

Governmental Responses to Terrorism in Autocracies: Evidence from China

Online Appendix

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Data Collection

We collected our data from four main sources, which are (1) widely used database on terrorism, such as the Global Terrorism Database, RAND Database of Worldwide Terrorism Incidents, and Minorities at Risk Organizational Behavior, (2) English language news media, such as New York Times, Reuters, and Radio Free Asia, (3) widely used and recognized non-state-run Chinese websites, such as Sina, Tencent, ifeng and Sohu, and (4) secondary data from existing scholarly work, such as Bovingdon (2010) and Reed and Raschke (2010).

For an incident to be included in our dataset, it has to meet all the criteria below.

1. The incident must be initiated by ethnic Uyghurs.
2. The incident must occur in China.
3. The incident must be premeditated.
4. The incident must entail some level of violence.
5. The incident must be motivated by political, religious, or social concerns.
6. The act must be in fact carried out by the perpetrators.

It is worth noting that criteria (3), (4) and (6) exclude from our dataset some incidents that are recorded by other scholars, such as Bovingdon (2010) and Cao et al. (2018). Specifically, criterion (4) requires an incident to entail some level of violence, which leads us to drop some non-violent protests, demonstrations, and strikes, such as two student protests in March 2003 that happened in Khorgos and Manas respectively and Korla tax drivers' strike that lasted three days in April 2005 (Bovingdon 2010).

Criteria (3) and (6) together exclude from our sample another three main types of incidents that are widely included in other datasets. First, impulsive violence is dropped (Babcock et al 2014). An example of this is an incident on April 5, 2003, in which Tokhti, an assistant in the family-planning office, was killed by the husband of a pregnant woman being examined (Bovingdon 2010, Appendix). Second, acts of collective political violence that have strong spontaneous components, as in riots, demonstrations, or revolts, are also dropped.

Among these riots, the most notable ones would be the Ghulja Riot on February 5, 1997 and the Urumqi Riot on July 5, 2009. Third, plans that are not physically carried out and preemptive violence initiated by the police are also excluded from our sample. Examples include the gun battle that happened on August 7, 2001 in Quca where “police surprised a house full of suspected separatists; 4 died in the gun battle, including the chief, Chen Ping; a cache of weapons was reportedly found; report of a plan to storm a government building and raise the Uyghur flag” (Bovingdon 2010, Appendix), or the six weapon-production cases captured by the government between 1990 and 2005 (Cao et al 2018b).

On this last point, we follow GTD’s inclusion criterion that the attackers must be “out the door,” en route to execute the attack. However, attacks that were physically carried out but failed still meet this criterion, and therefore are included in our dataset. An example of this would be the failed bombing on September 5, 1993 in Yengisar county, in which an explosive device was set up on the front door of the apartment of the Director of the County Public Security Bureau, but was detected and removed before it exploded.

Descriptive Statistics

Table A.1 below shows the decomposition of all attacks in our dataset. From 1990 to 2014, a total of 137 attacks have been identified according to our inclusion criteria. Despite our best efforts, there are still 15 incidents for which the casualty data are missing, and 17 incidents for which the weapon type or tactic data are missing¹.

¹ These 17 attacks are coded as non-bombing in statistical analyses. The ambiguity about weapons involved usually happens when the event is an assault or a murder in which explosive devices are unlikely to be used.

Appendix Table A.1 – Data Decomposition

Total Number of Attacks		137
Casualty		
	Number of Killed	518
	Number of Injured	843
Target Selection (count)		
	Civilians	57
	Government Related	80
Weapon/Tactic (count)		
	Knives	54
	Bombing	58
	Gun	12
	Incendiary Devices	14
	Vehicle-ramming	6
	Poisoning	1
Note: Some attacks involve the use of more than one weapon type or tactic		

Figure A.1 below plots the temporal variation of the distribution of weapon/tactic types. From the graph, we can see that the first wave (1990-2001) was slightly dominated by relatively more sophisticated weapons. Among the total of 76 incidents in the first wave, bombing or explosive devices were used 35 times, knives or other sharp objects 17 times, guns 11 times, incendiary devices 4 times, and there is also 1 poisoning case. The second wave, however, was more cold-weapon-oriented. Knives or other sharp objects were used 37 times as the major weapon in 61 attacks of the second wave, while bombing or explosive devices were used 23 times and guns were only used once. The use of incendiary devices and vehicle-ramming also increased in the second wave, which were used 10 times and 6 times respectively.

