Supplemental Appendix to Accompany "The Differential Effects of 'Democratic' Institutions on Dissent in Dictatorships"

This Supplemental Appendix accompanies Woo, Ae sil, and Courtenay R. Conrad. 2018. "The Differential Effects of 'Democratic' Institutions on Dissent in Dictatorships," Forthcoming at the *Journal of Politics.*

Replication files to implement the empirical models in our main article and in this Supplemental Appendix are available in the JOP Data Archive on Dataverse (`http://thedata.harvard.edu/dvn/dv/jop`) and the authors' websites.

In Section 1 below, we address the robustness of the matched empirical results presented in our article. In Section 2, we show that the results presented in our article are robust to myriad empirical specifications. Finally, in Section 3, we present figures of several substantive effects that are not presented in our main article.

1 Robustness of Matched Results

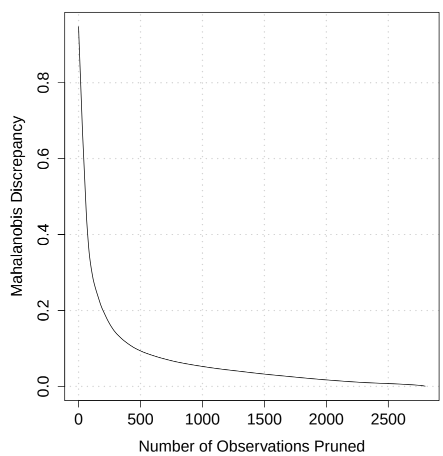
Although matching is a useful means of relaxing parametric assumptions in regression estimations (Ho et al., 2007), matching entails making other subjective choices. For example, researchers who use matching techniques must make consequential decisions about whether to prioritize certain covariates, what balance metric to use, and how to tradeoff between balance and sample size (Miller, 2014). In what follows, we show the robustness of our matched empirical results to (1) changes in the tradeoff between sample size and balance, and (2) respecification of our matched models to account for challenges associated with matching time-series cross-sectional (TSCS) data.

1.1 Tradeoff Between Sample Size and Balance in Matched Models

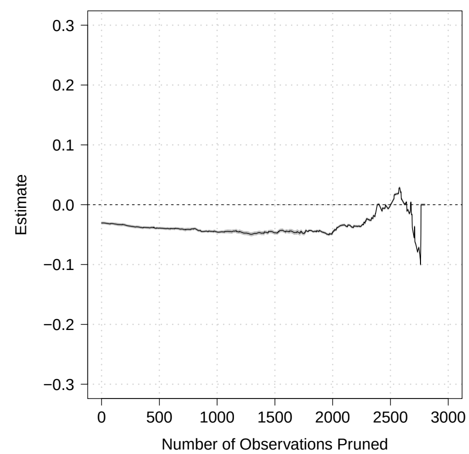
King, Lucas and Nielsen (2017) emphasize the tradeoff that exists in optimizing balance and sample size when matching. According to (King, Lucas and Nielsen, 2017, 473), "[i]f the subset identified by the matching method is too small, the reduction in model dependence (and hence bias) achieved will be counterbalance by an unacceptably high variance. Similarly, the small variance associated with a large matched data subset may be counterbalanced by unacceptably high levels of imbalance."

Existing matching methods optimize on either balance or sample size. For example, matching by propensity score fixes sample size while maximizing balance; matching by the coarsened exact matching (CEM) fixes balance while maximizing sample size. King, Lucas and Nielsen (2017) developed the matching frontier as a solution to jointly optimize both balance and sample size. The matching frontier reports a set of matched samples such that no other possible subset of the same size has lower imbalance than the one reported in the matching frontier. By finding the matching frontier, King, Lucas and Nielsen (2017) argue, researchers can choose the appropriate matching solution in one step instead of tweaking the matching process manually to optimize on balance and sample size.

