Supplementary information for

Bribes and Bombs: The Effect of Corruption on Terrorism

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A Additional Data Information

Table A.1: Summary statistics

	mean	sd	min	max
Terrorist attacks (GTD)	1.400	1.844	0.000	8.971
Domestic terrorist attacks (GTD)	13.424	86.887	0.000	3098.000
Transnational terrorist attacks (GTD)	2.155	8.459	0.000	223.000
Attacks against government (GTD)	9.872	51.656	0.000	1775.000
Attacks not against government (GTD)	14.598	79.546	0.000	2633.000
Political corruption (VDEM)	0.485	0.299	0.002	0.967
Executive corruption index (VDEM)	0.475	0.309	0.004	0.981
Legislature corrupt activities (VDEM)	0.012	1.382	-3.781	3.347
Judicial corruption decision (VDEM)	-0.220	1.498	-3.643	2.954
Public sector corrupt exchanges (VDEM)	0.017	1.491	-4.104	3.099
Population (WDI)	2.869	1.561	0.060	7.928
GDP per capita (WDI)	2.160	1.354	0.161	5.449
Democracy (KG)	0.573	0.402	0.000	1.000
State failure (PITF)	0.497	1.470	0.000	20.000
Infant mortality rate (WDI)	67.206	69.039	1.800	372.400
Electoral democracy index (VDEM)	48.401	28.563	1.400	94.800
Civil warfare (MPEV)	0.175	0.828	0.000	6.000
International war (MPEV)	0.053	0.508	0.000	7.000
GDP growth (WDI)	3.855	6.366	-64.047	149.973
Women political empowerment (VDEM)	0.652	0.212	0.105	0.967
Males 15-24 share (WDI)	31.419	7.508	10.235	51.171
Population growth (WDI)	1.733	1.494	-9.081	17.511
Muslim Population Share (WRD)	23.909	35.174	0.000	98.533
Oil rents (WDI)	3.924	9.910	0.000	88.866
Net ODA received (WDI)	4.610	8.159	-0.675	94.946
Left-wing government (VDEM)	0.244	0.304	0.000	1.000
General government expenditure (WDI)	16.002	6.764	0.000	135.809
Health equality (VDEM)	0.494	1.485	-3.271	3.689
Educational equality (VDEM)	0.447	1.462	-3.102	3.634
Political accountability (VDEM)	0.499	0.980	-1.979	2.090
Protest (CNTS)	0.474	0.861	0.000	4.585
Military expenditures (NMC)	5.391	31.170	0.000	693.600
Military personnel (NMC)	142.666	372.364	0.000	4750.000
Territorial authority (VDEM)	91.955	9.395	39.857	100.000
Observations	6726			

Notes: Detailed information on variable definitions can be found at the following sources: **CNTS:** cntsdata.com; **GTD:** start.umd.edu/gtd; **KG:** sites.google.com/view/klaus-gruendler/democracy-dataset; **MPEV:** systemicpeace.org/inscrdata.html; **NMC:** correlatesofwar.org/data-sets/national-material-capabilities; **PITF:** scip.gmu.edu/political-instability-task-force; **VDEM:** v-dem.net; **WDI:** databank.worldbank.org/source/world-development-indicators; **WRD:** worldreligiondatabase.org.

