0.5403. So there is not enough statistical evidence to reject the RE assumption. However, as we are dealing with political, economic, social country-level variables, our regressors probably correlate with the unobserved country effect (Wooldridge, 2010), so we opted for fixed effects. Indeed, the best AIC and BIC are the ones of FE.

We also estimate a negative binomial model including lagged variables (see Appendix B). In particular, corruption is lagged by five years[3], while the other variables are lagged by one year. The relationship becomes even stronger under this specification, consistently positive and, in the first three specifications, statistically significant at the 1% level.
Looking at the other main control variables, it can be seen that GDP per capita growth is always negative related to the incidence of political violence, in particular in specification from 5 and 6, when we also control for regime type and military expenditure. It is in line with the literature that sees economic wellness as an indicator of reducing conflicts and violence. Population growth, instead, seems not in line with the literature, as we see is negatively associated to political violence incidence in a, almost always, significant way. Then exclusion by social group is significantly related to political violence, especially while controlling for regime type. Regime type interacted with regime end type is always strongly negative related to political violence, that means the more a regime change and become democratic the less is the political violence. The interaction is useful to control for the type of regime change, as not always these changes bring a more democratic regime. Finally, military expenditure has a positive and strong relation with the incidence of political violence. All these results are confirmed also in the lagged version (Appendix B).

Looking at climate change and violence with the Standardized Precipitation Evapotranspiration Index calculated over a 12-month timescale, it can be seen that is not significantly related to political violence incidence and the relation is negative. Same behavior for the quadratic SPEI, that stay always negative and not significantly related to the attacks incidence. However, if we look at the average marginal effects it can be noted that a one unit increase in SPEI leads to an increase in the attacks, but not in significant way. At the same time an increase in extreme weather events ($SPEI^2$) leads to a decrease in the number of the attacks in an almost always significant way. This can be due to the fact that when there are extreme weather events they affects also the violent activities, diminishing their resources and capacities. Finally, if we look at the lagged version (Appendix B) the findings show a strong and negative relation of the SPEI with the violence incidence, while there is a positive and strong relation with $SPEI^2$ and violence incidence. This can be explained by the fact that past extreme weather events in countries with weak institutions may increase the violence also because there has been a bad resource management after the extreme climatic event, so grievances and discontent increase.
To improve the model trying to better control for the zero in our data. But before stepping into the Zero Inflated Negative Binomial model, we decided to look also at the effect of corruption on the brutality of the attacks.

[3] We lag corruption of 5 years because of possible links with the government turnover and elections.

Table 4: Effect of corruption on attacks incidence in Sub-Saharan Africa (1970-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
Count of the Attacks						
Political corruption index	0.619***	0.559***	0.520**	0.450**	0.221	0.193
	(0.193)	(0.203)	(0.205)	(0.213)	(0.215)	(0.238)
GDP per capita growth (%)		-0.008	-0.008	-0.008	-0.012**	-0.013**
		(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Population growth (%)		-0.068**	-0.067**	-0.068**	-0.070***	-0.073**
		(0.028)	(0.028)	(0.028)	(0.024)	(0.029)
SPEI (annual)			-0.055	-0.062	-0.012	-0.070
			(0.058)	(0.059)	(0.058)	(0.064)
$SPEI^2$			-0.005	-0.005	-0.027	-0.060
			(0.058)	(0.058)	(0.056)	(0.062)
Exclusion by Social Group index				0.231	1.207***	1.161***
				(0.205)	(0.231)	(0.252)
Regimes type					0.387***	0.283***
					(0.041)	(0.044)
Regime end type					0.123***	0.082***
					(0.015)	(0.016)
Regimes of the world × Regime end type					-0.029***	-0.019***
					(0.004)	(0.004)
Military expenditure (log)						0.110***
						(0.042)
Constant	-2.094***	-1.845***	-1.828***	-1.927***	-3.628***	-3.240***
	(0.137)	(0.160)	(0.163)	(0.186)	(0.252)	(0.272)
Obs	2254	2103	2052	2052	2052	1652
AIC	7424.900	7123.400	7114.600	7115.400	6989.600	5855.200
BIC	7436.300	7146.000	7148.400	7154.700	7045.900	5914.700
Wald chi²	10.300	15.490	15.990	17.430	133.800	91.130

Negative Binomial with Fixed Effects. Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Average Marginal Effects of corruption on attacks incidence

	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption index	33.15**	37.91**	35.50*	31.18*	27.75*	36.48
	(16.15)	(18.18)	(18.24)	(18.81)	(16.39)	(25.42)
GDP per capita growth (%)		-0.348	-0.439	-0.330	-0.538	-0.850
		(0.283)	(0.344)	(0.295)	(0.350)	(0.710)
Population growth (%)		-0.247	-0.529	-0.408	-0.583	-1.435
		(0.582)	(0.739)	(0.801)	(0.790)	(1.354)
SPEI (annual)			1.589	1.413	0.600	0.706
			(1.245)	(1.352)	(1.335)	(1.726)
$SPEI^2$			-3.563***	-3.607**	-2.857*	-3.338
			(1.374)	(1.571)	(1.465)	(2.246)
Exclusion by Social Group index				16.56	32.47*	36.98
				(12.20)	(18.19)	(27.09)
Regime type					1.776	2.767
					(1.404)	(1.857)
Regime end type					1.233	1.304
					(0.764)	(1.382)
Military expenditure (log)						3.070
						(2.150)
Obs	2458	2294	2193	2193	2193	1764

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.1.2 Effects of corruption on brutality of political violence

In this section we use the dependent variable victims, that is the sum of killed and wounded to see the relation between corruption and political violence brutality. The main empirical findings presented in Table 6 and 7 can be summarized as follows. Political corruption has a positive impact on the brutality of political violence in specifications 1 to 5. In these specifications, indeed, an increase in corruption is associated with an increase in the victims of the attacks. In the first three specification, this relation is particularly significant, but when we add control variables like exclusion by social group, the significance of political corruption's impact decreases. In specification 6, political corruption even changes sign. When regime type interacted with regime end type and military expenditure, corruption becomes negative and not significant at all. However, the average marginal effects show that a one unit increase in corruption index is related with a super positive and strong increase in the number of victims, that arrives around 240 in specification 5. In the lagged version (see Appendix B) corruption is positively and strongly related to violence brutality only in the first three specifications, while the

others are non significant and even negative. So we can say that past corruption is more link with violence incidence than brutality.
Looking at the other main control variables, it can be seen that the lagged number of victims, which represents the number of killed plus the wounded in the dataset, and recalls the contest theory of Caruso and Schneider (2013) on terrorism brutality, is always strong and positive, indicating a strong link with past violence. On the other hand, GDP per capita growth is always negative related to the brutality of political violence, in particular, in specifications 5 and 6, when we control for exclusion by social group and youth unemployment. Population growth, instead, is non-significant in all the specifications, even if is always negative related to the brutality of the attacks and becomes significant in specification 5 and 6. Then, exclusion by social group and regime type interacted per regime end type have a strong and significant relationship with political violence brutality. When there is higher exclusion by social group and less democratic changes the number of victims increases. Finally, military expenditure shows a positive but non-significant coefficient in the baseline regression. However, the average marginal effects indicate that a one-unit increase in military expenditure is associated with approximately 25 additional victims of attacks, and this effect is statistically significant. This suggests that, although the baseline coefficient may not reach conventional significance levels, the marginal effects reveal a meaningful and robust relationship with political violence. The lagged version confirms all these relations (Appendix B).

Looking at the climate-violence nexus with the Standardized Precipitation Evapotranspiration Index calculated over a 12-month timescale, it can be seen that is not significantly related to political violence brutality and almost always negatively related. However, when looking at its average marginal effects, we see an instable control variable with a great standard error, but also a significant confirmation of the literature that says that extreme weather events have a negative impact on violence, because violent actors are also hit by climate change. This is confirmed also in the lagged version (Appendix B) where the SPEI and its quadratic term are both significantly negative related with violence brutality.

Given these findings, the next step in the analysis is to explore the relationship between political corruption and the incidence and brutality of terrorism using a Zero-Inflated Negative Binomial (ZINB) model. This will allow us to account for excess zeros in the data, helping us to reduce the standard errors of our variables and assessing whether the significance and direction of the relationships change under a different model specification.

Table 6: Effects of corruption on political violence brutality in Sub Saharan-Africa (1970-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
Victims						
Lagged Victims$_{t-1}$	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Political corruption index	0.434**	0.449**	0.440**	0.260	-0.009	-0.001
	(0.199)	(0.206)	(0.209)	(0.220)	(0.220)	(0.242)
GDP per capita growth (%)		-0.006	-0.006	-0.006	-0.011*	-0.014**
		(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Population growth (%)		-0.039	-0.040	-0.042	-0.049*	-0.071**
		(0.029)	(0.030)	(0.029)	(0.027)	(0.031)
SPEI (annual)			-0.007	-0.023	0.000	-0.034
			(0.063)	(0.064)	(0.063)	(0.069)
SPEI^2			-0.033	-0.033	-0.053	-0.072
			(0.063)	(0.063)	(0.062)	(0.067)
Exclusion by Social Group index				0.526**	1.410***	1.280***
				(0.209)	(0.236)	(0.259)
Regimes type					0.439***	0.363***
					(0.045)	(0.049)
Regime end type					0.154***	0.124***
					(0.016)	(0.017)
Regimes of the world × Regime end type					-0.037***	-0.029***
					(0.004)	(0.005)
Military expenditure (log)						0.068
						(0.043)
Constant	-2.729***	-2.595***	-2.574***	-2.782***	-4.604***	-4.202***
	(0.140)	(0.164)	(0.169)	(0.189)	(0.266)	(0.286)
Obs	2159	2018	2018	2018	2018	1628
AIC	9523.000	9120.500	9124.200	9119.800	8983.200	7634.700
BIC	9540.000	9148.500	9163.400	9164.700	9044.900	7699.500
Wald chi²	233.700	227.300	227.700	228.400	328.600	233.500

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Average Marginal Effects of corruption on political violence brutality

	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption index	215.0**	239.9**	234.4**	218.1*	240.3*	366.2
	(101.7)	(115.0)	(117.3)	(132.3)	(139.6)	(237.5)
GDP per capita growth (%)		-1.675	-2.011	-1.587	-3.787	-5.008
		(1.227)	(1.406)	(1.227)	(2.891)	(4.326)
Population growth (%)		-3.380	-4.387	-3.674	-5.541	-9.113
		(2.433)	(3.244)	(3.466)	(5.907)	(8.961)
SPEI (annual)			11.03	9.988	-1.383	3.051
			(9.994)	(11.34)	(11.32)	(15.30)
$SPEI^2$			-22.28**	-25.31**	-19.15*	-21.87
			(9.951)	(11.65)	(11.61)	(16.20)
Exclusion by Social Group index				136.1*	240.8**	285.1*
				(69.74)	(110.8)	(146.1)
Regime type					9.339	11.58
					(9.715)	(13.25)
Regime end type					9.788	11.71
					(6.082)	(10.32)
Military expenditure (log)						25.38*
						(15.26)
Obs	2458	2294	2193	2193	2193	1764