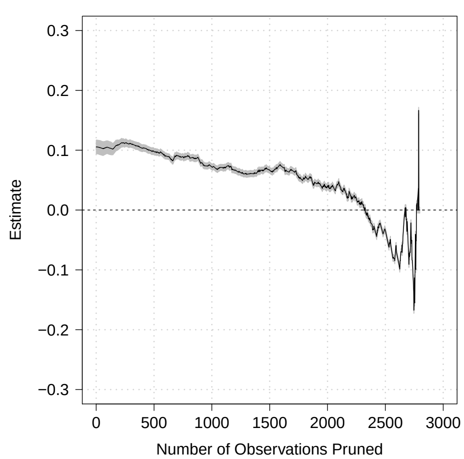
The results reported in our article are robust to matching using the matching frontier, as shown in Figure 1. The top left panel is the L_1 frontier. The y-axis indicates the degree to which the sample is balanced. $L_1 = 1$ represents the highest level of imbalance in the sample; $L_1 = 0$ represents the lowest level of imbalance. The x-axis shows the number of observation pruned for matching. In our data, we have approximately 2,800 country-year observations. The reduction in imbalance from trading off (im)balance for sample size is steep until pruning reaches about 500 observations. After about 500 observations are pruned, the reduction in imbalance becomes smaller as we prune more observations.



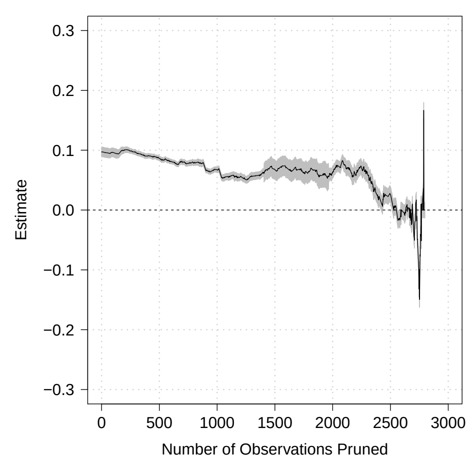
(a) L_1 Matching Frontier



(b) Effect of Institutions on Coups



(c) Effect of Institutions on Demonstrations



(d) Effect of Institutions on Riots

Figure 1: Matching Frontier Results (King, Lucas and Nielsen, 2017)

The top-right panel of Figure 1 displays the estimated effect of nominally democratic institutions on coups along that frontier (i.e., we as prune additional observations). As expected, the estimated effect of nominally democratic institutions on coups are negative across the majority of the frontier. The estimates show some instability after more than 2,000 observations are pruned from the data. Higher variance as more observations are pruned is to be expected King, Lucas and Nielsen (2017). The bottom-left panel and the bottom-right panel display the estimated effect of nominally democratic institutions on demonstrations and riots, respectively. In support of H2, the estimated effect of nominally democratic institutions are both positive across the majority of the frontier. Similar to our results on coups, the estimates show some instability after more than 2,000 observations are pruned; again this variance is to be expected when such a large number of observations are pruned. Overall, the results using the Matching Frontier (King, Lucas and Nielsen, 2017) are supportive of our hypotheses and provide additional evidence that our empirical results are robust to changes in the assumptions required by CEM matching techniques.

1.2 Matching with Time-Series Cross Sectional Data

In the matched analyses reported in our article, we use time-series cross-sectional (TSCS) data; the country-year is our unit of observation. Each observation represents a panel-time period, such that observations of the same unit in different time-periods are recorded in our matched dataset. According to Nielsen and Sheffield (2009), standard matching methods match *observations* rather than panels and suggest that, in the case of TSCS data, treated *panels* should be matched with control *panels*. Matching observations within the same panel may be problematic; the assumption of independence between treated units and control units could be violated due to temporal dependence across observations (Young, 2008).

There is not yet a consensus on the "best" procedure for matching TSCS data. We follow Nielsen (2016), who provides an example of how to match TSCS data using the lags of the covariates. The idea is that we treat all of the lags as possible confounders and condition on them to match countries. In order to implement this strategy, we created four lagged variables (i.e., t-1, t-2, t-3, and t-4) of each of our six covariates (i.e., GDPPC, GDPPC Growth, Trade Openness, Military Leader, Communist, and Cold War). We then included the lags of the covariates in the CEM process to produce a matched sample. Table 1 shows the results of this robustness check. The negative sign on co-optation for coups is consistent with our expectation (H1), but it does not reach traditional levels of statistical significance. The positive signs on co-optation for anti-government demonstration and riots are consistent with our expectation (H2) and significant at traditional levels of statistical significance.