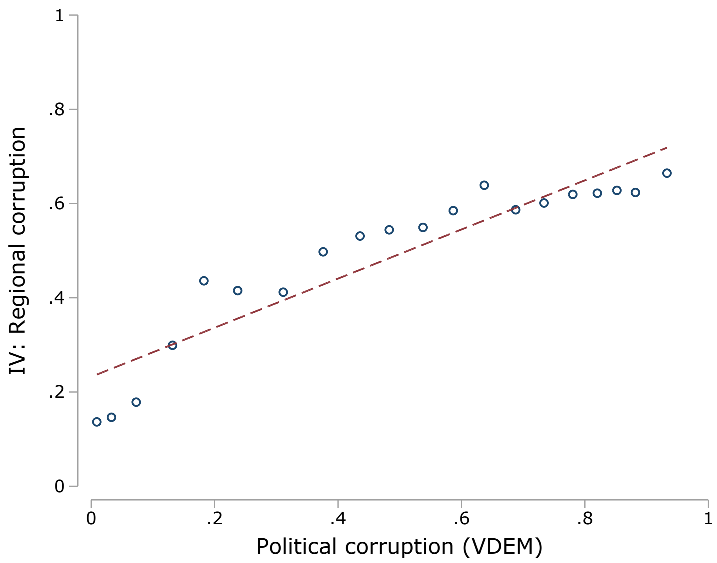
Table A.2: Country list

Americas			Czech Republic	CZE	H	**South Asia**		
Argentina	ARG	M	Denmark	DNK	H	Afghanistan	AFG	L
Barbados	BRB	H	Estonia	EST	H	Bangladesh	BGD	M
Bolivia	BOL	M	Finland	FIN	H	Bhutan	BTN	M
Brazil	BRA	M	France	FRA	H	India	IND	M
Canada	CAN	H	Georgia	GEO	M	Maldives	MDV	M
Chile	CHL	H	Germany	DEU	H	Nepal	NPL	M
Colombia	COL	M	Greece	GRC	H	Pakistan	PAK	M
Costa Rica	CRI	M	Hungary	HUN	H	Sri Lanka	LKA	M
Cuba	CUB	M	Iceland	ISL	H	**Sub-SaharanAfrica**		
Dominican Republic	DOM	M	Ireland	IRL	H	Angola	AGO	M
Ecuador	ECU	M	Italy	ITA	H	Benin	BEN	M
El Salvador	SLV	M	Kazakhstan	KAZ	M	Botswana	BWA	M
Guatemala	GTM	M	Kosovo	XKX	M	Burkina Faso	BFA	L
Guyana	GUY	M	Kyrgyz Republic	KGZ	M	Burundi	BDI	L
Haiti	HTI	L	Latvia	LVA	H	Cabo Verde	CPV	M
Honduras	HND	M	Lithuania	LTU	H	Cameroon	CMR	M
Jamaica	JAM	M	Luxembourg	LUX	H	Central African Republic	CAF	L
Mexico	MEX	M	Moldova	MDA	M	Chad	TCD	L
Nicaragua	NIC	M	Montenegro	MNE	M	Comoros	COM	M
Panama	PAN	H	Netherlands	NLD	H	Congo, Dem. Rep.	COD	L
Paraguay	PRY	M	North Macedonia	MKD	M	Congo, Rep.	COG	M
Peru	PER	M	Norway	NOR	H	Cote d'Ivoire	CIV	M
Suriname	SUR	M	Poland	POL	H	Equatorial Guinea	GNQ	M
Trinidad and Tobago	TTO	H	Portugal	PRT	H	Eritrea	ERI	L
United States	USA	H	Romania	ROU	H	Eswatini	SWZ	M
Uruguay	URY	H	Russian Federation	RUS	M	Ethiopia	ETH	L
Venezuela, RB	VEN	M	Serbia	SRB	M	Gabon	GAB	M
East Asia and the Pacific			Slovakia	SVK	H	Gambia, The	GMB	L
Australia	AUS	H	Slovenia	SVN	H	Ghana	GHA	M
Cambodia	KHM	M	Spain	ESP	H	Guinea	GIN	L
China	CHN	M	Sweden	SWE	H	Guinea-Bissau	GNB	L
Fiji	FJI	M	Switzerland	CHE	H	Kenya	KEN	M
Hong Kong SAR	HKG	H	Tajikistan	TJK	L	Lesotho	LSO	M
Indonesia	IDN	M	Turkey	TUR	M	Liberia	LBR	L
Japan	JPN	H	Turkmenistan	TKM	M	Madagascar	MDG	L
North Korea	PRK	L	Ukraine	UKR	M	Malawi	MWI	L
Korea, Rep.	KOR	H	United Kingdom	GBR	H	Mali	MLI	L
Lao PDR	LAO	M	Uzbekistan	UZB	M	Mauritania	MRT	M
Malaysia	MYS	M	**Middle East and North Africa**			Mauritius	MUS	H
Mongolia	MNG	M	Algeria	DZA	M	Mozambique	MOZ	L
Myanmar	MMR	M	Bahrain	BHR	H	Namibia	NAM	M
New Zealand	NZL	H	Djibouti	DJI	M	Niger	NER	L
Papua New Guinea	PNG	M	Egypt, Arab Rep.	EGY	M	Nigeria	NGA	M
Philippines	PHL	M	Iran, Islamic Rep.	IRN	M	Rwanda	RWA	L
Singapore	SGP	H	Iraq	IRQ	M	Sao Tome and Principe	STP	M
Solomon Islands	SLB	M	Israel	ISR	H	Senegal	SEN	M
Thailand	THA	M	Jordan	JOR	M	Seychelles	SYC	H
Timor-Leste	TLS	M	Kuwait	KWT	H	Sierra Leone	SLE	L
Vanuatu	VUT	M	Lebanon	LBN	M	Somalia	SOM	L
Vietnam	VNM	M	Libya	LBY	M	South Africa	ZAF	M
Europe and Central Asia			Malta	MLT	H	South Sudan	SSD	L
Albania	ALB	M	Morocco	MAR	M	Sudan	SDN	L
Armenia	ARM	M	Oman	OMN	H	Tanzania	TZA	M
Austria	AUT	H	Qatar	QAT	H	Togo	TGO	L
Azerbaijan	AZE	M	Saudi Arabia	SAU	H	Uganda	UGA	L
Belarus	BLR	M	Syria	SYR	L	Zambia	ZMB	M
Belgium	BEL	H	Tunisia	TUN	M	Zimbabwe	ZWE	M
Bosnia and Herzegovina	BIH	M	United Arab Emirates	ARE	H			
Bulgaria	BGR	M	West Bank and Gaza	PSE	M			
Croatia	HRV	H	Yemen, Rep.	YEM	L			
Cyprus	CYP	H						

Notes: Country list covered in the main estimation sample. Income groups Low, Middle, High indicated.

B Robustness of Instrumental-Variable Approach

Figure B.1: Correlation between corruption and exposure to regional corruption



Note: Figure plots the level of corruption (pooled to bins) against the level of exposure to corruption through geographically and economically proximate countries, the main instrument (1970–2018 average).

B.1 Alternative Instrument Construction

We consider alternative ways to construct our instrumental variable to address concerns that our results are only due to construction idiosyncrasies. First, instead of relying on six world regions, we consider eighteen UN world regions to construct the instrumental variable.[18] Second, instead of considering three income levels (low-, middle-, and high-income economies), we rely on WDI to differentiate between low-, lower-middle-, upper-middle- and high-income status. Third, there may be concerns that our income classifications are endogenous to terrorism or corruption. While we believe these concerns to be small, given that our income classifications are very broad and that the economic effects of terrorism tend to be small (Sandler 2018; Gaibulloev and Sandler 2019), we still address this concern by fixing the country-specific income status at 1995–levels.[19] Finally, we consider geographical proximity but not economic proximity by weighting corruption abroad with the log capital distance between two countries. Table B.1 shows that alternative constructions of the instrumental variable which account for both geographical and economic proximity yield findings that are comparable to our baseline estimates reported in Table 1. The IV-diagnostics are sound.

18. World regions: Caribbean; Central Asia; Eastern Africa; Eastern Asia; Eastern Europe; Melanesia; Middle Africa; Northern Africa; Northern America; Northern Europe; South America; South-Eastern Asia; Southern Africa; Southern Asia; Southern Europe; Western Africa; Western Asia; and Western Europe.

19. The WDI report consistent income classifications from 1990 onward. For this robustness check, we choose the 1995-WDI income classifications because this allows us to also consider countries that have only recently become independent, thus maximizing the number of observations.

B.2 Placebo Instruments

Next, we consider whether the use of placebo instrumental variables affects our estimates (e.g., Christian and Barrett 2017). First, we randomly assign the values of our baseline instrument to other countries. For instance, this could mean that the values of the instrument associated with the United States for the 1970–2018 period are assigned to Egypt. Second, we perform the same randomization separately for each year. For instance, the values of the baseline instrument associated with the United States for 1970 could be assigned to Nigeria, the values for 1971 to France, and so on. For both placebo IVs, the idea is to undo the geographical and economic ties between regional and local corruption that we argue are essential to the relevance and validity of our baseline instrumental-variable approach. Hence, they should — by construction — share no association with local corruption and thus neither be be relevant nor helpful in identifying the impact of local corruption on terrorism. By contrast, finding that the association between regional and local corruption survives the randomization may indicate that this association is spurious, e.g., driven by (non-linear) background trends (e.g., Christian and Barrett 2017). As shown in Table B.1, the placebo instruments are unable to identify the effect of corruption on terrorism and the associated IV-diagnostics point to weak instruments. This raises confidence that our initial identification strategy is sound and that previously reported estimates of local corruption on terrorism are not spurious.