Appendix Figure A.1: Weapon or Tactic Types

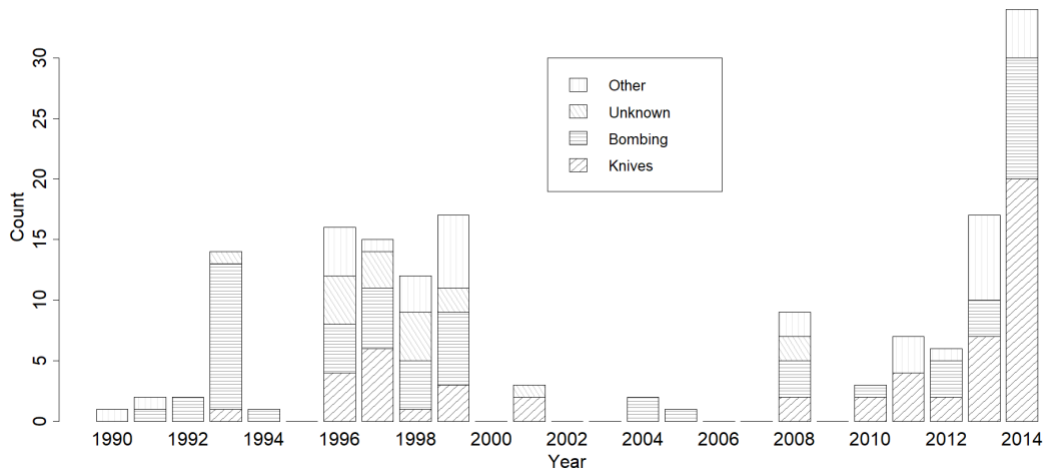


Table A.2 below shows the comparison between incidents that were timely acknowledged by *People's Daily* and those that were not mentioned. Table A.3 presents the summary statistics of all variables used in the statistical analysis.

Appendix Table A.2 – Reported vs. Unreported

		Reported Incidents	Unreported Incidents
Number of incidents		17	120
Casualties	Death per incident	10.35	3.23
	Injured per incident	26.12	3.8
Target Selection			
(Nnumber of incidents)	Civilian	8	49
	Government	9	71
Weapon Type			
(Total time used)	Knives	9	45
	Bombing	7	51
	Incendiary Devices	5	9
	Guns	0	12
	Vehicle-ramming	4	2
	Poisoning	0	1
Note: (1) Reported incidents refer to incidents that were timely acknowledged by People's Daily.			
(2) Some attacks involve the use of multiple weapons/tactics.			