Table 1 about here

2 Other Robustness Checks

Our results are robust to an alternative measure of coup attempts from Powell and Thyne (2011). Using data from Powell and Thyne (2011), we created a dependent variable coded 1 if a country-year experiences either a failed or successful first coup attempt and 0 otherwise. Using data from Powell and Thyne (2011) generates a dataset with 91 dictatorships from 1950 to 2006. Table 2 shows the robustness of our results to this alternative operationalization of our first dependent variable. The first two columns of the table report coefficient estimates from logit models with the unmatched sample. Column 3 and Column 4 report coefficient estimates from logit models with the matched CEM sample. Consistent with H1, the results from both samples show co-optative institutions to be negatively correlated with coups.

Table 2 about here

Our results on popular dissent are also robust to alternative operationalizations. In their analysis of repression and dissent, Ritter and Conrad (2016) collapsed event data on dissent from the Social Conflict Analysis Database (SCAD) (Salehyan et al., 2012) into the province-day data for all African states. We collapse province-day data from Ritter and Conrad (2016) to the country-year to match the unit of observation in the empirical tests reported in our article. Using these data, we generated three binary variables indicating the presence of a Spontaneous Demonstration, an Organized Riot, and a Spontaneous Riot. Merging these variables with the data used in our original analyses generated a dataset that includes data on 43 African dictatorships from 1990-2006. Tables 3 and 4 show the robustness of our results to these alternative measures of dissent. Table 3 shows results using the unmatched sample. All types of dissent in the unmatched sample are positively correlated with co-optative institutions. Table 4 shows results using the matched sample. All types of dissent in the matched sample are also positively correlated with co-optative institutions.

Tables 3 and 4 about here

In our main models, we measure our dependent variables using binary measures of coups and popular dissent. Our results are robust to using the original counts of elite coups, anti-government demonstrations, and riots from Banks (2010). Tables 5 and 6 show the robustness of our results to using negative binomial models with the aforementioned counts in both the unmatched and matched samples. As expected, elite coups are negatively correlated with co-optative institutions; anti-government demonstrations and riots are positively correlated with co-optative institutions.

Tables 5 and 6 about here

Our results are robust to the inclusion of a lagged dependent variable (Tables 7 and 8).

Tables 7 and 8 about here

Our results are also robust to the inclusion of a third order polynomial time counter to account for temporal dependence (Carter and Signorino, 2010). In the models that follow, we add t, t^2, and t^3 as additional aggressors so that the regression can serve as a third-order Taylor series approximation to the hazard. "t" refers to the number of years (duration) since the last event was observed. Tables 9 and 10 show that the are results are robust to the inclusion of the third order polynomial time counter in both the unmatched and matched samples.

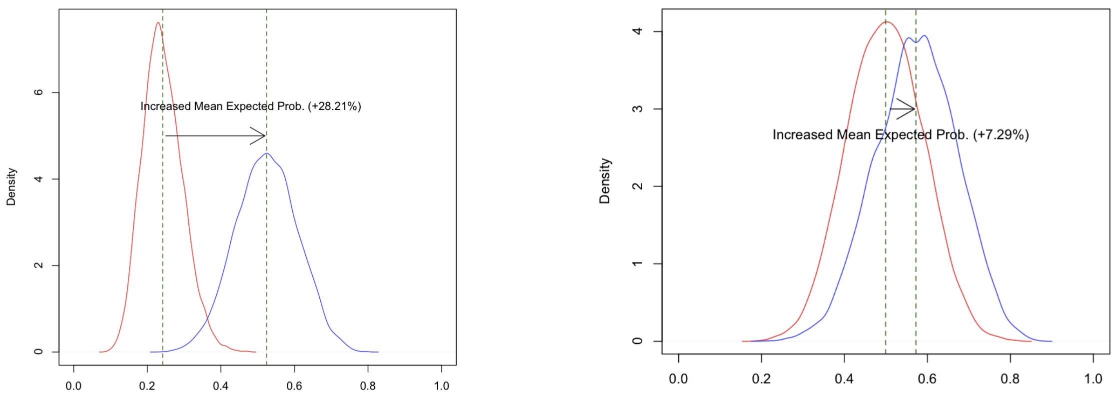
Tables 9 and 10 about here

Finally, our results are robust to models that include country random effects models with clustered standard errors, as shown in Table 11.