Table B.1: Alternative IV specifications and approaches

	Alternative IV construction				Placebo IVs	
	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption	13.747**	7.561**	9.820**	12.832**	-7.297	2.418
	(4.620)	(2.333)	(3.307)	(29.472)	(26.388)	(21.754)
Population	0.713	1.420**	1.158*	0.965	2.591	1.829
	(0.656)	(0.436)	(0.474)	(2.864)	(2.110)	(1.737)
GDP per capita	1.131**	0.783**	0.977**	1.104**	-0.027	0.494
	(0.430)	(0.282)	(0.347)	(1.692)	(1.490)	(1.249)
Democracy	1.560*	0.882*	1.175**	1.272*	-0.259	0.484
	(0.640)	(0.372)	(0.437)	(0.614)	(2.029)	(1.679)
State failure	0.346**	0.323**	0.333**	0.347**	0.325**	0.328**
	(0.059)	(0.053)	(0.056)	(0.076)	(0.053)	(0.050)
First stage						
Regional exposure	0.235**	0.447**	0.445**	15.407**	-0.002	-0.002
	(0.072)	(0.115)	(0.109)	(4.322)	(0.005)	(0.004)
Effective F-statistic	10.556	15.187	16.708	12.705	0.268	0.257
AR p-value	0.000	0.000	0.000	0.000	0.752	0.358
AR CI	[7.37,34.8]	[4.36,17.4]	[4.63,20.1]	[7.09,28.1]	[full grid]	[full grid]
Observations	6609	6703	6703	6585	6837	6628
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country $\boldsymbol{X}$	✓	✓	✓	✓	✓	✓

Notes: OLS regression on the number of terrorist attacks (IHS) in t+1. *Model 1* uses 18 more detailed instead of 6 UN geographical regions. *Model 2* uses WDI income levels and *Model 3* fixes the income level at 1995 WDI values. *Model 4* constructs the instrument using geographical proximity (corruption abroad weighted by the log capital distance). Two placebo tests are shown in *Model 5* (random assignment of an IV value to another country) and *Model 6* (random assignment of an IV value to another country within a given year). Robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

B.3 Regional Shocks

The exclusion restriction may also be violated by the influence of shocks that are correlated within regions and might simultaneously affect local corruption and terrorism. For example, political corruption in geographically and economically proximate countries may encourage terrorism in these countries, which, in turn, could spill-over to the country of interest and promote terrorism in this country as well. Empirical evidence concerning this contagion effect of terrorism is provided by, e.g., Cliff and First (2013) and discussed in Krieger and Meierrieks (2011). To address such concerns, we control for a series of time-varying variables that ought to capture the role of regionally correlated economic, political, institutional and demographic shocks. In detail, these shocks are defined as the yearly average level of population size, per capita income, democracy, state failure terrorism, economic growth, human rights, globalization, freedom of religion, property rights and quality of bureaucracy for countries that are geographically and economically proximate to the country of interest. Additional information on variable operationalization and data sources is provided in Table A.1. As reported in Table B.2, adjusting for these regional shocks does not affect our main empirical conclusion: higher levels of political corruption lead to more terrorist activity. The estimated effects and associated IV-diagnostics are sound and comparable to our baseline estimates even when we control for *all* regional shocks at the same time.

Table B.2: Influence of Regional Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Political corruption	6.947**	9.701**	6.933**	6.822**	3.902*	7.105**	6.891**	7.367**	9.215**	8.414**	4.417*	5.473*
	(2.235)	(3.137)	(2.312)	(2.315)	(1.732)	(2.413)	(2.324)	(2.443)	(2.929)	(2.885)	(1.780)	(2.778)
Population	0.215											-0.293
	(0.480)											(0.427)
GDP p.c.		1.165*										0.704†
		(0.457)										(0.366)
Democracy			-0.543									0.329
			(0.592)									(0.669)
State failure				0.076								-0.169
				(0.156)								(0.120)
Terrorism					0.540**							0.427**
					(0.091)							(0.110)
Economic growth						0.005						-0.012
						(0.012)						(0.011)
Human rights							-0.001					0.001
							(0.003)					(0.003)
Globalization								0.059†				0.030
								(0.030)				(0.026)
Freedom of Religion									-0.708**			-0.618*
									(0.249)			(0.291)
Property Rights										-2.020		1.866
										(1.499)		(1.963)
Bureaucracy											-0.596**	-0.372
											(0.192)	(0.255)
First stage												
Regional exposure	0.518**	0.532**	0.513**	0.520**	0.474**	0.527**	0.516**	0.509**	0.517**	0.527**	0.546**	0.509**
	(0.141)	(0.149)	(0.152)	(0.148)	(0.151)	(0.154)	(0.148)	(0.142)	(0.141)	(0.147)	(0.165)	(0.153)
Effective F-statistic	13.427	12.699	11.422	12.414	9.800	11.790	12.169	12.838	13.428	12.901	10.964	11.114
AR p-value	0.001	0.000	0.002	0.001	0.029	0.000	0.001	0.001	0.000	0.000	0.013	0.014
AR CI	[3.81,16.6]	[5.45,24.5]	[3.81,17.1]	[3.81,18.0]	[1.36,13.0]	[3.81,19.6]	[3.81,17.7]	[4.09,19.3]	[4.90,20.4]	[4.36,20.4]	[1.71,12.6]	[1.01,16.2]
Observations	6726	6716	6726	6726	6726	6648	6726	6702	6726	6726	6726	6624
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country $\boldsymbol{X}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: OLS regression on the number of terrorist attacks (IHS) in t+1. Table presents results of the main specification while additionally adjusting for the mean value of specific shocks of countries within a region. Robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