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Preliminary evidence with Zero Inflated Negative Binomial model

The second stage of our empirical strategy tries to improve the negative binomial model with a Zero-Inflated Negative Binomial model to control for the country-year observation with no terrorist activity and victims (e.g., Ubay et al.,2024; Tran et al.,2012). So, the model that accounts for excess zero in the count of terrorism (i) attacks or (ii) victims (Y_i), influenced by corruption (X_i) and other controls, is a two part mixture model structured as follows:

- Count Component (negative binomial) is conditional on not being a structural zero and the expected number of attacks or victims follows a negative binomial distribution:

$$\mu_i = \exp\left(\mathbf{x}_i^\top \beta\right) \tag{5}$$

where μ_i is the expected count for observation i, $\mathbf{x}_i$ is a vector of controls, and β is a vector of regression coefficients

- Zero-inflation Component (Logit or Probit Model) measures the probability that an observation is from the always-zero group and is modeled as[4]:

$$\pi_i = \frac{1}{1 + \exp\left(-\mathbf{z}_i^\top \gamma\right)} \tag{6}$$

where π_i is the probability that observation i is a structural zero (i.e., always zero), $\mathbf{z}_i$ is a vector of controls, and γ is a vector of coefficients. For example countries with high GDP per capita growth have more probability to be in the always-zero because of the well-know negative relation between economic growth and conflict or violence. Therefore, if the coefficient related to corruption (X_i) is bigger than 0 ($\beta_X > 0$), then an increase in corruption is associated with an increase in the expected number of victims or attacks, conditional on not being a structural zero. On the other side, if $\gamma_X < 0$, then an increase in corruption decreases the likelihood that a country is in the always-zero group (i.e., makes terrorism more likely to occur at all).

We also measure the average change in expected count of Y_i for a one-unit increase in X_i, accounting for both the count and zero-inflation parts.

$$\text{AMEs}_{x_k} = \frac{1}{N} \sum_i \frac{\partial \mathbb{E}[Y_i \mid X_i]}{\partial x_{k,i}}$$

The first term captures how X_{ik} increases the expected number of events among non-structural-zero observations, while the second term captures how X_{ik} changes the probability of being a structural zero. A positive marginal effect indicates that an increase in corruption raises the overall incidence or brutality of political violence.

The graphs below show the necessity of using the ZINB model to improve the analysis because the attacks and victims distribution in our sample present a lot of zeros. The graphs show, indeed, the frequency distribution of events, where the X-axis corresponds to the count of the attacks from 0 to 50 (Figure 1), and the count of the victims from 0 to 50 (Figure 2)[5].

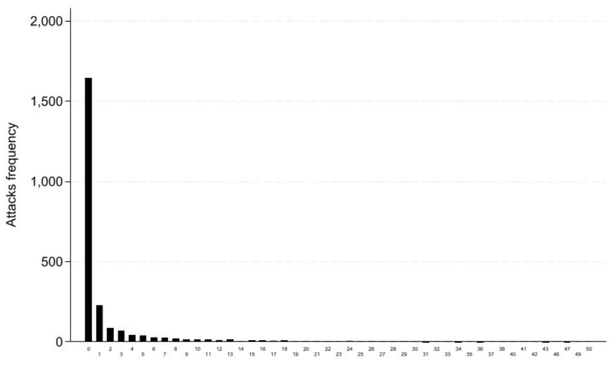

Figure 1: Distribution of the attacks

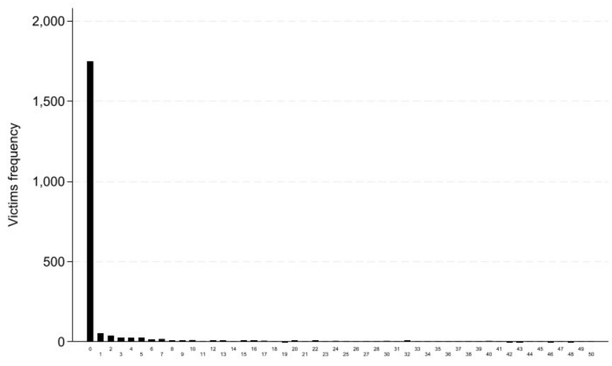

Figure 2: Distribution of the victims

[4]We compare the ZINB logit and ZINB probit, see in Appendix B, and we opted for the ZINB logit.

[5]To improve readability, we display the distribution of attacks and victims only up to 50. For higher values, the frequency remains low (often 1), with attacks reaching a maximum of 842 and victims up to 10,058.

4.2.1 The effect of corruption on political violence incidence

In this section we discuss the results of the zero-inflated negative binomial regression with dependent variable the count of the attacks. The main findings in Table 8 and 9 show that, once taken into account the possibility of being in a zero group, there is a strong and positive relation of political corruption with the incidence of political violence. In all the specification, controlling for the zero, an increase in corruption is associated with an increase in the number of attacks in our sample. Moreover, looking at the AIC, the BIC and the log likelihood we can see that specification 6 is the one that better fits our model. This means that when there are high levels of corruption, low levels of GDP per capita growth, an increase in water precipitations, exclusion by social group, a non democratic government and high military expenditure, terrorists attacks are more likely to occur within a country. The impact of corruption on the incidence of political violence, looking at its average marginal effects, is positive and significant in the first three specification of Table 9 and a unit increase in corruption is associated with an increase of almost 50 attacks on average. The findings of the lagged version of the regression (Appendix B) confirm this relation and show a always strong and highly significant association between corruption and violence incidence.
Looking at the other main control variables, it can be seen that GDP per capita growth is always significant and negative related to the incidence of political violence, reducing the number of attacks at almost two times, if there is a unit increase in GDP per capita growth. Population growth, instead, is majorly non-significant and negative in all the specifications, except for the 6 where it become significant. The exclusion by social group has a strong positive and significant relationship with political violence incidence in all the specification. The regime type interacted with the regime type end is always strong and negatively related, meaning less democracies is linked with more terrorist attacks. Military expenditure, instead, is positive related but not significant. All these relations are confirmed also in the lagged version (Appendix B).

Examining the climate change and violence relation with the Standardized Precipitation-Evapotranspiration Index (SPEI), a notable difference emerges compared to the negative binomial model: SPEI is statistically significant, and its significance increases as model complexity grows. In specifications 4 and 6, the coefficient is both positive and significant, indicating that higher levels of precipitation are associated with an increased number of attacks. This relation is confirmed also looking at Table 9 with its average marginal effects, even if the impact is not really significant. This can suggest that and increase in precipitations in low-income countries with weak institutions and ongoing political violence, may contribute to a rise of violence. In the lagged version, however, this relation is confirmed almost always positive but non significant (Appendix B). Looking at the ($SPEI^2$) the narration is still valid because there is a negative relationship with extreme weather conditions and political violence incidence. This implies that in contexts already prone to terrorism, extreme weather events may diminish the operational capacity or resources of terrorist groups, leading to a reduction in the number of attacks. In this case the lagged version confirm the strong negative relation.

Table 8: Effects of corruption on political violence incidence

	(1)	(2)	(3)	(4)	(5)	(6)
Count of the Attacks						
Political corruption index	3.844***	4.021***	3.722***	2.919***	2.638***	2.857***
	(0.336)	(0.347)	(0.367)	(0.405)	(0.404)	(0.536)
GDP per capita growth (%)		-0.036***	-0.044***	-0.033**	-0.052***	-0.071***
		(0.014)	(0.014)	(0.015)	(0.016)	(0.018)
Population growth (%)		-0.025	-0.040	-0.008	-0.038	-0.104**
		(0.043)	(0.046)	(0.049)	(0.051)	(0.053)
SPEI (annual)			0.249*	0.294**	0.201	0.281**
			(0.135)	(0.133)	(0.129)	(0.141)
$SPEI^2$			-0.191	-0.229*	-0.229*	-0.173
			(0.133)	(0.129)	(0.127)	(0.138)
Exclusion by Social Group index				1.652***	2.827***	2.575***
				(0.376)	(0.489)	(0.559)
Regime type					0.581***	0.567***
					(0.082)	(0.091)
Regime end type					0.236***	0.196***
					(0.028)	(0.035)
Regime × Regime end type					-0.049***	-0.043***
					(0.007)	(0.008)
Military expenditure (log)						0.092
						(0.163)
Constant	-0.049	-0.077	0.335	-0.146	-3.187***	-2.813***
	(0.239)	(0.247)	(0.287)	(0.299)	(0.500)	(0.621)
inflate						
GDP per capita (log)	2.803***	2.853***	2.737***	2.691***	2.620***	2.886***
	(0.550)	(0.564)	(0.548)	(0.526)	(0.498)	(0.599)
Constant	-26.530***	-27.040***	-26.100***	-25.670***	-24.930***	-27.330***
	(5.265)	(5.404)	(5.237)	(5.013)	(4.734)	(5.668)
/						
lnalpha	1.924***	1.919***	1.891***	1.869***	1.802***	1.758***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.054)	(0.058)
Obs	1433	1432	1370	1370	1370	1150
AIC	6480.0	6475.5	6438.8	6420.9	6373.3	5409.1
BIC	6506.3	6512.3	6485.8	6473.1	6441.2	5479.8
DF	1	3	5	6	9	10
Log likelihood	-3235.0	-3230.7	-3210.4	-3200.4	-3173.7	-2690.6

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Average Marginal Effects of corruption on political violence incidence in Sub-Saharan Africa (1970-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption index	54.53*	60.09*	58.65*	46.62	43.94	51.15
	(28.12)	(30.90)	(31.80)	(33.99)	(30.79)	(43.51)
GDP per capita (log)	-1.732**	-1.722**	-1.725**	-1.796**	-2.233***	-2.090**
	(0.721)	(0.710)	(0.679)	(0.730)	(0.864)	(0.939)
GDP per capita growth (%)		-0.543	-0.686	-0.525	-0.872	-1.275
		(0.461)	(0.539)	(0.505)	(0.650)	(1.248)
Population growth (%)		-0.379	-0.629	-0.125	-0.640	-1.871
		(1.008)	(1.203)	(1.296)	(1.357)	(2.152)
SPEI (annual)			3.929	4.702*	3.351	5.025
			(2.444)	(2.676)	(2.657)	(3.771)
SPEI^2			-3.010	-3.656	-3.816	-3.090
			(1.997)	(2.321)	(2.434)	(2.724)
Exclusion by Social Group index				26.39	47.09*	46.09
				(18.90)	(28.30)	(38.80)
Regime type					1.886	2.979
					(2.192)	(2.306)
Regime end type					1.647	1.336
					(1.052)	(1.768)
Military expenditure (log)						1.646
						(6.862)
Obs	1433	1432	1370	1370	1370	1150

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.2 The effect of corruption on political violence brutality

We tested also the relation between corruption and political violence brutality using as dependent variable the number of the victims with our ZINB model.