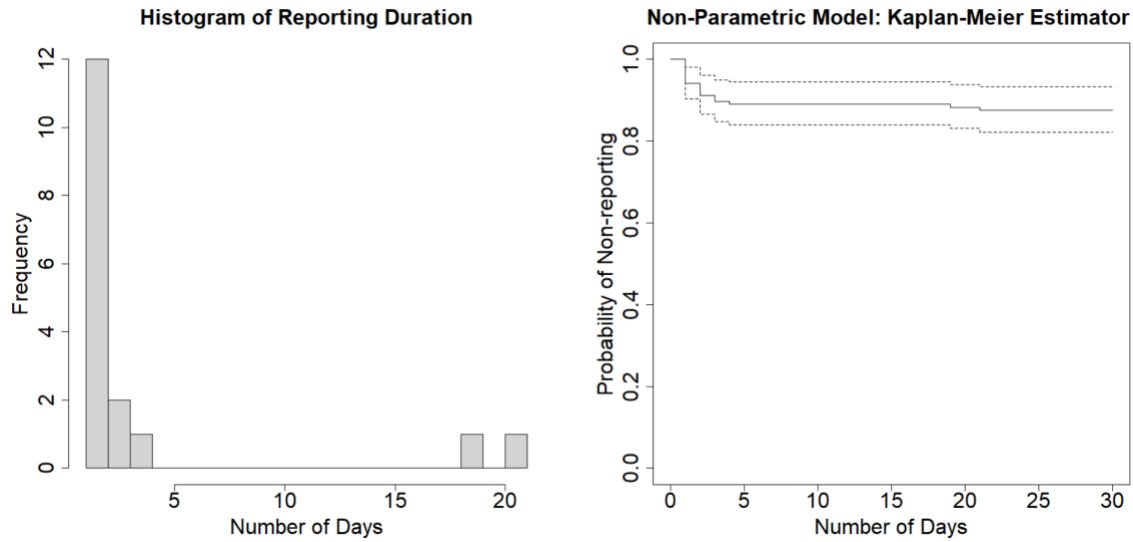
Appendix Table A.3 – Summary Statistics

Variables	N	Mean	St. Dev.	Min	Max
Dependent Variable					
Duration (days)	137	320.19	119.51	1	365
Key Independent Variables					
Growth (%)	137	9.08	2.14	3.93	14.28
CCI	137	99.71	2.10	97.03	104.17
Li-Index (%)	137	8.23	3.44	4.19	14.44
Majority Frequency (%)	137	49.57	12.61	26.67	77.78
Majority Frequency: G20 (%)	137	49.73	10.14	23.08	71.43
Majority Frequency: Security Council Members (%)	137	37.28	10.60	20.00	70.00
US-China Distance	137	3.56	0.48	2.69	4.35
Natural Disaster	137	85.62	35.91	12	128
External Condition	117	6.85	1.91	1	10
Internal Condition	117	5.59	2.55	1	10
Control Variables					
Target Civilian	137	0.42	0.49	0	1
Urban	137	0.36	0.48	0	1
Sensitive Period	137	0.18	0.38	0	1
Casualty	122	11.01	23.50	0	172
Bombing	137	0.42	0.50	0	1
Internet Penetration (%)	137	18.08	21.33	0.00	47.55
China Ideal Point	137	-0.85	0.33	-1.60	-0.16
Global Terrorist Incidents (Logged)	137	8.34	0.92	6.75	9.61

The left-hand side of Figure A.2 shows the distribution of the reporting duration of uncensored observations, and the right-side graph plots the non-parametric Kaplan-Meier (KM) estimator of the survival function. The average length of the wait-to-report periods for those that are reported is 3.88 days. As the histogram of reporting duration shows, the length of the durations cluster on short-periods. Indeed, more than half of those reported attacks (8 out of 17) are reported only one day after their occurrences, while an attempted hijacking of the CZ 6901 from Urumqi to Beijing on March 7, 2008 took 21 days to be mentioned in *People's Daily*, which is the longest duration of all reported incidents. The non-parametric Kaplan-Meier (KM) plot reveals the same pattern in a different way. The KM plot shows how the estimated probability of survival changes over time. In our case, survival means that an incident remains *unreported* by *People's Daily*. Therefore, the right-hand side KM plot indicates that the probability of being *not reported* decreases over time or the probability of being *reported* increases over time. However, most of the variations in the probability of being not reported

(or reported) happen within about seven days after the occurrence of the event; the estimated survival curve tends to be relatively stable after seven days. In other words, if an event is not reported within seven days after the occurrence, there is a great chance that it will never be reported in the future. In addition, the KM plot also indicates that the probability of being reported for any incident is relatively low, smaller than 20 percent, on average. Our main interest here is to investigate what factors may lead to the immediate report of these attacks given such a low average probability of being reported.

Appendix Figure A.2: Distribution of Reporting Durations and KM Estimator



Test of Proportional Hazards Assumption

Central to the Cox model is the proportional hazards (PH) assumption. The PH assumption holds if the ratio of the hazards for individuals i and j are independent of t and are constant for all t :

$$\frac{h_i(t)}{h_j(t)} = e^{\beta(x_i - x_j)}$$

We rely on scaled Schoenfeld residuals, gained from each Cox model (Models 1-7 in Table 1 and Models 8-13 in Table 2 in the text), to test nonproportionality. The logic behind scaled Schoenfeld residuals test is straightforward, which, in fact, is a test of nonzero slope in a generalized linear regression of scaled Schoenfeld residuals on time (Grambsch and Therneau 1994).