C Additional Robustness Checks

C.1 Changes to Baseline Model

To investigate whether changes to our baseline model matter to our empirical conclusions, we proceed as follows. First, we replace the GDP per capita variable with a country's infant mortality (WDI data) as an alternative indicator of economic development, replace our democracy measure with an electoral democracy index as an alternative measure of democratic development (VDEM data) and replace the state failure measure with a variable accounting for the extent of civil warfare within a country from Marshall (2019). Second, we consider whether a country's level of economic or political development share a non-linear relationship with terrorism by amending our baseline model with quadratic terms of both variables. For instance, earlier contributions by Enders et al. (2016) and Gaibulloev et al. (2017) point to such non-linearities. Third, we run a model without the state failure variable, given that this variable may constitute a "bad control". Moreover, we run a model where we amend our baseline model with the lag of the dependent variable and region-specific trends (operationalized as interactions between the year-fixed effects and region-fixed effects for the six UN world regions we use to construct our instrumental variable). These latter robustness checks help to assess whether dynamics in terrorism or at the regional level matter to our empirical findings. The findings of Table C.1 indicate that our main empirical results are not due to idiosyncratic choices related to the specification of our baseline model. We continue to find that political corruption leads to more terrorist activity, regardless of which variant of the baseline model we run. For instance, we find that employing alternative indicators for economic and political development as well as state failure is of little consequence to our findings. Additionally, there is no convincing evidence that economic development or democracy are non-linearly related to terrorism. We also assess non-linear interactive effects of democracy and corruption in Model 7 of Table C.1. The negative interaction coefficient of the country's level of democracy and the instrumented level of corruption indicates that democracies may be able to mitigate the negative consequences of corruption. However, the interaction is not statistically significant. Finally, we run an additional model that includes a set of common correlated effects (i.e., interactions between the various cross-sectional means of the explanatory variables and the country-fixed effects) to accommodate concerns regarding cross-sectional dependence, as in Pesaran (2006) (see also Gaibulloev et al. 2014). We find that adding these common correlated effects as controls also does not change our main empirical conclusion of an unfavorable effect of corruption on terrorism. Note that we do not report the various interactions themselves that form the common correlated effects due to a lack of space and because they cannot be interpreted in a meaningful way.

Table C.1: Changes to Baseline Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Political corruption	7.704**	6.697**	6.379**	7.447**	6.802**	2.445*	7.599**	10.622**
	(2.454)	(2.599)	(2.224)	(2.540)	(2.636)	(1.031)	2.445*	(2.511)
Population	1.242*	0.990*	1.203**	1.475**	1.285**	0.183	1.604**	0.784
	(0.485)	(0.491)	(0.446)	(0.451)	(0.410)	(0.171)	(0.403)	(0.529)
Democracy	0.737*	0.768*	0.743*			0.307*	2.201	0.895**
	(0.371)	(0.378)	(0.335)			(0.140)	(1.370)	(0.160)
GDP per capita	0.580*		1.298**	0.750**	0.751**	$0.166^{\dagger}$	0.638*	-0.281
	(0.284)		(0.422)	(0.289)	(0.284)	(0.096)	(0.272)	(0.179)
State failure		0.308**	0.328**	0.327**	0.330**	0.094**	0.319**	0.152**
		(0.053)	(0.051)	(0.053)	(0.052)	(0.016)	(0.053)	(0.023)
Infant mortality		-0.000						
		(0.004)						
GDP per capita^2			$-0.143^{\dagger}$					
			(0.076)					
Electoral democracy				0.016**	0.043**			
				(0.007)	(0.017)			
Electoral democracy^2					-0.000			
					(0.000)			
Civil war								
Attacks						0.649**		
						(0.021)		
Democ. × corruption							-2.356	
							(2.191)	
First stage								
Regional exposure	0.519**	0.466**	0.502**	0.491**	0.516**	0.456**	-0.234*	
	(0.147)	(0.155)	(0.143)	(0.149)	(0.149)	(0.160)	(0.097)	
Exposure × democ.							0.691**	
							(0.157)	
Effective F-statistic	12.418	8.993	12.282	11.212	12.029	8.158	6.423	
AR p-value	0.000	0.004	0.002	0.001	0.000	0.003	0.005	
AR CI	[4.36,19.6]	[3.27,22.9]	[3.27,17.4]	[4.09,22.0]	[4.36,20.1]	[1.21,10.9]		
Observations	6726	6666	6726	6726	6726	6726	6726	6726
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Year × region FE						✓		

Notes: OLS regression on the number of terrorist attacks (IHS) in t+1. Table present results when changing the baseline specification. *Model 1* excludes state failure variable; *Model 2* replaces GDP per capita with infant mortality; *Model 3* add a squared term for GDP per capita; *Model 4* replaces the democracy dummy with the continuous electoral democracy index; *Model 5* adds a squared term for the binary democracy indicator; *Model 6* adds the number of terrorist attacks (t) and year-by-region fixed effects; *Model 7* estimates non-linear interactive effects of democracy and corruption; *Model 8* implements a common correlated effects regression within a GMM framework. Robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

C.2 Lag Length Selection and Long-Run Estimates

To study both the role of the inclusion of different lags of the dependent and independent variables and the long-run relationship between corruption and terrorism, we consider an *autoregressive distributed lag* (ADL) model of the following form:

$$terrorism_{i,t} = \beta_1 * terrorism_{i,t-1} + \beta_2 * corruption_{i,t} + \beta_3 * corruption_{i,t-1} + \alpha_i + \tau_t + \varepsilon_{i,t}, \tag{8}$$

Here, we explain present values of terrorism using information on past realizations of terrorism (i.e., a lag of the dependent variable) as well as on contemporaneous and past realizations of corruption. Thus, this ADL(1,1) model utilizes one lag of terrorism as well as contemporaneous and one-year lagged values of corruption. This model also includes country-fixed and year-fixed effects. While not shown in the estimation equation, in some specifications we also account for our main set of baseline controls (which enter the model with the same lag structure as the corruption variable). The inclusion of lagged values of the dependent variable may introduce a Nickell bias to our estimates. However, we do not expect this bias to be overly influential, given that the time dimension of our data is fairly substantial (the average number of years per country is approximately 39).

As shown by De Boef and Keele (2008), our ADL(1,1) model can be transformed into an *error-correction model* (ECM) of the following form:

$$\Delta terrorism_{i,t} = \beta_1 * \Delta corruption_{i,t} + \rho^i [terrorism_{i,t-1} - \omega_i * corruption_{i,t-1}] + \alpha_i + \tau_t + \varepsilon_{i,t}, \tag{9}$$

where Δ refers to the first-difference operator. The error-correction term is given by $\rho[terrorism_{t-1} - \omega * corruption_{t-1}]$. We report the (panel) ECM results in Table C.2, focusing on two important estimates that are readily available when using the ECM formulation of an ADL model. First, the regression coefficient ρ indicates the speed of adjustment to the long-run equilibrium relationship between terrorism and corruption, whereby this coefficient ought to be statistically significant (indicating the existence of a long-run relationship) and lie between [0;-1] (implying dynamic stability). Second, we can calculate the long-run effect of corruption on terrorism via $[-\omega \div \rho]$. Below, we estimate both OLS- and IV-variants of the ECM. For the IV-variants, we use lagged first-differences of our instrument (regional corruption) or lagged levels of this instrument, respectively, depending on whether we instrument the first-differences or levels of local corruption.