The results in Table 10 and 11, show that in countries more prone to have political violence, political corruption is positively and is strongly associated with violence brutality, in specification 1,2 and 6. If we look at the AIC, the BIC and the log likelihood we can see that specification 6 is the one that better fits our model. This means that when there are high levels of corruption, low levels of GDP per capita growth, an increase in water precipitations, high exclusion by social group, non democratic regime change and high military expenditure, countries are more likely to see and increase in the number of victims due to terrorist attacks within their territory. Indeed, the average marginal effects confirm the positive impact of corruption on political violence brutality, even if the one unit increase in corruption doesn't impact always significantly on brutality. The lagged version (see Appendix B) confirm this positive and strong relation, in particular for the specifications from 1 to 3 and the 6. Looking at the other main control variables, it can be seen that GDP per capita growth is always negative related to the brutality of political violence. Population growth, instead, is non-significant in all the specifications but positively related with the number of victims. The exclusion by social group has always a strong positive and significant relationship with political violence brutality. While the regime change into a more democratic type is negatively related to the number of victims, significantly only in the last specification. Military expenditure, instead, is positive and strongly significant related with the number of victims in all the specifications. This suggest that military spending in countries where there is political violence, lack of accountability at institutional level and low income per capita level can lead to more brutal attacks by terrorist groups. The lagged version confirm all these relations (Appendix B).

Examining the relation between climate change and violence with the Standardized Precipitation-Evapotranspiration Index (SPEI), it emerges that SPEI is always statistically positive and significant in all the specifications, indicating that higher levels of precipitation are associated with an increased number of victims. The average marginal effects, moreover, indicate that an increase in SPEI index leads to an almost always significant increase in the number of victims of around 30 times. The ($SPEI^2$), instead, appears negatively related and non significant. This implies that in contexts already prone to terrorism, with an historical weakness in institutions, high military spending and a repressive government, countries that experience more precipitations are more likely to have a great number of victims. In the lagged version, instead, the lagged SPEI is negatively related but not always significant; while the $SPEI^2$ is always strong and negatively related to violence brutality.

Table 10: Effects of corruption on political violence brutality in Sub-Saharan Africa (1970-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
Victims						
Lagged corruption$_{t-1}$	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Political corruption index	1.293***	1.564***	1.369***	0.249	0.201	0.916*
	(0.417)	(0.423)	(0.410)	(0.484)	(0.487)	(0.549)
GDP per capita growth (%)		-0.050***	-0.054***	-0.047***	-0.046***	-0.033*
		(0.013)	(0.013)	(0.013)	(0.013)	(0.018)
Population growth (%)		0.026	0.022	0.042	0.047	0.020
		(0.030)	(0.030)	(0.033)	(0.035)	(0.046)
SPEI (annual)			0.513***	0.474***	0.451***	0.591***
			(0.132)	(0.130)	(0.132)	(0.138)
SPEI^2			0.006	-0.032	-0.017	0.030
			(0.128)	(0.124)	(0.126)	(0.128)
Exclusion by Social Group index				1.828***	1.841***	1.463***
				(0.394)	(0.483)	(0.523)
Regime type					0.107	0.173*
					(0.095)	(0.097)
Regime end type					0.037	0.096***
					(0.034)	(0.035)
Regime type × Regime end type					-0.013	-0.028***
					(0.008)	(0.009)
Military expenditure (log)						0.407**
						(0.170)
Constant	3.162***	2.853***	3.126***	2.692***	2.429***	1.844***
	(0.338)	(0.355)	(0.347)	(0.359)	(0.599)	(0.630)
inflate						
GDP per capita (log)	0.938***	0.957***	0.855***	0.901***	0.869***	0.729***
	(0.132)	(0.146)	(0.136)	(0.163)	(0.149)	(0.142)
Constant	-7.900***	-8.139***	-7.321***	-7.803***	-7.495***	-6.293***
	(1.246)	(1.396)	(1.277)	(1.561)	(1.421)	(1.312)
lnalpha	1.607***	1.636***	1.572***	1.612***	1.578***	1.418***
	(0.165)	(0.175)	(0.167)	(0.182)	(0.176)	(0.181)
Obs	1433	1432	1370	1370	1370	1150
AIC	8130.000	8116.300	8069.200	8048.100	8051.100	6922.800
BIC	8161.600	8158.400	8121.400	8105.600	8124.200	6998.600
DF	2	4	6	7	10	11
Log likelihood	-4059.000	-4050.100	-4024.600	-4013.100	-4011.600	-3446.400

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Average Marginal Effects of corruption on political violence brutality

	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption index	333.9*	60.09*	396.5*	342.7	317.1	443.7
	(177.6)	(30.90)	(217.2)	(246.6)	(201.6)	(306.1)
GDP per capita (log)	-28.76***	-1.722**	-27.97***	-26.66***	-27.36***	-27.33**
	(9.688)	(0.710)	(10.14)	(10.13)	(9.529)	(11.09)
GDP per capita growth (%)		-0.543	-4.086	-3.441	-4.346	-5.447
		(0.461)	(2.565)	(2.517)	(3.481)	(4.817)
Population growth (%)		-0.379	-4.692	-2.943	-3.615	-7.414
		(1.008)	(4.057)	(3.940)	(5.779)	(8.132)
SPEI (annual)			37.10**	35.52*	25.27	38.13*
			(17.13)	(19.22)	(18.07)	(22.34)
$SPEI^2$			-10.96	-18.08	-17.92	-11.97
			(11.17)	(13.37)	(13.78)	(15.16)
Exclusion by Social Group index				168.1*	235.9*	237.0
				(91.80)	(139.6)	(181.8)
Regime type					7.493	10.04
					(12.10)	(13.94)
Regime end type					8.467*	7.776
					(5.049)	(7.137)
Military expenditure (log)						24.69
						(45.35)
Obs	1433	1432	1370	1370	1370	1150

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Preliminary evidences of the Linear regression model

The third stage of our empirical analysis involves transforming the count variable into a continuous one and estimating the relation between corruption and political violence incidence and brutality on population using a OLS regression. Specifically, we build two continuous dependent variables that are: 1. the rate of the number of attacks on the total population of a country i in the time t; 2. the rate of the victims of the attacks on the total population of a country i in the time t. To do that we use the following model:

$$\text{Attacks or Victims Rate}_{it} = \left(\frac{\text{Count of the Attacks or Victims }_{it}}{\text{Total Population}_{it}} \right) \times 100{,}000 \tag{7}$$

Where Attaks rate or Victims rate_{it} are standardized as the attacks or victims rate per 100,000 people in country i at time t. To estimate the effect of corruption on political violence incidence, we specify the following OLS model:

$$\text{Attacks or Victims Rate}_{it} = \beta_0 + \beta_1 \text{Corr}_{it} + \beta_2 \mathbf{X}_{it} + \alpha_i + \delta_t + \varepsilon_{it} \tag{8}$$

Where Corr_{it} is the political corruption index, followed by $\mathbf{X}_{it}$ the vector of control variables. Then there are country fixed effects[6] α_i, time fixed effects δ_t and ε_{it} is the error term. The same structure has been applied for

[6]As first step we run a Hausman test with all the control variables to understand if fixed or random effects where preferred. The empirical results show a chi-square statistic of 52.32 with a p-value of 0.000. So we reject the null hypothesis and prefer the fixed

victims rate.

4.3.1 The effect of corruption on political violence incidence

In this section we discuss the results of out linear model with OLS regression that focuses on the relation between the attacks rate and violence incidence. The Table 12 shows in almost all the specification a strong and positive relation with corruption and attacks rate, meaning that an increase in political corruption can lead to an increase in the incidence of political violence per 100.000 inhabitants within a country. Nevertheless, looking at the specification 6, we see a loss of significance in corruption that should be more investigated. So we can say that for all the specification, except of the 6, a one-unit increase in corruption is associated with an average increase of 0.25 attacks, holding other factors constant. However, if we look at the lagged version of the regression, with 5 years lagged corruption (see Appendix B), also specification 6 is positively and strongly related to violence incidence.
Looking at the other main control variables, it can be seen that GDP per capita growth is always negative related to the incidence of political violence, and it becomes particularly strongly negative related in the specification with military expenditure. Population growth follows the same path, become more significantly negative related to the attacks rate, especially while controlling for military expenditure. In this regression exclusion by social group is not significant, while the regime interacted variable instead is always negative and highly significant. Additionally, military expenditure consistently demonstrates a positive and significant linear relationship with the attacks rate. This pattern suggests that in countries with weak institutions and decreasing economic growth, where there is an increasing allocation of resources in the military sector and the regime changes are not towards democracy, violence is more likely to occur and attacks to increase. The lagged version, also in this case, confirm these relations.

Examining the relation between climate change and violence with the Standardized Precipitation-Evapotranspiration Index (SPEI), we can say that an increase in precipitation is associated with an increase in the attacks rate, but this relation is not significant in the overall model. At the same time, extreme weather events are negatively associated with the attacks rate, but even in this case the relation is not significant. The lagged version, instead shows that the past climate variability and past weather extreme events are negatively linked with violence incidence, but in a non significant way.

effects (see Appendix B).

Table 12: Effect of corruption on attacks rate with fixed effects in Sub-Saharan Africa (1970-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption index	0.262***	0.288***	0.285***	0.288***	0.259***	0.039
	(0.043)	(0.048)	(0.049)	(0.049)	(0.048)	(0.030)
GDP per capita growth (%)		-0.001	-0.000	-0.000	-0.000	-0.002***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population growth (%)		-0.001	-0.001	-0.001	0.000	-0.005**
		(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
SPEI			0.003	0.003	0.002	0.002
			(0.008)	(0.008)	(0.008)	(0.005)
$SPEI^2$			-0.006	-0.007	-0.009	-0.006
			(0.007)	(0.007)	(0.007)	(0.004)
Exclusion by Social Group index				0.055	-0.042	0.001
				(0.058)	(0.065)	(0.040)
Regime type					0.025***	0.014***
					(0.006)	(0.004)
Regime end type					0.019***	0.007***
					(0.002)	(0.001)
Regime type $\times$ Regime end type					-0.005***	-0.002***
					(0.001)	(0.000)
Military expenditure (log)						0.010***
						(0.003)
Constant	-0.105***	-0.118***	-0.115***	-0.147***	-0.183***	-0.018
	(0.027)	(0.032)	(0.033)	(0.047)	(0.053)	(0.033)
Obs	2458	2294	2193	2193	2193	1764
R^2 (Within)	0.015	0.016	0.016	0.017	0.050	0.034
R^2 (Between)	0.023	0.023	0.023	0.036	0.030	0.113
R^2 (Overall)	0.010	0.012	0.012	0.015	0.030	0.035
AIC	188.600	159.900	106.500	107.500	36.900	-2358.100
BIC	200.200	182.800	140.600	147.400	93.830	-2297.800
F-test	36.370	12.180	7.123	6.086	12.640	6.027

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3.2 The effect of corruption on political violence brutality

Looking at the effect of corruption on political violence brutality that use the victims rate as dependent variable, we can see in Table 13 that corruption is positively and strongly related to the victims rate in all the specifications, except for the 6. Apart from the last specification where the influence of military expenditure should be more investigated, the results show that a one unit increase in corruption leads to an increase of around 0.7 in the victims number over the population of a country in Sub-Saharan Africa. In the lagged version the positive and strong relation with violence brutality and corruption is confirmed, and also the lack of significance of specification 6 (see Appendix B).