Table 11 about here

3 Additional Substantive Effects

Figure 2 shows the substantive effect of co-optation on anti-government demonstrations. As noted in the article, we chose to relegate these figures to the Supplemental Appendix.present in the text of our article.



(a) Unmatched Sample (b) Matched Sample

Figure 2: Change in the Expected Probability of an Anti-Government Demonstration With (Red) and Without a Co-optative Legislature (Blue)

Table 1: The Relationship Between Dictatorial Legislatures and Coups (Matched with Covariate Lags)

	Dependent variables:					
	DV: Elite Coups		DV: Anti-Gov Demonstration		DV: Riots	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	-0.825	-0.291	0.670^{***}	0.703^{***}	0.909^{***}	0.883^{***}
	(0.576)	(0.669)	(0.237)	(0.246)	(0.234)	(0.240)
GDPPC		-12.449^{***}		0.115		0.910
		(4.431)		(0.725)		(0.727)
GDPPC Growth		0.303^{***}		0.057		0.075^{*}
		(0.104)		(0.042)		(0.043)
Trade Openness		0.042^{**}		-0.005		-0.002
		(0.018)		(0.006)		(0.006)
Military Leader		-0.677		0.199		0.491
		(0.902)		(0.419)		(0.427)
Communist		-1.370		0.409		0.247
		(1.446)		(0.661)		(0.681)
Cold War		0.495		-0.793^{**}		-0.339
		(1.470)		(0.352)		(0.360)
Constant	-3.025^{***}	-4.121^{**}	-1.797^{***}	-1.305^{**}	-1.848^{***}	-2.248^{***}
	(0.278)	(2.011)	(0.167)	(0.663)	(0.170)	(0.694)
Observations	2,789	2,789	2,789	2,789	2,789	2,789
Log Likelihood	-71.523	-56.245	-227.187	-219.239	-229.196	-221.804
Akaike Inf. Crit.	147.046	128.489	458.374	454.477	462.392	459.609

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2: The Relationship Between Dictatorial Legislatures and Coups from Powell and Thyne (2011)

	Unmatched		*Matched*	
	DV: Coups		DV: Coups	
	(1)	(2)	(3)	(4)
Co-optation	-0.663^{***}	-0.592^{***}	-0.675^{***}	-0.654^{***}
	(0.189)	(0.208)	(0.202)	(0.203)
GDPPC		-0.028^{***}		-0.473
		(0.009)		(0.362)
GDPPC Growth		-0.602^{***}		-0.030^{*}
		(0.225)		(0.016)
Trade Openness		-0.003		-0.001
		(0.002)		(0.003)
Military Leader		0.665^{***}		0.689^{***}
		(0.176)		(0.199)
Communist		-1.937^{***}		-0.876
		(0.596)		(0.590)
Cold War		-0.093		0.079
		(0.202)		(0.197)
Constant	-2.577^{***}	-2.319^{***}	-2.396^{***}	-2.436^{***}
	(0.095)	(0.267)	(0.111)	(0.279)
Observations	2,734	2,734	2,734	2,734
Log Likelihood	-599.816	-559.790	-443.047	-430.631
Akaike Inf. Crit.	1,203.632	1,135.579	890.095	877.263

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3: The Relationship Between Dictatorial Legislatures and Dissent from SCAD (Unmatched)