Providing a series of ECM estimates is expected to add to the robustness of our main empirical results in several ways. First, it allows us to consider how the inclusion of lagged values of the dependent and independent variables matters to our statistical inferences. In Table C.2, we not only consider the (panel) ECM equivalent of an ADL(1,1) model but also ADL(2,2) and ADL(3,3) model variants to account for potentially more complex lag structures. Second, the transformation of the data (first-differencing) and the inclusion of an ECM allows us to consider non-stationarity in both the terrorism and corruption series, making a spurious regression less likely (e.g., Engle and Granger 1987). Third, calculating the speed of adjustment and long-run effect of corruption and terrorism enables us to assess how quickly the terrorism and corruption series converge to a specific state of long-run equilibrium. This, in turn, may have important policy implications, e.g., concerning how quickly anti-corruption measures may result in reduced terrorist activity. Finally, finding that the dynamic models we estimate as part of our robustness checks mimic the (more parsimonious) static models we present in the main text ought to increase confidence in the soundness of these static estimates.

Regardless of whether we run an OLS- or IV-model and regardless of which lag structure and set of controls we consider, we always find that there is a statistically significant and positive long-run relationship between corruption and terrorism. Similar to the static estimates reported in the main text, the IV-estimates tend to be larger compared to their OLS-counterparts. What is more, the size of the estimated long-run effect of corruption on terrorism is similar to the static estimates reported in the main text. The speed of adjustment estimates are also sound (i.e., they are statistically significant and correctly sized and signed). These latter estimates show how long it takes for the terrorism and corruption series to equilibrate once there is a disturbance in the long-run relationship between both variables (due to, say, a shock in corruption). Specification (8) in Table C.2 provides an example, in which we deliver a speed of adjustment of approximately $\rho = -0.3$ and a long-run effect of corruption on terrorism of approximately $[-\omega \div \rho] = 9$. This implies that terrorism will change by $0.3 * 9 = 2.7$ in $t+1$, by $0.3 * (9 - 2.7) = 1.89$ in $t + 2$ and so on. That is, the two series appear to equilibrate rather quickly, suggesting that increased corruption (reduced corruption) may lead to (attenuate) terrorist conflict rather swiftly. In sum, the findings reported in Table C.2 suggest that our (static but more parsimonious) main results are not affected by different lag structures (with respect to both the dependent and main explanatory variable) and non-stationarity as well as cointegration.

Table C.2: Long-run estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ADL Equivalent →	(1,1)	(2,2)	(3,3)	(1,1)	(1,1)	(2,2)	(3,3)	(1,1)
Long-Run Effect Corruption	1.219†	1.346†	1.569†	1.298*	7.115**	8.470*	6.827†	7.057**
	(0.634)	(0.736)	(0.811)	(0.650)	(2.252)	(4.031)	(3.528)	(2.209)
ECM Estimate	-0.246**	-0.198**	-0.185**	-0.250**	-0.252**	-0.213**	-0.185**	-0.255**
	(0.020)	(0.017)	(0.016)	(0.020)	(0.020)	(0.022)	(0.021)	(0.020)
Estimation Method	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Additional Controls	No	No	No	Yes	No	No	No	Yes
Anderson-Rubin (p-value)					0.000	0.000	0.000	0.000
Observations	6600	6474	6346	6558	6598	6470	6340	6558
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Dependen variable is always the number of terrorist attacks (IHS transformation). Additional controls are for population size, per capita income, democracy and state failure. They enter Models (4) and (8) in the short-run component of the model in first differences. Robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

One concern about the use of EC models as the one we estimate above is that such models may only be appropriate in the presence of cointegration between the variables of interest. However, as extensively discussed by De Boef and Keele (2008), cointegration is not a necessary condition for the use of ECM. Rather, "the ECM is useful for stationary and integrated data alike" (De Boef and Keele 2008, p.199). In Table

C.3, we nevertheless report findings from a series of panel cointegration tests following Kao (1999). We can reject the null hypothesis of no cointegration between terrorism and corruption for almost all test variants we run; the alternative hypothesis is that all panels are cointegrated. That is, the panel cointegration tests provide additional (albeit not truly necessary) evidence that an ECM approach is indeed sound for our setting.

Table C.3: Panel cointegration test results

Test Variant	Test Statistic (p-value)	Test Statistic (p-value)	Test Statistic (p-value)
Modified Dickey-Fuller t	-7.03	-12.28	-14.74
	(0.00)	(0.00)	(0.00)
Dickey-Fuller t	7.76	-12.62	-14.27
	(0.00)	(0.00)	(0.00)
Augmented Dickey-Fuller t	0.60	-2.97	-3.69
	(0.27)	(0.00)	(0.00)
Unadjusted modified Dickey-Fuller t	-30.53	-37.80	-40.60
	(0.00)	(0.00)	(0.00)
Unadjusted Dickey-Fuller t	-17.73	-21.73	-22.86
	(0.00)	(0.00)	(0.00)
Baseline controls	No	Yes	Yes
Cross-sectional means removed	No	No	Yes

Notes: Null hypothesis is no cointegration against the alternative that all panels are cointegrated. Baseline controls are for population size, per capita income, democracy and state failure. When they are included, we test for cointegration between terrorism, corruption as well as all controls. Removal of cross-sectional means may ameliorate concerns about cross-sectional dependence in the data. p-values reported in parentheses.

C.3 Additional Control Variables

To examine whether our results are robust to the inclusion of further covariates, we amend our baseline model with (1) further politico-institutional variables (the political empowerment of women, left-wing incumbency and involvement in international wars), (2) further demographic variables in the form of the male youth burden (i.e., males aged 15-29 as a share of males between the ages of 15 and 64), population growth and the Muslim population share and (3) additional socioeconomic controls (economic growth, oil rents, foreign development assistance and government size). The choice of these controls follows the literature on the determinants of terrorism and corruption (e.g., Krieger and Meierrieks 2011; Dimant and Tosato 2018). Information on the operationalization and sources of these additional controls is provided in Table A.1. We show in Table C.4 that our main empirical conclusion — that corruption fuels terrorism — is not due to our choice of controls. With respect to the additional controls, we only find a statistically significant and positive association between terrorism and a country's Muslim population share. Potentially, this finding reflects the rise of Islamist terrorism especially after the end of the Cold War (e.g., Gaibulloev and Sandler 2019).