Looking at the other main control variables, it can be seen that GDP per capita growth is always negative related to the brutality of political violence, and it becomes particularly strongly negative in the specification with military expenditure. Population growth follows the same path, always negative and highly significant related to victims rate. Exclusion by social group is positive and significantly related to victims in specification 4, but while controlling for regime and military expenditure it lose its significance and turns negative. Instead, regime type interacted with regime end type and military expenditure are always strongly related with the number of victims and the brutality of political violence. This means that in context with less democratic regime change and high military expenditure the number of victims due to terrorist attacks increases. The lagged version confirm these relations.

Focusing on the role of climate change and its link with violence, we can say that also in this case the Standardized Precipitation-Evapotranspiration Index (SPEI) is positively related with violence brutality, but not in a significant way. At the same time, extreme weather events are negatively related in a non significant way. This means that overall the impact of climate change when looking at corruption and institutional weaknesses is not a good predictor. However, if we look at the lagged version the relation with SPEI and violence brutality remains non significant, but the past extreme weather events are, instead, strongly and negatively linked with violence brutality. This confirm the hypothesis of climate change that impact also terrorist activities.

Table 13: Effect of corruption on victims rate with fixed effects in Sub-Saharan Africa (1970-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption index	0.690**	0.701**	0.763**	0.799**	0.629**	-0.215
	(0.309)	(0.302)	(0.316)	(0.316)	(0.315)	(0.350)
GDP per capita growth (%)		-0.009*	-0.010**	-0.009*	-0.008	-0.024***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Population growth (%)		-0.115***	-0.119***	-0.123***	-0.112***	-0.190***
		(0.027)	(0.028)	(0.028)	(0.028)	(0.029)
SPEI (annual)			0.056	0.047	0.044	0.049
			(0.053)	(0.053)	(0.052)	(0.055)
SPEI^2			-0.032	-0.038	-0.052	-0.035
			(0.048)	(0.048)	(0.047)	(0.049)
Exclusion by Social Group index				0.694*	-0.011	-0.257
				(0.374)	(0.420)	(0.470)
Regime type					0.165***	0.137***
					(0.039)	(0.041)
Regime end type					0.122***	0.089***
					(0.015)	(0.016)
Regime type × Regime end type					-0.031***	-0.022***
					(0.004)	(0.004)
Military expenditure (log)						0.096**
						(0.038)
Constant	-0.114	0.166	0.174	-0.232	-0.403	0.563
	(0.193)	(0.200)	(0.214)	(0.306)	(0.345)	(0.393)
Obs	2409	2258	2158	2158	2158	1740
R^2 (Within)	0.091	0.124	0.125	0.126	0.157	0.101
R^2 (Between)	0.315	0.388	0.381	0.397	0.341	0.314
R^2 (Overall)	0.108	0.141	0.141	0.149	0.153	0.094
AIC	9498.600	8384.900	8113.100	8111.600	8040.600	6220.000
BIC	9516.000	8413.600	8152.900	8157.000	8103.000	6285.500
F-test	118.100	77.980	50.120	43.500	39.150	17.230

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Model comparison

4.4.1 The effect of corruption on political violence incidence

In this section we are going to compare the three model used to see if our independent variable, political corruption, has a robust relation with political violence incidence. First of all, we have grouped some variable, so there can be found: economic and population controls which include GDP per capita growth and population growth; climate controls that include the SPEI and SPEI^2; the social controls that include the exclusion by social group; the political and military controls that include the regime type and the military expenditure.

Looking at the results we can see that political corruption is positive and significant in almost all models. In particular, in the ZINB model. In the Negative Binomial model the relation is strong and positive in the less complex specifications and the independent variable has the same behavior in OLS regression, the relation is positive and significant in simple forms, but weakens after full controls, especially when controlling for military expenditure. Therefore, it can be said that the corruption–violence incidence link is robust and positive in all the count models and linear model, but the significance change when political and military controls are added. Then, knowing that the models are not directly comparable, if we want to look at the AIC and BIC among similar model families the best models are the followings. In the negative binomial we have the lower AIC and BIC in specification 3. In the ZINB model the best overall is specification 6, and in the OLS the best one is the latter, specification 9. To conclude, across all model specifications, the political corruption index shows a consistent and positive association with the incidence of political violence. This relationship is particularly robust and statistically significant in the ZINB model, even after the inclusion of economic, climatic, social and political-military controls. The better performance of the ZINB model tell us that the great number of zero has an impact in the regressions and that already prone to terrorist context are more likely to experience violence.

Table 14: Model comparison: Effect of corruption on violence incidence

	(NB)	(NB)	(NB)	(ZINB)	(ZINB)	(ZINB)	(OLS)	(OLS)	(OLS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Attacks									
Political corruption index	0.520**	0.450**	0.193	3.722***	2.919***	2.857***	0.285***	0.288***	0.039
	(0.205)	(0.213)	(0.238)	(0.367)	(0.405)	(0.536)	(0.049)	(0.049)	(0.030)
Economic and population controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Climate change controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Social control	NO	YES	YES	NO	YES	YES	NO	YES	YES
Political and military controls	NO	NO	YES	NO	NO	YES	NO	NO	YES
Constant	-1.828***	-1.927***	-3.240***	0.335	-0.146	-2.813***	-0.115***	-0.147***	-0.018
	(0.163)	(0.186)	(0.272)	(0.287)	(0.299)	(0.621)	(0.033)	(0.047)	(0.033)
inflate									
GDP per capita (log)				2.737***	2.691***	2.886***			
				(0.548)	(0.526)	(0.599)			
Constant				-26.096***	-25.671***	-27.334***			
				(5.237)	(5.013)	(5.668)			
/									
lnalpha				1.891***	1.869***	1.758***			
				(0.053)	(0.053)	(0.058)			
Obs	2052.000	2052.000	1652.000	1370.000	1370.000	1150.000	2193.000	2193.000	1764.000
R^2 (Within)							0.016	0.017	0.034
R^2 (Between)							0.023	0.036	0.113
R^2 (Overall)							0.012	0.015	0.035
AIC	7114.621	7115.355	5855.151	6438.768	6420.887	5409.138	106.470	107.543	-2358.067
BIC	7148.380	7154.741	5914.658	6485.771	6473.113	5479.803	140.628	147.394	-2297.838
LR chi²									
DF	5.000	6.000	10.000	5.000	6.000	10.000	51.000	52.000	54.000
Log likelihood	-3551.310	-3550.677	-2916.575	-3210.384	-3200.444	-2690.569	-47.235	-46.771	1190.033

The Negative Binomial and OLS are with Fixed Effects. Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4.2 The effect of corruption on political violence brutality

We discuss here in Table 15 the results of our model comparison that look at the relation between corruption and political violence brutality. We can see that political corruption is positive and significantly related to violence brutality in almost all models but with some differences. In the Negative Binomial model the relation is strong and positive in the less complex specifications, but it loses significance when adding the political controls and military expenditure. In the ZINB model, instead, corruption is always positive and significantly related to violence brutality, but it still loses significance when controlling for social exclusion. Then, in the OLS the behavior of political corruption is similar but is much more strong and significantly positive the relation with violence brutality. The only exception is specification 9, when we control for political al military factors. Therefore, it can be said that the corruption–violence brutality link is robust and generally positive in our models, but the significance and sign change when military expenditure is added as control variable. This reaction will be better investigated with our IV model. Finally, knowing that the models are not directly comparable, if we want to look at the AIC and BIC among similar model families the best models are always the full ones, where we control for all the control variables.

Table 15: Model comparison. Effects of corruption on violence brutality

	(NB) (1)	(NB) (2)	(NB) (3)	(ZINB) (4)	(ZINB) (5)	(ZINB) (6)	(OLS) (7)	(OLS) (8)	(OLS) (9)
Victims									
Political corruption index	0.440**	0.260	-0.001	1.369***	0.249	0.916*	0.763**	0.799**	-0.215
	(0.209)	(0.220)	(0.242)	(0.410)	(0.484)	(0.549)	(0.316)	(0.316)	(0.350)
Lagged Victims$_{t-1}$	0.000***	0.000***	0.000***	0.003***	0.003***	0.003***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Economic and population controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Climate change controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Social control	NO	YES	YES	NO	YES	YES	NO	YES	YES
Political and military controls	NO	NO	YES	NO	NO	YES	NO	NO	YES
Constant	-2.574***	-2.782***	-4.202***	3.126***	2.692***	1.844***	0.174	-0.232	0.563
	(0.169)	(0.189)	(0.286)	(0.347)	(0.359)	(0.630)	(0.214)	(0.306)	(0.393)
inflate									
GDP per capita (log)				0.855***	0.901***	0.729***			
				(0.136)	(0.163)	(0.142)			
Constant				-7.321***	-7.803***	-6.293***			
				(1.277)	(1.561)	(1.312)			
/									
lnalpha				1.572***	1.612***	1.418***			
				(0.167)	(0.182)	(0.181)			
Obs	2018.000	2018.000	1628.000	1370.000	1370.000	1150.000	2158.000	2158.000	1740.000
R^2 (Within)							0.125	0.126	0.101
R^2 (Between)							0.381	0.397	0.314
R^2 (Overall)							0.141	0.149	0.094
AIC	9124.178	9119.841	7634.747	8069.165	8048.115	6922.840	8113.145	8111.622	6219.957
BIC	9163.447	9164.720	7699.488	8121.391	8105.563	6998.552	8152.884	8157.037	6285.497
LR chi²									
DF	6.000	7.000	11.000	6.000	7.000	11.000	52.000	53.000	55.000
Log likelihood	-4555.089	-4551.921	-3805.374	-4024.583	-4013.057	-3446.420	-4049.573	-4047.811	-3097.979

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Robustness checks and alternative estimations

5.1 Climate change interacted with corruption

To better investigate climate change impact in our main model, we try to interact the Standardize Evaporization-Transpiration index with political corruption to look at the effect on the dependent variable.

The results in Table 16 show that the impact of corruption interacted with our climate control variable (SPEI) on political violence incidence is positive and slightly significant only in the negative binomial model. In our best model, the ZINB, and in the OLS the relation is negative ans non significant at all. However, it is interesting to see that when political corruption is significant, the SPEI tends to be not significant in its relation with violence incidence. Anyway from the findings, we know that their interaction is not really significant in our models. Looking at the findings of Table 17 we have a general positive relation between the corruption interacted with SPEI and violence brutality. This relation is particularly significant in the negative binomial model, when we do not take into account the zeros in our data, and here the corruption-climate interaction is always highly strong and positive. However, in the ZINB model and in the OLS, this relation is never significant meaning that in general, the corruption-climate interaction doesn't impact directly violence brutality. Anyway, comparing this table with the previous one, it can be said that the corruption-climate interaction is more linked with violence brutality that violence incidence. Still the Standardized Evapotranspiration–Precipitation Index alone, in this case of country-level analysis, is insufficient to capture the relationship between climate variability and violence, indicating the need for further study. Notably, in our sample countries like Guinea experienced extreme climatic events, while also having great level of corruption and population growth; however, Guinea is not between the most violent countries. Furthermore, the countries with high SPEI values includes several island states, such as Mauritius, Comoros, and Cape Verde, that are among the least violent and least corrupted over the examined period.