Appendix Table A.4: Global chi-square tests of the proportional hazards assumption

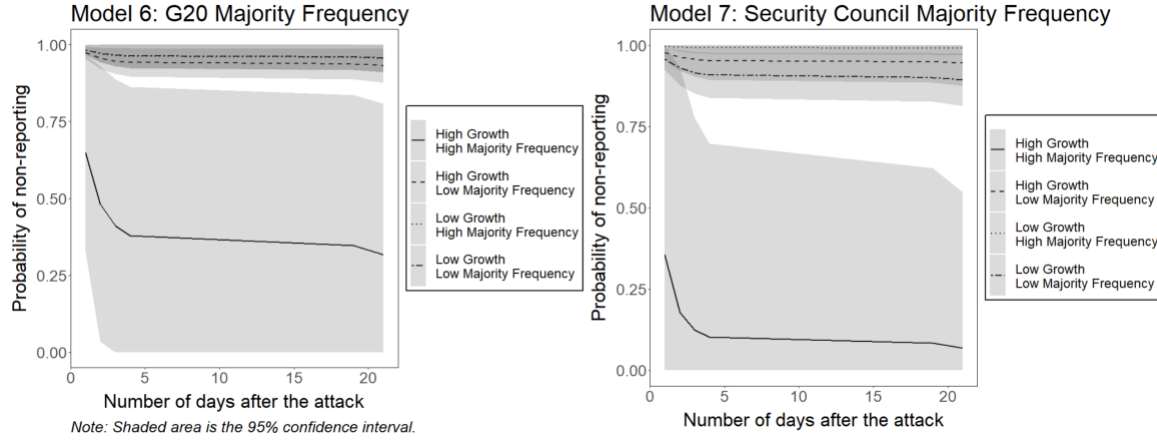
	chisq	df	p
Model 1	3.29	3	0.35
Model 2	4.82	5	0.44
Model 3	11.12	9	0.27
Model 4	7.37	9	0.60
Model 5	8.65	9	0.47
Model 6	11.93	9	0.22
Model 7	10.88	9	0.28
Model 8	11.20	11	0.43
Model 9	12.17	9	0.20
Model 10	8.73	10	0.56
Model 11	13.18	10	0.21
Model 12	15.15	10	0.13
Model 13	14.17	10	0.17

Table A.4 presents the global chi-squared tests of the proportional hazards assumption for each Cox model reported in the text. Given that all these p-values are greater than 0.05, we cannot reject the null hypothesis that there is no significant relationship between residuals and time (the Schoenfeld residuals are independent of time). Therefore, the proportional hazards assumption is satisfied.

Additional Model Results and Robustness Checks

Figure A.3 plots the four-case simulations for Model 6 and 7, which shows almost identical patterns as the one we presented in Figure 4 of the paper.

Appendix Figure A.3: Probability of Non-reporting: Model 6 and Model 7



Model A1, A2, A3, and A4 replicate Model 10, 11, 12 and 13 presented in the paper, but drop GDP growth rate as a control variable. The results are presented in Table A.5, which are largely consistent with those reported in the paper.

Appendix Table A.5: Alternative Model Specifications

	Cox PH Models			
	(A1)	(A2)	(A3)	(A4)
Natural Disaster	-0.032 (0.028)	-0.020 (0.016)		
Majority Frequency	0.142*** (0.031)			
US-China Distance		-3.549*** (0.982)		
Internal Condition			0.432** (0.203)	0.363 (0.222)
External Condition			0.446** (0.197)	0.348* (0.199)
Natural Disaster × Majority Frequency	-0.003*** (0.001)			
Natural Disaster × US-China Distance		0.060*** (0.023)		
Internal Condition × External Condition			0.200*** (0.069)	0.163** (0.070)
Internet Penetration	0.096*** (0.035)	0.052** (0.023)	0.123*** (0.028)	0.073* (0.040)
Sensitive Period	-0.456 (0.675)	0.959* (0.526)	0.884* (0.525)	0.549 (0.509)
Casualty	0.029*** (0.007)	0.020*** (0.006)	0.022*** (0.007)	0.024*** (0.007)
Urban	0.745 (0.565)	0.426 (0.549)	0.108 (0.506)	0.205 (0.514)
Target Civilian	-1.144* (0.640)	-0.900 (0.600)	-0.244 (0.484)	-0.347 (0.491)
Bombing	0.224 (0.463)	0.400 (0.476)	0.189 (0.411)	0.228 (0.385)
Observations	122	122	103	57
Max. Possible R ²	0.734	0.734	0.779	0.904
Log Likelihood	-58.784	-62.140	-54.853	-53.660
LR Test	44.024***	37.313***	45.788***	26.155***

Note: Table entries are coefficients obtained from Cox proportional hazards models. Robust standard errors clustered on the incident are in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Logit Model Results, Binning Estimator, and Kernel Estimator

Table A.6 below shows the results from basic logistic models using GDP growth rate and UN voting majority (both are centered on their mean values) as measures of domestic and international environments, in which the dependent variable is simply whether each incident was acknowledged/not acknowledged. In all these models, the interaction term remains significant and in the anticipated direction.