	Dependent variables:					
	Spontaneous Demonstration		Organized Riot		Spontaneous Riot	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	0.360*	0.325	0.869**	0.845**	0.700***	0.679***
	(0.192)	(0.209)	(0.338)	(0.364)	(0.203)	(0.221)
GDPPC		0.013		0.011		0.008
		(0.010)		(0.016)		(0.011)
GDPPC Growth		0.714**		1.088**		0.824***
		(0.299)		(0.470)		(0.304)
Trade Openness		0.001		−0.006		0.001
		(0.003)		(0.005)		(0.003)
Military Leader		0.683***		0.802***		0.579***
		(0.198)		(0.308)		(0.203)
Communist						
Cold War		−0.372		−0.475		−0.355
		(0.304)		(0.565)		(0.323)
Constant	−1.128***	−1.633***	−2.876***	−3.113***	−1.443***	−1.955***
	(0.155)	(0.288)	(0.297)	(0.492)	(0.170)	(0.307)
Observations	588	588	588	588	588	588
Log Likelihood	-351.804	-342.588	-178.922	-173.328	-337.944	-330.357
Akaike Inf. Crit.	707.608	699.176	361.845	360.655	679.888	674.714

Note: None of authoritarian countries available for SCAD from 1990-2006 was communist.
*p<0.1; **p<0.05; ***p<0.01

Table 4: The Relationship Between Dictatorial Legislatures and Dissent from SCAD (Matched)

	Dependent variable:					
	Spontaneous Demonstration		Organized Riot		Spontaneous Riot	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	0.558*	0.556*	0.683	0.792	0.543*	0.530*
	(0.288)	(0.293)	(0.476)	(0.509)	(0.296)	(0.307)
GDPPC		0.355		10.526***		1.739
		(1.119)		(2.335)		(1.148)
GDPPC Growth		0.013		−0.052		0.031
		(0.025)		(0.044)		(0.028)
Trade Openness		−0.001		−0.070***		−0.005
		(0.006)		(0.018)		(0.006)
Military Leader		0.636**		1.025**		1.040***
		(0.278)		(0.500)		(0.298)
Communist						
Cold War		−2.428		−14.636		−2.279
		(2.673)		(958.598)		(2.685)
Constant	−1.328***	−1.655***	−2.762***	−2.012***	−1.416***	−2.061***
	(0.240)	(0.392)	(0.413)	(0.634)	(0.246)	(0.424)
Observations	588	588	588	588	588	588
Log Likelihood	-160.885	-156.562	-82.664	-66.107	-156.092	-145.197
Akaike Inf. Crit.	325.770	327.124	169.327	146.213	316.185	304.394

Note: None of authoritarian countries available for SCAD from 1990-2006 was communist.
*p<0.1; **p<0.05; ***p<0.01

Table 5: The Relationship Between Dictatorial Legislatures, Elite Coups & Popular Dissent Counts (Unmatched)

	Dependent variables:					
	DV: Elite Coups		DV: Anti-Gov Demonstration		DV: Riots	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	-0.756^{***}	-0.616^{**}	0.926^{***}	0.933^{***}	0.887^{***}	1.052^{***}
	(0.226)	(0.243)	(0.129)	(0.136)	(0.123)	(0.130)
GDPPC		-0.508^{**}		0.080		-0.097
		(0.244)		(0.092)		(0.097)
GDPPC Growth		-0.018		-0.019^{***}		-0.023^{***}
		(0.011)		(0.007)		(0.007)
Trade Openness		-0.003		-0.012^{***}		-0.010^{***}
		(0.003)		(0.002)		(0.002)
Military Leader		0.575^{***}		0.181		0.086
		(0.204)		(0.140)		(0.133)
Communist		-0.395		-0.085		-0.278
		(0.354)		(0.199)		(0.192)
Cold War		0.149		-0.283^{**}		0.512^{***}
		(0.246)		(0.143)		(0.143)
Constant	-2.877^{***}	-2.853^{***}	-1.250^{***}	-0.448^{**}	-1.422^{***}	-1.212^{***}
	(0.110)	(0.322)	(0.084)	(0.201)	(0.081)	(0.198)
Observations	2,800	2,800	2,800	2,800	2,800	2,800
Log Likelihood	-510.948	-495.623	-2,001.493	-1,966.330	-1,878.890	-1,836.899
θ	0.296^{**}(0.116)	0.388^{**}(0.163)	0.113^{***}(0.008)	0.130^{***}(0.009)	0.135^{***}(0.010)	0.163^{***}(0.013)
Akaike Inf. Crit.	1,025.897	1,007.245	4,006.987	3,948.661	3,761.779	3,689.798