Table 16: Effect of corruption interacted with SPEI on political violence incidence

	(NB)	(NB)	(NB)	(ZINB)	(ZINB)	(ZINB)	(OLS)	(OLS)	(OLS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Attacks									
Political corruption index	0.531**	0.293	0.277	2.887***	2.527***	2.737***	0.285***	0.258***	0.038
	(0.219)	(0.218)	(0.242)	(0.448)	(0.442)	(0.586)	(0.049)	(0.049)	(0.030)
SPEI (annual)	-0.331*	-0.292*	-0.402**	0.350	0.408	0.464	0.013	0.006	0.007
	(0.176)	(0.171)	(0.189)	(0.357)	(0.355)	(0.389)	(0.023)	(0.022)	(0.013)
Political corruption index × SPEI (annual)	0.435	0.454*	0.544*	-0.097	-0.363	-0.325	-0.018	-0.006	-0.008
	(0.267)	(0.258)	(0.289)	(0.581)	(0.576)	(0.636)	(0.037)	(0.036)	(0.022)
GDP per capita growth (%)	-0.008	-0.012**	-0.013**	-0.033**	-0.054***	-0.073***	-0.000	-0.000	-0.002***
	(0.005)	(0.005)	(0.006)	(0.015)	(0.016)	(0.019)	(0.001)	(0.001)	(0.001)
Population growth (%)	-0.069**	-0.071***	-0.074**	-0.008	-0.042	-0.108**	-0.001	0.000	-0.005**
	(0.028)	(0.024)	(0.029)	(0.049)	(0.051)	(0.053)	(0.004)	(0.004)	(0.002)
$SPEI^2$	0.011	-0.012	-0.046	-0.228*	-0.231*	-0.173	-0.007	-0.009	-0.006
	(0.058)	(0.056)	(0.062)	(0.129)	(0.127)	(0.138)	(0.008)	(0.007)	(0.004)
Exclusion by Social Group index	0.260	1.246***	1.214***	1.658***	2.809***	2.571***	0.053	-0.043	-0.001
	(0.206)	(0.232)	(0.253)	(0.378)	(0.492)	(0.561)	(0.058)	(0.065)	(0.040)
Regime type		0.392***	0.288***		0.576***	0.563***		0.025***	0.014***
		(0.041)	(0.044)		(0.082)	(0.091)		(0.006)	(0.004)
Regime end type		0.124***	0.082***		0.238***	0.197***		0.019***	0.007***
		(0.015)	(0.016)		(0.029)	(0.034)		(0.002)	(0.001)
Regime type × Regime end type		-0.030***	-0.019***		-0.049***	-0.043***		-0.005***	-0.002***
		(0.004)	(0.004)		(0.007)	(0.008)		(0.001)	(0.000)
Military expenditure (log)			0.107***			0.085			0.010***
			(0.042)			(0.163)			(0.003)
Constant	-1.994***	-3.699***	-3.324***	-0.129	-3.097***	-2.721***	-0.144***	-0.182***	-0.016
	(0.191)	(0.256)	(0.276)	(0.316)	(0.521)	(0.647)	(0.048)	(0.054)	(0.034)
inflate									
GDP per capita (log)				2.690***	2.616***	2.880***			
				(0.526)	(0.497)	(0.598)			
Constant				-25.660***	-24.880***	-27.280***			
				(5.014)	(4.731)	(5.657)			
/									
lnalpha				1.869***	1.802***	1.757***			
				(0.053)	(0.054)	(0.058)			
Obs	2052	2052	1652	1370	1370	1150	2193	2193	1764
R^2 (Within)							0.017	0.051	0.034
R^2 (Between)							0.035	0.030	0.111
R^2 (Overall)							0.015	0.030	0.034
AIC	7114.700	6988.500	5853.600	6422.900	6374.900	5410.900	109.300	38.880	-2356.200
BIC	7159.700	7050.400	5918.500	6480.300	6448.000	5486.600	154.900	101.500	-2290.500
Wald chi²	19.460	136.200	94.600	140.000	194.000	137.000			
F-test							5.247	11.370	5.489

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Effect of corruption interacted with SPEI on political violence brutality

	(NB)	(NB)	(NB)	(ZINB)	(iNB)	(ZINB)	(OLS)	(OLS)	(OLS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
main									
Lagged victims$_{t-1}$	0.000***	0.000***	0.000***	0.003***	0.003***	0.003***			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Political corruption index	0.447**	0.142	0.154	0.334	0.319	1.118*	1.236***	0.995***	-0.058
	(0.226)	(0.224)	(0.246)	(0.517)	(0.513)	(0.594)	(0.331)	(0.329)	(0.354)
SPEI (annual)	-0.634***	-0.571***	-0.641***	0.275	0.147	0.226	-0.060	-0.105	-0.109
	(0.191)	(0.185)	(0.202)	(0.459)	(0.451)	(0.421)	(0.152)	(0.150)	(0.154)
Political corruption index × SPEI (annual)	0.983***	0.924***	0.991***	0.290	0.449	0.574	0.168	0.253	0.272
	(0.286)	(0.277)	(0.306)	(0.645)	(0.640)	(0.633)	(0.248)	(0.244)	(0.257)
GDP per capita growth (%)	-0.005	-0.011*	-0.013**	-0.047***	-0.046***	-0.031	-0.008*	-0.007	-0.023***
	(0.006)	(0.006)	(0.007)	(0.013)	(0.013)	(0.019)	(0.005)	(0.005)	(0.006)
Population growth (%)	-0.043	-0.052*	-0.071**	0.042	0.046	0.017	-0.144***	-0.132***	-0.210***
	(0.030)	(0.027)	(0.031)	(0.033)	(0.035)	(0.046)	(0.029)	(0.029)	(0.030)
SPEI^2	0.009	-0.016	-0.039	-0.043	-0.035	0.006	-0.031	-0.042	-0.026
	(0.063)	(0.061)	(0.066)	(0.126)	(0.127)	(0.129)	(0.051)	(0.050)	(0.049)
Exclusion by Social Group index	0.598***	1.491***	1.380***	1.832***	1.870***	1.474***	0.691*	0.295	0.103
	(0.210)	(0.239)	(0.262)	(0.394)	(0.483)	(0.522)	(0.390)	(0.437)	(0.473)
Regime type		0.446***	0.370***		0.115	0.183*		0.196***	0.149***
		(0.045)	(0.049)		(0.095)	(0.098)		(0.041)	(0.042)
Regime end type		0.154***	0.123***		0.037	0.098***		0.137***	0.090***
		(0.016)	(0.017)		(0.034)	(0.035)		(0.015)	(0.016)
Regime type × Regime end type		-0.038***	-0.030***		-0.013	-0.028***		-0.031***	-0.021***
		(0.004)	(0.005)		(0.008)	(0.009)		(0.004)	(0.004)
Military expenditure (log)			0.065			0.425**			0.102***
			(0.042)			(0.171)			(0.038)
Constant	-2.945***	-4.741***	-4.356***	2.634***	2.321***	1.678**	-0.354	-0.844**	0.288
	(0.198)	(0.271)	(0.292)	(0.382)	(0.617)	(0.659)	(0.322)	(0.361)	(0.399)
inflate									
GDP per capita (log)				0.903***	0.871***	0.734***			
				(0.164)	(0.150)	(0.145)			
Constant				-7.824***	-7.511***	-6.348***			
				(1.576)	(1.430)	(1.349)			
/									
lnalpha				1.614***	1.579***	1.427***			
				(0.183)	(0.176)	(0.184)			
Obs	2018.000	2018.000	1628.000	1370.000	1370.000	1150.000	2193.000	2193.000	1764.000
R² (Within)							0.020	0.055	0.060
R² (Between)							0.145	0.164	0.204
R² (Overall)							0.030	0.049	0.057
AIC	9110.016	8974.111	7626.238	8049.914	8052.645	6924.035	8476.396	8400.935	6370.721
BIC	9160.505	9041.430	7696.374	8112.585	8130.983	7004.795	8521.941	8463.558	6436.425
Wald chi²	238.448	338.047	243.161	265.279	268.548	252.485			
F-test							6.119	12.523	9.864

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Instrumental Variable Approach

To address the inconsistencies in some specifications of our models, particularly when controlling for military expenditure in the linear model, we complement our analysis with an instrumental variables (IV) strategy. This approach serves as a robustness check and allows us to address endogeneity concerns surrounding our key explanatory variable, political corruption. By isolating the exogenous variation in corruption, the IV framework enables us to estimate its causal impact on both the incidence and the brutality of political violence.

We use two external instruments: state ownership of the economy and government censorship of the media. Both instruments are well grounded in the existing literature linking institutional structures to corruption levels. State ownership has long been associated with higher corruption risks, especially in contexts where political elites retain control over major economic sectors. Quinn (2008) shows that majority state ownership increases opportunities and incentives for corrupt or inefficient behavior, as political and managerial elites often use national resources for short-term personal or political gains rather than for long-term economic objectives. His cross-national analysis highlights state ownership, GDP per capita, government spending, and democratic governance as key predictors of corruption and bureaucratic inefficiency.

Media freedom represents a second key determinant of corruption. A free press plays an essential role in disseminating information, enforcing social accountability, and increasing the political cost of engaging in corrupt behavior. In democratic contexts, where civil participation is higher and elections allow citizens to sanction misconduct, press freedom serves as an important deterrent against corruption. Empirical studies, including Treisman (2000) and Bhattacharyya and Hodler (2015), provide robust evidence that both democratization and media freedom reduce corruption, and that these two forces reinforce each other. Bhattacharyya and Hodler (2015), for instance, demonstrate that democratization and media freedom are complements in the fight against corruption, using panel data from 129 countries between 1980 and 2007.

Drawing on this literature, our IV strategy leverages variation in state ownership and media censorship to isolate the exogenous component of political corruption, thereby strengthening the credibility of our causal estimates on political violence.

5.2.1 Linear Regression with IV

Our first robustness check that employs an instrumental variables (IV) approach use a linear model with a continuous dependent variable. We instrument political corruption with state ownership of the economy and government censorship of the media, and then estimate the model using two-stage least squares. The results in Table 18 indicate that the instruments are valid and relevant: both are strongly significant in the first-stage regression, suggesting that they effectively address the endogeneity concerns related to corruption.