Appendix Table A.6: Logit Regression

	Logit Models			
	(A5)	(A6)	(A7)	(A8)
Growth	-0.509 (0.333)	0.337 (0.348)	-0.557 (0.514)	0.250 (0.600)
Majority Frequency	0.094*** (0.030)	0.072** (0.033)	0.182*** (0.057)	0.156*** (0.059)
Growth × Majority Frequency	0.040* (0.021)	0.043** (0.020)	0.087** (0.041)	0.079** (0.037)
Internet Penetration		0.104*** (0.016)		0.095*** (0.022)
Sensitive Period		1.449** (0.687)		1.596* (0.836)
Casualty			0.069*** (0.021)	0.076*** (0.024)
Urban			1.300* (0.719)	0.778 (0.753)
Target Civilian			-1.771* (0.932)	-2.181** (0.931)
Bombing			-0.680 (1.011)	-0.669 (0.996)
Constant	-2.633*** (0.432)	-5.783*** (0.601)	-3.797*** (0.947)	-6.447*** (1.086)
Observations	137	137	122	122
Log Likelihood	-43.270	-34.925	-27.139	-22.743
Akaike Inf. Crit.	94.540	81.850	70.279	65.486

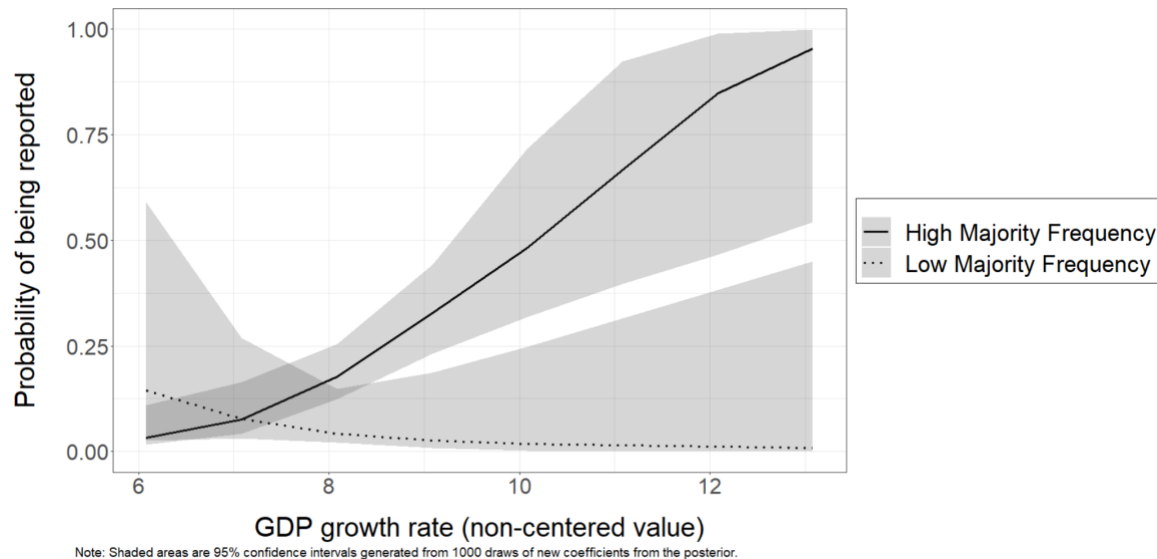
Note: Table entries are coefficients obtained from Logit models. Robust standard errors clustered on the incident are in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Figure A.4 below plots the predicted probability of being reported by People's Daily varies over the GDP growth rate when the frequency of being a majority in UN voting is held at low and high values respectively (one standard deviation below and above the mean) based on Model A8. When *Majority Freq* is high, the probability of timely official coverage increases from 0.25 to 0.44, and then to 0.72 as the GDP growth rate increases from 8% to 9%, and

then to 10%. In contrast, when the frequency of being a majority in UN voting is low, this probability remains low even when domestic conditions are favorable.