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: The Relationship Between Dictatorial Legislatures, Elite Coups Popular Dissent (Matched)

	Dependent variable:					
	DV: Elite Coups		DV: Anti-Gov Demonstration		DV: Riots	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	-0.765^{***}	-0.716^{***}	0.234^{*}	0.291^{**}	0.657^{***}	0.594^{***}
	(0.248)	(0.247)	(0.138)	(0.135)	(0.130)	(0.129)
GDPPC		-1.049^{**}		0.924^{***}		0.367
		(0.459)		(0.233)		(0.224)
GDPPC Growth		-0.040^{**}		-0.003		0.004
		(0.019)		(0.012)		(0.012)
Trade Openness		0.003		-0.016^{***}		-0.011^{***}
		(0.003)		(0.002)		(0.002)
Military Leader		0.989^{***}		0.240		0.153
		(0.247)		(0.149)		(0.143)
Communist		0.628		0.050		0.002
		(0.488)		(0.261)		(0.246)
Cold War		-0.039		-0.601^{***}		-0.009
		(0.237)		(0.146)		(0.139)
Constant	-2.765^{***}	-3.064^{***}	-0.685^{***}	0.026	-1.309^{***}	-0.830^{***}
	(0.133)	(0.349)	(0.093)	(0.201)	(0.092)	(0.195)
Observations	2,800	2,800	2,800	2,800	2,800	2,800
Log Likelihood	-369.906	-355.470	-1,655.848	-1,620.497	-1,403.022	-1,383.431
θ	0.318^{**} (0.145)	0.466^{**} (0.236)	0.136^{***} (0.010)	0.158^{***} (0.012)	0.186^{***} (0.017)	0.207^{***} (0.019)
Akaike Inf. Crit.	743.812	726.941	3,315.696	3,256.993	2,810.043	2,782.863

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: The Relationship Between Dictatorial Legislatures, Elite Coups & Popular Dissent with a Lagged DV (Unmatched)

	Dependent variables:					
	DV: Elite Coups		DV: Anti-Gov Demonstration		DV: Riots	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	-0.838^{***}	-0.736^{***}	0.564^{***}	0.567^{***}	0.550^{***}	0.675^{***}
	(0.238)	(0.257)	(0.110)	(0.118)	(0.109)	(0.119)
Elite Coups$_{t-1}$	1.423^{***}	1.210^{***}				
	(0.285)	(0.291)				
GDPPC		-0.025^{**}		-0.010		-0.011^{*}
		(0.010)		(0.006)		(0.006)
GDPPC Growth		-0.564^{**}		0.057		-0.009
		(0.261)		(0.087)		(0.092)
Trade Openness		-0.002		-0.009^{***}		-0.008^{***}
		(0.003)		(0.002)		(0.002)
Military Leader		0.537^{***}		0.037		0.072
		(0.208)		(0.124)		(0.123)
Communist		-0.419		-0.139		-0.180
		(0.377)		(0.178)		(0.177)
Cold War		-0.048		-0.268^{**}		0.212
		(0.242)		(0.122)		(0.130)
Anti-Gov Demonstration$_{t-1}$			1.615^{***}	1.513^{***}		
			(0.118)	(0.120)		
Riots$_{t-1}$					1.529^{***}	1.412^{***}
					(0.118)	(0.121)
Constant	-3.032^{***}	-2.862^{***}	-2.296^{***}	-1.554^{***}	-2.269^{***}	-1.912^{***}
	(0.116)	(0.317)	(0.082)	(0.180)	(0.081)	(0.186)
Observations	2,799	2,799	2,799	2,799	2,799	2,799
Log Likelihood	-458.281	-442.794	-1,112.837	-1,091.988	-1,120.131	-1,098.179
Akaike Inf. Crit.	922.562	903.588	2,231.674	2,201.976	2,246.262	2,214.358
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 8: The Relationship Between Dictatorial Legislatures, Elite Coups & Popular Dissent with a Lagged DV (Matched)