Turning to the second stage, political corruption emerges as strongly and positively associated with both the incidence and the brutality of political violence. Holding all other variables constant, a one-unit increase in corruption is associated with an increase of 0.5 in violence incidence, while the number of victims (violence brutality) rises by 4.6 units. These findings support the interpretation that corruption plays an important role in escalating both the incidence and brutality of political violence.

The IV estimates also confirm the expected relationships for several control variables. GDP per capita growth remains strongly and negatively associated with political violence, in line with the literature. Population growth is consistently negative as well, although with lower statistical precision. The SPEI index and its quadratic term do not show significant effects, indicating limited evidence for climatic pressure in this specification. Exclusion by social group is positively signed but not statistically significant, possibly due to collinearity with corruption. Finally, the interaction term between regime type and regime end type continues to display a negative and significant effect, supporting the idea that more democratic transitions reduce political violence. Military expenditure remains positive and strongly related to both violence incidence and brutality, reinforcing the robustness of this relationship across different models.

Table 18: IV corruption effect on political violence: incidence and brutality (FE)

	Attacks rate		Victims rate	
	(1) First stage	(2) Second stage	(3) First stage	(4) Second stage
Government censorship effort - Media	-0.012***		-0.012***	
	(0.004)		(0.004)	
State ownership of economy	0.038***		0.038***	
	(0.004)		(0.004)	
Political corruption index		0.544***		4.649**
		(0.159)		(1.836)
GDP per capita growth (%)		-0.002***		-0.024***
		(0.001)		(0.006)
Population growth (%)		-0.005*		-0.204***
		(0.003)		(0.031)
SPEI (annual)		0.008		0.095
		(0.005)		(0.062)
$SPEI^2$		-0.005		-0.025
		(0.004)		(0.052)
Exclusion by Social Group index		0.066		0.666
		(0.047)		(0.546)
Regime type		0.010**		0.104**
		(0.004)		(0.046)
Regime end type		0.007***		0.088***
		(0.001)		(0.016)
Regime type × Regime end type		-0.002***		-0.020***
		(0.000)		(0.005)
Military expenditure (log)		0.008**		0.083**
		(0.003)		(0.040)
Constant	0.673***		0.673***	
	(0.022)		(0.022)	
Obs	1764	1764	1764	1764
R^2 (Within)	0.090		0.090	
Anderson LM		69.872		69.872
Cragg-Donald F		36.183		36.183
Sargan		1.521		6.775
Sargan p-val		0.217		0.009

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.2 Control function or Two-Stage Residual Inclusion (2SRI)

The last robustness checks is the Control function approach or Two-Stage Residual Inclusion described in the paper of Terza (2017). This approach is useful in the cases of non linearity of the dependent variable and, indeed, we run it using the count of the attacks and the victims.

In the first stage, corruption is regressed with a pooled regression on the two excluded instruments, state ownership of the economy and government censorship of the media, together with the full set of controls. The residuals from this regression capture the endogenous component of corruption. In the second stage, we estimate a Zero-Inflated Negative Binomial model for political violence incidence and brutality including both the original corruption variable and the first-stage residual. This control function purges corruption of the endogenous variation and yields consistent estimates.

The instruments are strongly significant in the first stage, confirming their relevance. In the second stage, corruption remains positive and statistically significant in Table 19. This indicates that, once endogeneity is properly addressed, higher corruption causally increases both the incidence and the brutality of political violence.

Turning to the control variables, the negative relationship between GDP per capita growth and political violence is confirmed across both specifications, consistent with existing literature linking economic performance to lower conflict risk. Population growth is negatively and significantly associated with violence incidence, although it becomes insignificant in the brutality model. Exclusion by social group is positively related to both outcomes, but its effects are not statistically significant. The interaction between regime type and regime end type is negative and significant in the violence incidence model, suggesting that more democratic transitions tend to reduce violent events, while it becomes irrelevant when explaining violence brutality.

A particularly important result concerns military expenditure. Under the Control function approach, military spending becomes strongly and significantly associated with higher levels of both violence incidence and brutality. This supports the idea that in highly corrupt contexts, higher military expenditure may reinforce coercive capacity, crowd out social spending, and ultimately intensify violence dynamics.

Finally, regarding climate-related variables, the results in Table 19 the SPEI index is positive and highly significant for both political violence incidence and brutality, while its quadratic term remains insignificant. This suggests that increases in rainfall, rather than extreme droughts or floods, are associated with higher levels of violence, particularly in countries characterized by weak institutions, corruption, and high military spending. Such rainfall variability can affect agricultural yields, disrupt livelihoods, and heighten competition over resources. When institutions fail to manage these pressures effectively, the result may be an escalation of violence. This mechanism may be further amplified in countries that allocate substantial resources to the military instead of public goods, creating a vicious cycle in which corruption, inadequate climate adaptation, and rising violence reinforce each other.

These findings highlight that fighting corruption is essential not only for institutional quality but also for mitigating climate-related violence. Transparent management of public resources, especially in contexts where climate change threatens agricultural production and socio-economic stability, is crucial for preventing further escalation of political violence.

Table 19: Corruption effect on political violence using 2SRI (Attacks and Victims)

	Count of attacks		Victims	
	(1) First stage (OLS)	(2) Second stage (ZINB)	(3) First stage (OLS)	(4) Second stage (ZINB)
Government censorship effort - Media	0.037***		0.037***	
	(0.006)		(0.006)	
State ownership of economy	0.056***		0.056***	
	(0.006)		(0.006)	
Political corruption index		8.976***		4.382***
		(1.225)		(1.289)
Residuals		-6.421***		-3.878***
		(1.178)		(1.335)
Lagged victims$_{t-1}$				0.002***
				(0.000)
GDP per capita growth (%)		-0.044**		-0.030**
		(0.018)		(0.015)
Population growth (%)		-0.091*		0.009
		(0.049)		(0.038)
SPEI (annual)		0.378***		0.596***
		(0.139)		(0.136)
SPEI^2		-0.040		0.105
		(0.136)		(0.129)
Exclusion by Social Group index		0.792		0.634
		(0.608)		(0.561)
Regime type		0.435***		0.125
		(0.094)		(0.099)
Regime end type		0.145***		0.078**
		(0.035)		(0.036)
Regime type × Regime end type		-0.018*		-0.015
		(0.009)		(0.010)
Military expenditure (log)		0.391**		0.515***
		(0.161)		(0.169)
Constant	0.441***	-5.931***	0.441***	-0.006
	(0.022)	(0.820)	(0.022)	(0.899)
inflate				
GDP per capita (log)		2.894***		0.695***
		(0.644)		(0.129)
Constant		-27.533***		-5.969***
		(6.116)		(1.168)
/				
lnalpha		1.728***		1.364***
		(0.058)		(0.169)
Obs	1764	1150	1764	1150
Log-Lik	494.210	-2676.317	494.210	-3442.232
BIC	-898.715	5458.346	-898.715	6997.225
AIC	-964.419	5382.634	-964.419	6916.464

The second stage uses a ZINB model. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 *Discussion and conclusion*

This paper has examined the impact of political corruption on the incidence and brutality of political violence in 49 Sub-Saharan African countries from 1970 to 2020, with particular attention to the role of climate change. Building on two major strands of literature, corruption on the one hand, and terrorism and political violence on the other, our analysis evaluates how corruption shapes both the incidence and brutality of political violence, while controlling for economic performance, demographic trends, institutional factors, and environmental pressures. Across all empirical estimators, including fixed-effects Negative Binomial models, Zero-Inflated Negative Binomial models, and linear fixed-effects regressions, our main finding is remarkably consistent: corruption has a strong, positive, and statistically significant impact on both the incidence and brutality of political violence.

This relationship remains robust when re-estimating the models with lagged corruption (five years) and lagged controls (one year). In many cases, the lagged effects even strengthen the magnitude of the relationship, indicating that the consequences of corruption unfold over time and contribute to contemporary violence.

To further interrogate these relationships, we explore whether climate change interacts with corruption in shaping political violence. The evidence suggests that the direct effect of climate variability, measured through the SPEI index, is generally weak or insignificant in most baseline models, except in some specifications of the Negative Binomial estimator. This indicates either that the model is not fully capturing climate impacts or that country-level SPEI data may not adequately reflect localized environmental stressors. Nevertheless, when we introduce an instrumental variable approach for the linear model and a control function (2SRI) strategy for the count models to address endogeneity in corruption, the results become more informative. Under these causal frameworks, corruption remains a key driver of political violence, and climate variability, particularly increases in precipitation, emerges as a significant factor contributing to both the incidence and brutality of violent events. Importantly, this pattern suggests that rainfall variability, rather than extreme droughts or floods, is associated with higher levels of violence. In socio-political environments characterized by weak institutions, high corruption, and elevated military spending, changes in rainfall can disrupt agricultural yields, reduce livelihoods, and heighten competition over natural resources. When governments lack the capacity or will to manage these pressures effectively, grievances may deepen, recruitment into armed groups may increase, and violence can escalate. This dynamic is further amplified when resources are disproportionately allocated to the military instead of public goods, creating a vicious cycle in which corruption, inadequate climate adaptation, and political violence reinforce one another.

These findings underscore the central role of fighting corruption in reducing political instability and mitigating the security implications of climate change. Transparent and accountable management of public resources, especially in countries where livelihoods are tightly linked to environmental variability, is essential for preventing violence and promoting long-term stability. Strengthening institutions is therefore not only a governance objective but also a climate adaptation strategy.

Over a decade ago, at the rise of Boko Haram in Nigeria, Wole Soyinka warned against interpreting such movements as spontaneous or isolated. Instead, he linked their emergence to decades of political impunity and entrenched corruption. Although field evidence has long pointed to this connection, academic research has only recently begun to systematically analyze the corruption–terrorism nexus. This paper contributes to that growing agenda by providing rigorous empirical evidence on the causal relationship between corruption and political violence, reinforcing broader arguments about the necessity of accountable institutions for development and social peace (Acemoglu and Robinson, 2021). This aligns with Goal 16 of the 2030 Agenda for Sustainable Development, which highlights strong and inclusive institutions as a foundational condition for reducing all forms of violence.

By showing that corruption significantly increases both the incidence and brutality of political violence—and that climate variability can exacerbate these effects—this study highlights the urgent need to integrate anti-corruption efforts, institutional reform, and climate resilience into a unified policy framework for Sub-Saharan Africa. Without addressing corruption, strategies for peacebuilding or climate adaptation are likely to fall short. With stronger institutions, however, countries can better manage environmental pressures, allocate resources more equitably, and move closer toward peaceful and sustainable development.