Appendix Figure A.4: Predicted probability of being reported by People’s Daily



Hainmueller, Mummolo, and Xu (2019) argue that results from multiplicative interaction models might be biased due to violations of the linear interaction effect (LIE) assumption and the lack common support. They suggest that researchers should use simple scatterplots of raw data to detect these problems and apply two flexible estimation strategies (Binning Estimator and Kernel Estimator) if these problems are present. These procedures, however, best diagnose and adjust such issues in general linear regression models with continuous dependent variables (such as OLS).² The closest check that we can perform with our data is to apply these procedures to a binary version of our dependent variable

² All the cases replicated by Hainmueller, Mummolo, and Xu (2019) use continuous dependent variables and OLS regression.

(reported/not reported), converting the the logit models reported in Table A.10 into simple OLS regression models.

Appendix Figure A.5: Linear Interaction Diagnostic Plots

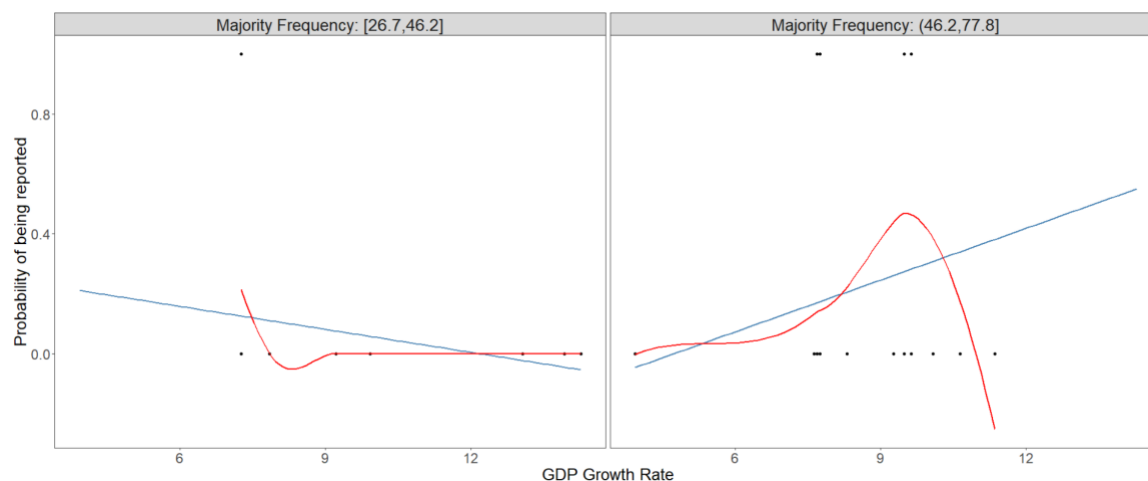


Figure A.5 provides scatterplots of the raw data with the linear regression lines (blue) and the LOESS fits (red). The two plots reveal that (1) there is evidence of an interaction effect as the slope of the line that captures the relationship between the probability of being reported and the value of GDP growth rate is weakly negative at low levels of *Majority Frequency* and positive at high levels of *Majority Frequency*; (2) there is sufficient common support as the observations are nearly equally distributed across two samples with low and high values of *Majority Frequency*; (3) the interaction effect might not be linear as the linear regression lines (blue) and the LOESS fits (red) diverge considerably, especially at high levels of *Majority Frequency*.³

Appendix Figure A.6: Marginal Effect of Growth Rate Conditional on Majority Frequency

³ This divergence might also result from the binary dependent variable.