Table C.4: Additional controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Political corruption	6.720**	6.953**	7.078**	7.934*	6.986**	6.878**	7.788**	6.855**	6.951**	5.891**	7.376*
	(2.248)	(2.551)	(2.393)	(3.291)	(2.430)	(2.318)	(2.443)	(2.318)	(2.476)	(1.998)	(3.291)
GDP growth	0.003										-0.003
	(0.004)										(0.006)
Women political empowerment		-0.474									-1.448
		(1.150)									(1.134)
International war			-0.044								-0.082
			(0.061)								(0.063)
Male population 15–24				-0.035							-0.001
				(0.034)							(0.033)
Population growth					-0.083						-0.042
					(0.061)						(0.052)
Muslim Population						0.028**					0.031†
						(0.010)					(0.019)
Oil rents							0.000				0.018
							(0.010)				(0.011)
Net ODA received								0.010†			0.013†
								(0.006)			(0.007)
Left-wing government									0.098		0.251
									(0.357)		(0.396)
Government consumption										0.019	0.025
										(0.012)	(0.017)
First stage											
Regional exposure	0.513**	0.492**	0.517**	0.453**	0.517**	0.520**	0.483**	0.520**	0.489**	0.544**	0.395**
	(0.144)	(0.154)	(0.149)	(0.154)	(0.150)	(0.148)	(0.124)	(0.148)	(0.141)	(0.155)	(0.124)
Effective F-statistic	12.668	10.229	12.027	8.699	11.933	12.413	15.168	12.430	12.095	12.328	10.086
AR p-value	0.002	0.002	0.001	0.004	0.001	0.001	0.002	0.001	0.002	0.003	0.025
AR CI	[3.54,17.1]	[3.54,21.5]	[3.81,19.0]	[3.67,35.4]	[3.81,19.6]	[3.81,18.2]	[4.36,18.0]	[3.81,18.2]	[3.54,19.3]	[3.13,15.5]	[2.77,27.8]
Observations	6671	6655	6452	6716	6724	6726	6392	6726	6726	6109	5547
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country $\boldsymbol{X}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: OLS regression on the number of terrorist attacks in (IHS) t+1. Table presents the main specification while adding additional control variables. Robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

C.4 Alternative Measurement of Terrorism

Different operationalizations of terrorism may also affect our empirical conclusions. For instance, Jetter and Stadelmann (2019) suggest that there can be substantial differences between the determinants of total and per capita terrorism. We consider the following alternative measurements of terrorism. First, we use a binary terrorism variable that is equal to unity when there is at least one terrorist incident per country–year observation and zero otherwise. Potentially, this variable is less susceptible to outliers in terrorism. Second, we employ the number of terrorist attacks per capita; as above, this variable is transformed using the inverse hyberbolic sine transformation. Third, instead of the number of terrorist attacks we use the number of terrorism victims (i.e., individuals wounded or killed in terrorist attacks). We use the total number of victims (hyberbolic sine transformed), a binary measure and the per capita number of terrorism victims (hyberbolic sine transformed). These variables reflect the ferocity rather than frequency of terrorism and may therefore be especially relevant for counter-terrorism policy. Finally, we follow Eckstein and Tsiddon (2004) and construct a terrorism index that is equal to the (hyberbolic sine transformed) sum of terrorist attacks and victims per country–year or the (hyberbolic sine transformed) per capita sum of attacks and victims, respectively. These two variables are thus composite indices simultaneously reflecting the frequency and ferocity of terrorism. As shown in Table C.5, regardless of which dependent variable we employ, more political corruption always leads to more terrorist activity. The associated first-stage regression results and IV-diagnostics are also always sound. Thus suggest that our main empirical conclusion is not due to the choice of a specific dependent variable.

In addition to the operationalization of terrorism, we consider different attack modes. Table C.6 restricts the dependent variable to each of the attack modes as defined by the GTD, showing that all but suicide attacks increase with higher levels of corruption. The effect sizes of terrorism by means of assassinations, bombings, and armed assaults are comparable; while hostage taking increases strongest relative to its baseline. While we are cautious to put too much weight on these findings, it could be interpreted as indication that economic motivations/grievances, which can be, if anything, best addressed by extortion in a hostage situation, are a key driver.

Finally, we study how corruption affects different types of terrorism, using data from the GTD as well as Enders et al. (2011) and Gaibulloev and Sandler (2019). For one, we differentiate between domestic and transnational terrorism. The former only concerns one country, so that the origin country of perpetrator and victim as well as the venue country of the attack are the same, while the latter concerns more than one country, e.g., because perpetrators and victims of an attack do not have the same nationality (Enders et al. 2011, p.321). For instance, domestic terrorism may be more responsive to grievances associated with political corruption (e.g., inequality), while transnational terrorism may be more strongly rooted in international political factors. Focusing on domestic terrorism also means ruling out that corrupt foreign governments support local terrorists, which could point to a violation of the exclusion restriction due to a direct effect of our instrument (regional corruption) on the outcome (local terrorism). By definition, foreign governments cannot be involved in domestic terrorism. Reassuringly, domestic terrorism is far more common than transnational terrorism (Gaibulloev and Sandler 2019), which suggests that this potential violation of the exclusion restriction should not matter to our analysis. Moreover, we differentiate between terrorist attacks against government and civilian targets. The former includes attacks against the military, police and government institutions, while the latter primarily refers to attacks against private citizens and business interests. Table C.7 shows that there are no systematic differences in the adverse impact of corruption on internal peace. We find that political corruption leads to more domestic as well as transnational terrorist activity to similar extent relative to the baseline. Also, corruption encourages both anti-government and anti-civilian terrorism. In sum, these results point to a generalized relationship between political corruption and terrorist activity.