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A Appendix A: Additional tables and figures

Table A.1: Sub-Saharan African Countries and their ISO Codes

Country	**ISO code**	**Country**	**ISO code**
Angola	AGO	Madagascar	MDG
Benin	BEN	Malawi	MWI
Botswana	BWA	Mali	MLI
Burkina Faso	BFA	Mauritania	MRT
Burundi	BDI	Mauritius	MUS
Cape Verde	CPV	Mozambique	MOZ
Cameroon	CMR	Namibia	NAM
Central African Republic	CAF	Niger	NER
Chad	TCD	Nigeria	NGA
Comoros	COM	Republic of the Congo	COG
Côte d'Ivoire	CIV	Rwanda	RWA
Democratic Republic of the Congo	COD	Sao Tome and Principe	STP
Djibouti	DJI	Senegal	SEN
Equatorial Guinea	GNQ	Seychelles	SYC
Eritrea	ERI	Sierra Leone	SLE
Eswatini	SWZ	Somalia	SOM
Ethiopia	ETH	South Africa	ZAF
Gabon	GAB	South Sudan	SSD
Ghana	GHA	Sudan	SDN
Guinea	GIN	Tanzania	TZA
Guinea-Bissau	GNB	The Gambia	GMB
Kenya	KEN	Togo	TGO
Lesotho	LSO	Uganda	UGA
Liberia	LBR	Zambia	ZMB
Madagascar	MDG	Zimbabwe	ZWE

B Appendix: Additional tables and figures

Table B.1: Hausman Test - Poisson

	(1)	(2)
	FE	RE
Count of the Attacks		
Political corruption index	1.175***	1.187***
	(0.105)	(0.105)
GDP per capita growth (%)	-0.045***	-0.045***
	(0.001)	(0.001)
Population growth (%)	-0.046***	-0.046***
	(0.007)	(0.007)
SPEI (annual)	-0.050***	-0.049***
	(0.014)	(0.014)
SPEI^2	-0.172***	-0.173***
	(0.016)	(0.016)
Exclusion by Social Group index	4.569***	4.555***
	(0.106)	(0.106)
Regimes of the world	0.617***	0.617***
	(0.014)	(0.014)
Regime end type	0.182***	0.182***
	(0.005)	(0.005)
Regimes of the world × Regime end type	-0.025***	-0.025***
	(0.001)	(0.001)
Military expenditure (log)	0.088***	0.088***
	(0.010)	(0.010)
Constant		-4.017***
		(0.267)
/		
lnalpha		1.018***
		(0.179)
Observations	1652	1764

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Effect of corruption on attacks incidence - Poisson regression

	(1)	(2)	(3)	(4)	(5)	(6)
Count of the Attacks						
Political corruption index	5.311***	5.396***	5.330***	5.296***	2.059***	1.175***
	(0.079)	(0.082)	(0.083)	(0.083)	(0.090)	(0.105)
GDP per capita growth (%)		-0.004***	-0.006***	-0.006***	-0.029***	-0.045***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population growth (%)		-0.001	-0.004	0.002	-0.012**	-0.046***
		(0.005)	(0.005)	(0.006)	(0.005)	(0.007)
SPEI (annual)			-0.040***	-0.017	0.003	-0.050***
			(0.014)	(0.014)	(0.014)	(0.015)
SPEI^2			-0.220***	-0.211***	-0.175***	-0.172***
			(0.016)	(0.016)	(0.015)	(0.016)
Exclusion by Social Group index				-0.956***	3.102***	4.569***
				(0.079)	(0.098)	(0.106)
Regimes of the world					0.982***	0.617***
					(0.014)	(0.014)
Regime end type					0.416***	0.182***
					(0.005)	(0.005)
Regimes of the world $\times$ Regime end type					-0.072***	-0.025***
					(0.001)	(0.001)
Military expenditure (log)						0.088***
						(0.010)
Obs	2254	2103	2052	2052	2052	1652
AIC	60007.700	58995.900	58779.200	58631.100	47483.400	38422.100
BIC	60013.500	59012.900	58807.400	58664.900	47534.100	38476.200
Wald chi²	4491.700	4315.300	4508.100	4593.900	10577.400	7195.300

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Effect of corruption on attacks brutality - Poisson regression

	(1)	(2)	(3)	(4)	(5)	(6)
Victims						
Lagged Victims$_{t-1}$	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Political corruption index	2.965***	3.101***	3.183***	3.179***	1.739***	0.889***
	(0.026)	(0.027)	(0.027)	(0.027)	(0.031)	(0.036)
GDP per capita growth (%)		-0.006***	-0.006***	-0.006***	-0.012***	-0.016***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population growth (%)		-0.078***	-0.078***	-0.078***	-0.071***	-0.102***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
SPEI (annual)			0.151***	0.157***	0.139***	0.135***
			(0.005)	(0.005)	(0.005)	(0.005)
SPEI^2			-0.009*	-0.004	-0.005	0.038***
			(0.005)	(0.005)	(0.005)	(0.005)
Exclusion by Social Group index				-0.439***	1.928***	2.377***
				(0.033)	(0.041)	(0.045)
Regime of the world					0.658***	0.491***
					(0.005)	(0.005)
Regime end type					0.287***	0.175***
					(0.002)	(0.002)
Regime × Regime end type					-0.055***	-0.031***
					(0.000)	(0.000)
Military expenditure (log)						0.122***
						(0.004)
Obs	2159	2018	2018	2018	2018	1628
AIC	369902.4	357915.4	356887.8	356715.5	314202.4	275089.6
BIC	369913.8	357937.8	356921.4	356754.8	314258.5	275148.9
Wald chi²	129662.5	130727.3	130142.9	130207.6	143598.1	112688.0

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Effect of corruption on attacks incidence - ZINB logit vs probit

	(1) logit	(2) probit	(3) logit	(4) probit	(5) logit	(6) probit
Sum of the Attacks						
Political corruption index	3.722***	3.726***	2.919***	2.916***	2.857***	2.860***
	(0.367)	(0.366)	(0.405)	(0.405)	(0.536)	(0.536)
GDP per capita growth (%)	-0.044***	-0.044***	-0.033**	-0.033**	-0.071***	-0.071***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.018)	(0.018)
Population growth (%)	-0.040	-0.040	-0.008	-0.008	-0.104**	-0.104**
	(0.046)	(0.046)	(0.049)	(0.049)	(0.053)	(0.053)
SPEI (annual)	0.249*	0.250*	0.294**	0.295**	0.281**	0.281**
	(0.135)	(0.135)	(0.133)	(0.133)	(0.141)	(0.141)
$SPEI^2$	-0.191	-0.191	-0.229*	-0.229*	-0.173	-0.172
	(0.133)	(0.133)	(0.129)	(0.129)	(0.138)	(0.138)
Exclusion by Social Group index			1.652***	1.660***	2.575***	2.578***
			(0.376)	(0.376)	(0.559)	(0.560)
Regime of the world					0.567***	0.567***
					(0.091)	(0.091)
Regime end type					0.196***	0.196***
					(0.035)	(0.035)
Regime of the world × Regime end type					-0.043***	-0.043***
					(0.008)	(0.008)
Military expenditure (log)					0.092	0.094
					(0.163)	(0.163)
Constant	0.335	0.327	-0.146	-0.154	-2.813***	-2.823***
	(0.287)	(0.287)	(0.299)	(0.298)	(0.621)	(0.621)
inflate						
GDP per capita (log)	2.737***	1.628***	2.691***	1.593***	2.886***	1.677***
	(0.548)	(0.288)	(0.526)	(0.280)	(0.599)	(0.305)
Constant	-26.100***	-15.550***	-25.670***	-15.210***	-27.330***	-15.900***
	(5.237)	(2.745)	(5.013)	(2.661)	(5.668)	(2.869)
/						
lnalpha	1.891***	1.899***	1.869***	1.876***	1.758***	1.763***
	(0.053)	(0.051)	(0.053)	(0.051)	(0.058)	(0.056)
Obs	1370	1370	1370	1370	1150	1150
AIC	6438.800	6438.400	6420.900	6420.400	5409.100	5408.800
BIC	6485.800	6485.400	6473.100	6472.600	5479.800	5479.400
DF	5	5	6	6	10	10
Log likelihood	-3210.400	-3210.200	-3200.400	-3200.200	-2690.600	-2690.400

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Panel OLS - Hausman Test

	(1) FE	(2) RE
Political corruption index	0.039	0.035
	(0.030)	(0.023)
GDP per capita growth (%)	-0.002***	-0.002***
	(0.001)	(0.001)
Population growth (%)	-0.005**	-0.007***
	(0.002)	(0.002)
SPEI (annual)	0.002	0.002
	(0.005)	(0.005)
SPEI^2	-0.006	-0.006
	(0.004)	(0.004)
Exclusion by Social Group index	0.001	0.044
	(0.040)	(0.028)
Regime of the world	0.014***	0.014***
	(0.004)	(0.003)
Regime end type	0.007***	0.006***
	(0.001)	(0.001)
Regime of the world × Regime end type	-0.002***	-0.002***
	(0.000)	(0.000)
Military expenditure (log)	0.010***	0.010***
	(0.003)	(0.003)
Constant	-0.018	-0.034
	(0.033)	(0.025)
Observations	1764	1764

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Hausman test results: ²(10) = 52.32 with p = 0.0000. So we prefer FE.

B.1 Lagged Variables

B.1.1 Negative Binomial with lagged variables

Table B.6: Effect of lagged corruption on political violence incidence with fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Sum of the Attacks						
Lagged Political corruption index$_{t-5}$	0.537***	0.558***	0.445**	0.275	-0.089	0.052
	(0.197)	(0.206)	(0.208)	(0.215)	(0.218)	(0.245)
Lagged GDP per capita growth (%)		-0.001	-0.001	0.000	-0.003	-0.004
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Lagged Population growth (%)		-0.043	-0.043	-0.045	-0.039	-0.073***
		(0.030)	(0.030)	(0.029)	(0.027)	(0.028)
Lagged SPEI (annual)			-0.172***	-0.186***	-0.142**	-0.176**
			(0.064)	(0.065)	(0.064)	(0.071)
Lagged SPEI^2			-0.181***	-0.182***	-0.193***	-0.216***
			(0.066)	(0.066)	(0.066)	(0.071)
Lagged Exclusion by Social Group index				0.585***	1.456***	1.462***
				(0.209)	(0.241)	(0.266)
Lagged Regime type					0.357***	0.263***
					(0.042)	(0.044)
Lagged Regime end type					0.105***	0.071***
					(0.015)	(0.016)
Lagged Regime type × Lagged Regime end type					-0.029***	-0.019***
					(0.004)	(0.004)
Lagged Military expenditure (log)						0.105**
						(0.044)
Constant	-1.897***	-1.796***	-1.672***	-1.925***	-3.305***	-3.029***
	(0.138)	(0.162)	(0.166)	(0.189)	(0.259)	(0.275)
Obs	2029	1913	1867	1867	1867	1512
AIC	7118.9	6842.4	6822.6	6816.9	6736.1	5600.5
BIC	7130.2	6864.6	6855.8	6855.6	6791.4	5659.0
Wald chi²	7.439	8.900	18.850	26.810	104.800	86.400