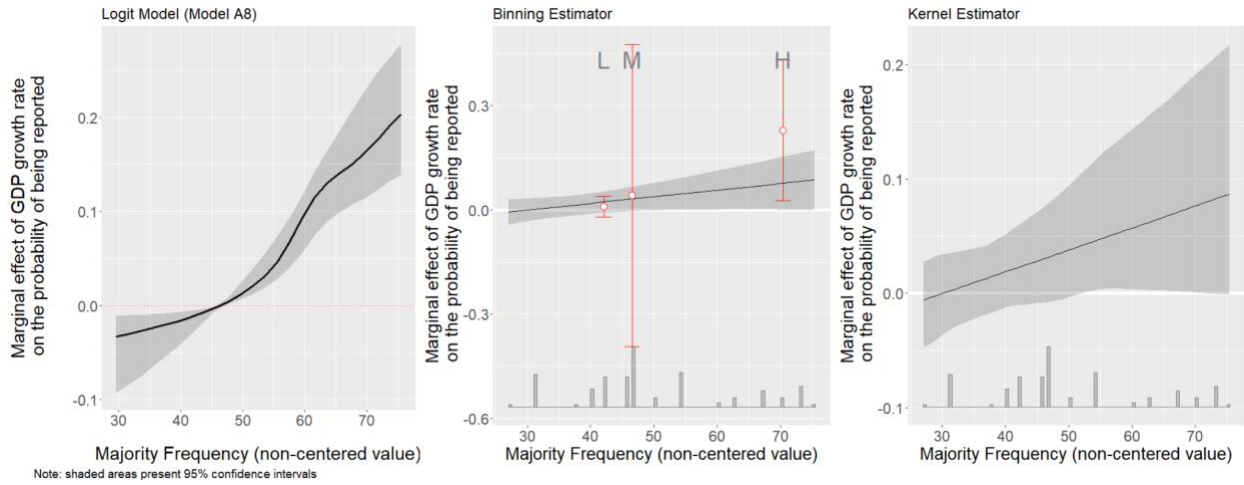


Figure A.6 indicates that the marginal effect of GDP growth rate on the probability of reporting varies at different values of *Majority Frequency* based on a logit model (left panel), binning estimator (center panel), and kernel estimator (right panel).⁴ All three plots demonstrate that the marginal effect of *Growth* tends to be positive and stronger as the value of *Majority Frequency* increases. The binning estimator for the GDP growth rate effect lines up very closely with the LIEs from the original model (OLS regression) at low and medium levels of *Majority Frequency*. At high levels of *Majority Frequency*, however, the binning estimator is larger than the OLS estimator. This suggests that the LIEs based on OLS regressions underestimate the positive marginal effect of GDP growth rate when *Majority Frequency* is high.⁵ The conditional marginal effect estimates from the kernel estimator in the right panel remain similar, although the magnitude of the effect becomes smaller and the optimal bandwidth selected by cross-validation is relatively larger.

Robustness Check: Ethnic Violence in China (EVC) Database

⁴ Control variables are included in all these models.

To assess the implications of the distinction between EVC data and our data for our findings, we added the necessary covariates to the EVC data and conducted robustness checks using EVC data (1990-2005) plus our post-2005 data. The *Casualty* variable is dropped in full EVC model because the EVC dataset doesn't have information on the number of casualties at event level. The results are reported in Appendix Table A.7 below, which shows that models using EVC data yield almost identical results.

Appendix Table A.7: Robustness Checks with EVC data

	Cox PH Models			
	(A9)	(A10)	(A11)	(A12)
	Our Data	Our Data+EVC Data	Our Data	Our Data+EVC Data
Growth	-0.454 (0.291)	-0.606** (0.295)	0.150 (0.362)	0.076 (0.399)
Majority Frequency	0.074*** (0.018)	0.085*** (0.021)	0.108*** (0.034)	0.098** (0.040)
Growth $\times$ Majority Frequency	0.030** (0.014)	0.036*** (0.013)	0.048** (0.021)	0.058** (0.023)
Internet Penetration			0.071*** (0.012)	0.087*** (0.019)
Sensitive Period			0.731 (0.521)	1.037* (0.546)
Casualty			0.023*** (0.007)	
Urban			0.357 (0.485)	0.399 (0.475)
Target Civilian			-0.897 (0.547)	-0.213 (0.462)
Bombing			0.317 (0.470)	0.531 (0.484)
Observations	137	149	122	129
Max. Possible R ²	0.702	0.678	0.734	0.719
Log Likelihood	-75.530	-75.405	-58.289	-65.440
LR Test	14.675***	17.910***	45.015***	32.710***

Note: Table entries are coefficients obtained from Cox proportional hazards models. Robust standard errors clustered on the incident are in parentheses.

*p<0.1; **p<0.05; ***p<0.01

⁵ This result is consistent with the nonlinear marginal effect based on the logit model plotted in the left panel. The logit model is a linear model in the log odds metric, the probability is a nonlinear transformation of log odds