Table C.5: Alternative terror measures

	Attacks			Victims			Attacks + victims	
	binary	per capita	log	IHS	binary	per capita	index	per capita
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Political corruption	1.837**	2.042**	2.738**	8.075**	1.614**	6.267**	8.522**	6.828**
	(0.631)	(0.626)	(0.894)	(2.738)	(0.587)	(2.127)	(2.824)	(2.239)
Population	0.179†	0.181†	0.451**	2.001**	0.234*	1.503**	1.909**	1.440**
	(0.106)	(0.107)	(0.153)	(0.531)	(0.099)	(0.435)	(0.536)	(0.445)
GDP per capita	0.106	0.144*	0.234*	0.745*	0.079	0.576*	0.777*	0.612*
	(0.070)	(0.069)	(0.102)	(0.340)	(0.067)	(0.260)	(0.345)	(0.268)
Democracy	0.230*	0.232*	0.325*	0.930*	0.216**	0.725*	0.989*	0.790*
	(0.089)	(0.094)	(0.133)	(0.418)	(0.081)	(0.328)	(0.429)	(0.344)
State failure	0.043**	0.074**	0.099**	0.470**	0.049**	0.413**	0.457**	0.405**
	(0.009)	(0.013)	(0.017)	(0.065)	(0.010)	(0.057)	(0.064)	(0.057)
First stage								
Regional exposure	0.520**	0.520**	0.520**	0.520**	0.520**	0.520**	0.520**	0.520**
	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)
Effective F-statistic	12.413	12.404	12.413	12.413	12.413	12.404	12.413	12.404
AR p-value	0.004	0.001	0.001	0.001	0.007	0.001	0.001	0.000
AR CI	[1.21,4.84]	[1.21,5.15]	[1.51,6.96]	[4.24,21.2]	[0.90,4.24]	[3.33,16.0]	[4.54,22.1]	[3.63,17.5]
Observations	6726	6725	6726	6726	6726	6725	6726	6725
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean DV	0.491	0.374	0.600	1.579	0.401	1.152	1.769	1.278

Notes: Table presents alternative operationalizations of terrorism attacks, victims, and indices. Attacks: models 1–3; victims: models 4–6. *Index* is defined as attacks plus victims. *Per capita* values divide the main DV by the population in a given year. *Binary* indicators equal 1 if attacks/victims in a given year are not 0. *log* transforms the number of attacks plus 1. *IHS* indicates Inverse Hyberbolic Sine Transformation. OLS, robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table C.6: Alternative attack modes

	All	Suicide	Hostage	Assassination	Bombing	Assault
	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption	6.878**	-0.052	2.440*	1.923†	4.775**	3.659*
	(2.318)	(1.011)	(1.088)	(1.117)	(1.688)	(1.501)
Population	1.471**	0.548*	0.909**	0.897**	1.229**	1.224**
	(0.434)	(0.257)	(0.244)	(0.262)	(0.379)	(0.323)
GDP per capita	0.744**	0.138	0.312*	0.366**	0.662**	0.491*
	(0.283)	(0.109)	(0.135)	(0.140)	(0.235)	(0.211)
Democracy	0.832*	0.051	0.346*	0.495**	0.612*	0.382†
	(0.345)	(0.086)	(0.158)	(0.144)	(0.263)	(0.224)
State failure	0.323**	0.083**	0.174**	0.186**	0.245**	0.269**
	(0.052)	(0.024)	(0.033)	(0.034)	(0.046)	(0.045)
First stage						
Regional exposure	0.520**	0.520**	0.520**	0.520**	0.520**	0.520**
	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)
Effective F-statistic	12.413	12.413	12.413	12.413	12.413	12.413
AR p-value	0.001	0.960	0.008	0.113	0.001	0.007
AR CI	[3.81,18.2]	[-2.72,2.12]	[0.90,6.96]	[0.30,6.36]	[2.42,12.1]	[1.51,10.6]
Observations	6726	6172	6726	6726	6726	6726
Mean DV	1.400	0.096	0.362	0.452	0.900	0.644
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Table distinguishes between five types of terrorist attack modes according to the GTD. OLS, robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table C.7: Types of terrorism

	Domestic		Transnational		Targets	
	Attacks	Victims	Attacks	Victims	Gov.	Civilian
	(1)	(2)	(3)	(4)	(5)	(6)
Political corruption	5.411**	6.617**	3.348*	3.430**	5.156**	6.063**
	(1.835)	(2.236)	(1.345)	(1.265)	(1.765)	(2.085)
Population	1.073**	1.638**	0.834**	1.153**	1.407**	1.218**
	(0.393)	(0.473)	(0.235)	(0.295)	(0.363)	(0.398)
GDP per capita	0.685**	0.777*	0.401**	0.428*	0.636**	0.694**
	(0.248)	(0.304)	(0.150)	(0.175)	(0.229)	(0.261)
Democracy	0.618*	0.732*	0.463*	0.395*	0.718**	0.663*
	(0.272)	(0.334)	(0.181)	(0.200)	(0.269)	(0.309)
State failure	0.265**	0.386**	0.168**	0.205**	0.275**	0.302**
	(0.048)	(0.061)	(0.029)	(0.037)	(0.048)	(0.049)
First stage						
Regional exposure	0.515**	0.515**	0.515**	0.515**	0.520**	0.520**
	(0.152)	(0.152)	(0.152)	(0.152)	(0.148)	(0.148)
Effective F-statistic	11.537	11.537	11.537	11.537	12.427	12.427
AR p-value	0.001	0.000	0.018	0.000	0.001	0.001
AR CI	[2.77,13.7]	[3.27,16.6]	[1.71,9.49]	[1.71,8.78]	[2.77,13.3]	[3.27,16.0]
Observations	6389	6389	6389	6389	6711	6711
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean DV	0.915	1.080	0.568	0.555	0.922	1.089

Notes: Table presents results for different types of terrorism attacks and victims from respective attacks (domestic vs. transnational) and distinguishes between governmental and civilian targets. OLS, robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

C.5 Sub-Sample Analysis

To investigate whether our main findings are driven by specific sub-sets of countries that, we drop from our full sample (1) all countries that were OECD members before 1990 (OECD countries tend to have low levels of political corruption), (2) all countries located in Sub-Saharan Africa (which tend to be comparatively more corrupt) as well as (3) all countries in South America or the Middle East and Northern Africa, respectively (both sets of countries tend to be strongly affected by corruption and terrorism). Furthermore, to reduce the potential impact of outliers, we identify those countries that see the highest levels of terrorism or corruption, respectively (i.e., countries with the top 10% mean-levels of terrorism or corruption) and drop all country-year observations for these countries from the sample. For instance, this means dropping all data on countries such as Colombia, Pakistan and France (for terrorism) and Haiti, Indonesia and Nigeria (for political corruption). Finally, we winsorize the terrorism or corruption variable, replacing the largest values of both variables by the respective values at the 90^{th} percentile of their distribution. This is another way to examine the influence of outliers on our estimates. As reported in Table C.8, regardless of which sub-sample we consider, we always find that political corruption promotes terrorist activity. Both in terms of statistical significance and economic substantiveness, the various estimates of the effect of corruption on terrorism mirror our baseline estimates of Table 1. This suggests that our main empirical finding is not driven by specific sub-sets of countries.