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Effect of lagged corruption on political violence brutality with fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Victims						
Lagged Victims	0.000	0.000	0.000	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Political corruption index$_{t-5}$	0.403**	0.492**	0.376*	0.134	-0.230	-0.109
	(0.202)	(0.208)	(0.210)	(0.219)	(0.220)	(0.244)
Lagged GDP per capita growth (%)		-0.004	-0.004	-0.003	-0.005	-0.006
		(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Lagged Population growth (annual %)		-0.020	-0.022	-0.025	-0.019	-0.043
		(0.030)	(0.030)	(0.029)	(0.026)	(0.027)
Lagged SPEI (annual)			-0.180**	-0.196***	-0.181**	-0.152**
			(0.070)	(0.071)	(0.070)	(0.074)
Lagged SPEI^2			-0.283***	-0.281***	-0.292***	-0.258***
			(0.074)	(0.074)	(0.073)	(0.076)
Lagged Exclusion by Social Group index				0.765***	1.550***	1.452***
				(0.212)	(0.245)	(0.268)
Lagged Regime type					0.395***	0.319***
					(0.045)	(0.049)
Lagged Regime end type					0.127***	0.101***
					(0.016)	(0.017)
Lagged Regime type × Lagged Regime end type					-0.035***	-0.027***
					(0.004)	(0.005)
Lagged Military expenditure (log)						0.068
						(0.045)
Constant	-2.601***	-2.580***	-2.408***	-2.721***	-4.206***	-3.954***
	(0.140)	(0.165)	(0.169)	(0.190)	(0.267)	(0.284)
Obs	1983	1861	1861	1861	1861	1512
AIC	9268.3	8866.7	8851.8	8840.7	8750.6	7410.3
BIC	9285.1	8894.4	8890.5	8884.9	8811.4	7474.2
Wald chi²	212.3	208.8	238.1	243.3	313.7	222.2

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.1.2 Zero-Inflated Negative Binomial with lagged variables

Table B.8: Effect of lagged corruption on political violence incidence

	(1)	(2)	(3)	(4)	(5)	(6)
Count of the Attacks						
Lagged Political corruption index$_{t-5}$	3.752***	3.820***	3.496***	2.845***	2.692***	3.028***
	(0.317)	(0.328)	(0.344)	(0.367)	(0.372)	(0.527)
Lagged GDP per capita growth (%)		-0.0168	-0.0216	-0.00639	-0.0351**	-0.0480**
		(0.0141)	(0.0150)	(0.0159)	(0.0157)	(0.0188)
Lagged Population growth (%)		0.000597	-0.0157	0.0157	-0.0237	-0.0660
		(0.0416)	(0.0450)	(0.0472)	(0.0496)	(0.0527)
Lagged SPEI			0.143	0.0401	-0.0338	0.126
			(0.138)	(0.137)	(0.134)	(0.153)
Lagged SPEI^2			-0.441***	-0.481***	-0.420***	-0.342**
			(0.130)	(0.127)	(0.127)	(0.141)
Lagged Exclusion by social group				1.766***	2.894***	2.486***
				(0.349)	(0.454)	(0.528)
Lagged Regime type					0.554***	0.543***
					(0.0794)	(0.0888)
Lagged Regime end type					0.221***	0.193***
					(0.0288)	(0.0360)
Lagged Regime type $\times$ Lagged Regime end type					-0.0464***	-0.0407***
					(0.00686)	(0.00808)
Lagged Military expenditure (log)						0.166
						(0.172)
Constant	0.0347	0.00723	0.497*	-0.225	-3.128***	-2.901***
	(0.224)	(0.234)	(0.263)	(0.290)	(0.488)	(0.623)
inflate						
GDP per capita (log)	2.739***	2.760***	2.640***	2.600***	2.540***	2.710***
	(0.534)	(0.543)	(0.532)	(0.511)	(0.496)	(0.546)
Constant	-25.86***	-26.09***	-25.12***	-24.77***	-24.15***	-25.59***
	(5.098)	(5.190)	(5.072)	(4.867)	(4.717)	(5.129)
/						
lnalpha	1.910***	1.911***	1.875***	1.847***	1.787***	1.744***
	(0.0543)	(0.0541)	(0.0537)	(0.0539)	(0.0553)	(0.0595)
Obs	1433	1431	1369	1369	1369	1139
AIC	6473.4	6469.3	6423.9	6399.8	6357.3	5352.2
BIC	6499.7	6506.1	6470.9	6452.0	6425.1	5422.7
DF	1	3	5	6	9	10
Log likelihood	-3231.7	-3227.6	-3203.0	-3189.9	-3165.6	-2662.1

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: Effect of lagged corruption on political violence brutality

	(1)	(2)	(3)	(4)	(5)	(6)
Victims						
Lagged Victims	0.00265***	0.00272***	0.00261***	0.00266***	0.00257***	0.00231***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Political corruption index$_{t-5}$	1.478***	1.474***	1.161***	0.311	0.344	1.703***
	(0.410)	(0.409)	(0.416)	(0.459)	(0.463)	(0.547)
Lagged GDP per capita growth (%)		-0.024**	-0.026**	-0.016	-0.019	-0.007
		(0.011)	(0.012)	(0.012)	(0.014)	(0.015)
Lagged Population growth (%)		0.027	0.021	0.047	0.044	0.033
		(0.032)	(0.0331)	(0.036)	(0.038)	(0.046)
Lagged SPEI			-0.121	-0.279**	-0.294**	-0.186
			(0.145)	(0.142)	(0.145)	(0.156)
Lagged SPEI^2			-0.490***	-0.511***	-0.474***	-0.496***
			(0.139)	(0.137)	(0.143)	(0.155)
Lagged Exclusion by social group				2.023***	1.942***	1.132**
				(0.370)	(0.475)	(0.499)
Lagged Regime type					0.069	0.152
					(0.088)	(0.098)
Lagged Regime type end					0.037	0.0979**
					(0.035)	(0.041)
Lagged Regime type × Lagged Regime type end					-0.009	-0.019**
					(0.008)	(0.009)
Lagged Military expenditure (log)						0.647***
						(0.182)
Constant	3.031***	2.954***	3.378***	2.535***	2.318***	1.304*
	(0.336)	(0.344)	(0.351)	(0.394)	(0.572)	(0.681)
inflate						
GDP per capita (log)	0.947***	0.942***	0.844***	0.881***	0.857***	0.742***
	(0.135)	(0.136)	(0.129)	(0.153)	(0.145)	(0.152)
Constant	-7.990***	-7.954***	-7.187***	-7.603***	-7.372***	-6.423***
	(1.274)	(1.286)	(1.211)	(1.469)	(1.378)	(1.415)
/						
lnalpha	1.614***	1.606***	1.561***	1.595***	1.570***	1.469***
	(0.166)	(0.170)	(0.165)	(0.180)	(0.177)	(0.188)
Obs	1433	1431	1369	1369	1369	1139
AIC	8126.6	8109.5	8069.3	8039.9	8044.3	6897.3
BIC	8158.2	8151.6	8121.5	8097.3	8117.4	6972.9
DF	2	4	6	7	10	11
Log likelihood	-4057.3	-4046.7	-4024.7	-4008.9	-4008.2	-3433.6

Standard errors in parentheses

Prob > chi2 = 0.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.1.3 Linear regression model with lagged variables

Table B.10: Effect of lagged corruption on political violence incidence

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Political corruption index$_{t-5}$	0.288***	0.320***	0.322***	0.336***	0.314***	0.0584*
	(0.047)	(0.051)	(0.051)	(0.051)	(0.052)	(0.032)
Lagged GDP per capita growth (%)		-0.000	-0.000	-0.000	-0.000	-0.00225***
		(0.000)	(0.000)	(0.000819)	(0.000)	(0.000)
Lagged Population growth (%)		-0.004	-0.004	-0.005	-0.003	-0.007***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
Lagged SPEI (annual)			-0.003	-0.005	-0.006	-0.000
			(0.008)	(0.008)	(0.008)	(0.005)
Lagged SPEI^2			-0.008	-0.010	-0.011	-0.008*
			(0.008)	(0.008)	(0.007)	(0.004)
Lagged Exclusion by social group				0.171***	0.053	0.042
				(0.065)	(0.073)	(0.044)
Lagged Regime type					0.025***	0.014***
					(0.006)	(0.003)
Lagged Regime end type					0.018***	0.005***
					(0.002)	(0.001)
Lagged Regime type × Lagged Regime end type					-0.004***	-0.001***
					(0.000)	(0.000)
Lagged Military expenditure (log)						0.010***
						(0.003)
Constant	-0.115***	-0.123***	-0.124***	-0.227***	-0.250***	-0.0361
	(0.029)	(0.034)	(0.035)	(0.052)	(0.059)	(0.036)
Obs	2213	2091	1999	1999	1999	1622
R^2 (Within)	0.016	0.019	0.021	0.024	0.052	0.039
R^2 (Between)	0.0216	0.037	0.035	0.077	0.085	0.359
R^2 (Overall)	0.009	0.012	0.013	0.021	0.033	0.049
AIC	331.4	271.9	210.9	205.8	153.9	-2084.7
BIC	342.8	294.5	244.5	245.1	209.9	-2025.4
Wald chi²						
F-test	36.71	13.51	8.521	8.261	12.01	6.417

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Effect of lagged corruption on political violence brutality

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Victims$_{t-1}$	0.001***	0.001***	0.001***	0.001***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Political corruption index$_{t-5}$	0.798**	0.873***	0.864***	0.924***	0.826**	0.0288
	(0.327)	(0.316)	(0.329)	(0.331)	(0.333)	(0.377)
Lagged GDP per capita growth (%)		-0.017***	-0.018***	-0.017***	-0.015***	-0.038***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Lagged Population growth (%)		0.022	0.025	0.020	0.028	-0.003
		(0.028)	(0.028)	(0.029)	(0.028)	(0.030)
Lagged SPEI (annual)			-0.031	-0.040	-0.047	0.002
			(0.056)	(0.056)	(0.056)	(0.059)
Lagged SPEI^2			-0.112**	-0.120**	-0.128**	-0.126**
			(0.050)	(0.051)	(0.050)	(0.052)
Lagged Exclusion by social group				0.704*	-0.020	-0.373
				(0.415)	(0.470)	(0.523)
Lagged Regime type					0.141***	0.112**
					(0.043)	(0.045)
Lagged Regime type end					0.090***	0.049***
					(0.016)	(0.017)
Lagged Regime type $\times$ Lagged Regime type end					-0.025***	-0.015***
					(0.004)	(0.004)
Lagged Military expenditure (log)						0.098**
						(0.042)
Constant	-0.157	-0.264	-0.210	-0.635*	-0.649*	0.283
	(0.203)	(0.210)	(0.224)	(0.336)	(0.381)	(0.432)
Obs	2213	2091	1999	1999	1999	1622
R^2 (Within)	0.0906	0.121	0.123	0.125	0.142	0.080
R^2 (Between)	0.278	0.236	0.241	0.267	0.263	0.368
R^2 (Overall)	0.105	0.134	0.135	0.140	0.138	0.077
AIC	8852.3	7862.6	7605.6	7604.6	7569.3	5896.4
BIC	8869.4	7890.9	7644.8	7649.4	7630.9	5961.1
Wald chi²						
F-test	107.6	69.99	45.58	39.51	32.25	12.45

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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