Table C.8: Sub-sample analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Political corruption	7.834**	7.664*	5.942**	8.727**	6.128**	7.179**	6.960**	6.141**
	(2.820)	(3.453)	(2.116)	(3.182)	(2.082)	(2.488)	(2.512)	(1.985)
Population	1.336**	1.651**	1.495**	1.267†	1.604**	1.500**	1.279**	1.026**
	(0.508)	(0.486)	(0.445)	(0.680)	(0.413)	(0.436)	(0.443)	(0.339)
GDP per capita	0.805*	0.876*	0.623*	0.882*	0.953**	0.737*	0.728*	0.548*
	(0.330)	(0.366)	(0.263)	(0.361)	(0.314)	(0.288)	(0.298)	(0.231)
Democracy	0.813*	1.155*	0.681*	0.827†	0.624*	0.785*	0.816*	0.703*
	(0.412)	(0.508)	(0.323)	(0.463)	(0.310)	(0.340)	(0.371)	(0.303)
State failure	0.325**	0.409**	0.319**	0.278**	0.347**	0.324**	0.347**	0.227**
	(0.053)	(0.091)	(0.052)	(0.057)	(0.057)	(0.052)	(0.052)	(0.041)
First stage								
Regional exposure	0.617**	0.485**	0.524**	0.487**	0.526**	0.498**	0.611**	0.520**
	(0.184)	(0.173)	(0.152)	(0.166)	(0.153)	(0.144)	(0.178)	(0.148)
Effective F-statistic	11.191	7.913	11.938	8.585	11.849	11.918	11.736	12.413
AR p-value	0.000	0.012	0.004	0.001	0.002	0.001	0.000	0.001
AR Ci	[5.05,24.2]	[4.04,51.5]	[3.03,15.1]	[5.05,37.3]	[4.04,16.1]	[4.04,20.2]	[4.04,21.2]	[4.04,16.1]
Observations	5574	4770	6155	6003	6210	6726	6316	6726
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: OLS regression on the number of terrorist attacks (IHS) in t+1. Table presents results of the main specification while excluding certain country groups one-by-one. *Model 1:* excludes OECD countries; *Model 2:* excludes SSA countries; *Model 3:* excludes South American countries; *Model 4:* excludes MENA countries; *Model 5:* excludes top 10% most corrupt countries; *Model 6:* winsorized extreme corruption (90%); *Model 7:* excludes top 10% terror-affected countries; *Model 8:* winsorized extreme terrorism (90%). Robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

D Types of Corruption/Conflict

Our main independent variable — political corruption — is a composite measure that accounts for corruption in the executive, legislature and judiciary as well as in the public sector. In this robustness check, we examine whether terrorist activity responds differently to different kinds of corruption. For example, executive corruption may be more visible and noticeable to the the public compared to corruption by the judiciary or in the public sector. As a consequence, "personalized" executive corruption may trigger a stronger terrorist response than more anonymous judicial or public sector corruption. To investigate whether different types of corruption share different relationships with terrorism, we exchange the political corruption index with the four individual corruption indices for executive, legislative, judicial and public sector corruption from VDEM (Coppedge et al. 2019). All variables are scaled so that higher levels of the respective corruption measure correspond to higher corruption levels. As shown in Table D.1, we find that corruption in the executive, legislative and judicial branches encourages more terrorist activity, where the associated IV-diagnostics are always sound. Overall, this tends to point to a generalized relationship between political corruption and terrorism. However, the effect of public sector corruption on terrorism — while having the expected sign — is not estimated precisely enough to fully support this notion. Most likely, this is due to the fact that in this case our usual instrumental variable is too weak to allow for a proper identification of associated causal effects.

Table D.1: Types of corruption

	Executive (1)	Legislative (2)	Judicial (3)	Public sector (4)
Corruption type	6.948*	6.601**	10.935**	24.947
	(2.733)	(2.391)	(3.867)	(21.161)
Population	1.435**	1.685**	1.828**	0.105
	(0.503)	(0.350)	(0.406)	(2.028)
GDP per capita	0.764*	0.630**	0.640*	1.197
	(0.330)	(0.237)	(0.279)	(0.830)
Democracy	1.352*	0.522†	0.686*	1.455
	(0.573)	(0.301)	(0.300)	(1.302)
State failure	0.320**	0.368**	0.299**	0.382**
	(0.055)	(0.051)	(0.053)	(0.089)
First stage				
Regional exposure	0.515**	0.450**	0.327**	0.143
	(0.161)	(0.139)	(0.092)	(0.135)
Effective F-statistic	10.199	10.499	12.563	1.130
AR p-value	0.001	0.007	0.001	0.001
AR CI	[3.54,27.2]	[3.27,19.9]	[5.90,34.0]	[10.9,...]
Observations	6726	6172	6726	6726
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Country $\boldsymbol{X}$	✓	✓	✓	✓

Notes: OLS regression on the number of terrorist attacks (IHS) in t+1. Table distinguishes between four main types of corruption: executive, legislative, judicial, and public sector. Robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table D.2: Other forms of violence and conflict

	Ethnic war (1)	Civil war (2)	Int. war (3)
Political corruption	-0.007	0.096	0.016
	(0.243)	(0.252)	(0.124)
First stage			
Regional exposure	0.541**	0.540**	0.540**
	(0.145)	(0.145)	(0.145)
Effective F-statistic	13.893	13.850	13.850
AR p-value	0.979	0.708	0.899
Observations	6458	6455	6455
Country FE	✓	✓	✓
Year FE	✓	✓	✓
Mean DV	0.081	0.049	0.012

Notes: Table presents a parsimonious 2SLS model of the effect of (exposure to regional) corruption on occurrences of ethnic, civil, and international war (all MPEV variables measured as binary indicators). Robust SE clustered at country level in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$