	Dependent variables:					
	DV: Elite Coupss		DV: Anti-Gov Demonstration		DV: Riotrs	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	-1.029^{***}	-1.009^{***}	0.226^{*}	0.231^{*}	0.336^{**}	0.354^{***}
	(0.267)	(0.269)	(0.126)	(0.127)	(0.132)	(0.133)
Elite Coups$_{t-1}$	1.156^{*}	0.836				
	(0.638)	(0.654)				
GDPPC		-0.805^{*}		0.709^{***}		0.578^{**}
		(0.482)		(0.233)		(0.252)
GDPPC Growth		-0.053^{***}		0.001		0.0001
		(0.019)		(0.012)		(0.013)
Trade Openness		0.004		-0.005^{**}		-0.010^{***}
		(0.003)		(0.002)		(0.002)
Military Leader		1.004^{***}		0.036		0.132
		(0.255)		(0.143)		(0.146)
Communist		0.655		0.156		−0.224
		(0.543)		(0.259)		(0.275)
Cold War		-0.469^{*}		-0.675^{***}		−0.149
		(0.253)		(0.139)		(0.143)
Anti-Gov Demonstration$_{t-1}$			1.364^{***}	1.371^{***}		
			(0.135)	(0.139)		
Riots$_{t-1}$					1.415^{***}	1.321^{***}
					(0.147)	(0.150)
Constant	-2.769^{***}	-3.004^{***}	-1.890^{***}	-1.548^{***}	-2.089^{***}	-1.655^{***}
	(0.133)	(0.353)	(0.096)	(0.189)	(0.102)	(0.202)
Observations	2,799	2,799	2,799	2,799	2,799	2,799
Log Likelihood	-299.330	-283.333	-773.971	-757.376	-736.571	-725.375
Akaike Inf. Crit.	604.660	584.666	1,553.943	1,532.752	1,479.142	1,468.750
Note:					*p<0.1; **p<0.05; ***p<0.01	

Table 9: The Relationship Between Dictatorial Legislatures and Coups & Popular Dissent by Third Order Polynomial Time Counter (Unmatched)

	Dependent variables:					
	DV: Elite Coups		DV: Anti-Gov Dmonstration		DV: Riots	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	-0.680^{***}	-0.654^{**}	0.502^{***}	0.503^{***}	0.499^{***}	0.600^{***}
	(0.242)	(0.259)	(0.109)	(0.119)	(0.109)	(0.120)
t_{Coups}	-0.207^{***}	-0.198^{***}				
	(0.053)	(0.054)				
t^2_{Coups}	0.009^{**}	0.009^{**}				
	(0.003)	(0.003)				
t^3_{Coups}	-0.0001^{**}	-0.0001^{**}				
	(0.0001)	(0.0001)				
GDPPC		-0.023^{**}		-0.009		-0.010^{*}
		(0.011)		(0.006)		(0.006)
GDPPC Growth		-0.470^{*}		0.067		-0.003
		(0.247)		(0.087)		(0.092)
Trade Openness		-0.002		-0.008^{***}		-0.007^{***}
		(0.002)		(0.002)		(0.002)
Military Leader		0.489^{**}		0.032		0.075
		(0.207)		(0.124)		(0.124)
Communist		-0.325		-0.128		-0.115
		(0.382)		(0.178)		(0.177)
Cold War		-0.188		-0.279^{**}		0.116
		(0.246)		(0.122)		(0.132)
$t_{Demonstration}$			-0.308^{***}	-0.297^{***}		
			(0.034)	(0.035)		
$t^2_{Demonstration}$			0.015^{***}	0.015^{***}		
			(0.003)	(0.003)		
$t^3_{Demonstration}$			-0.0002^{***}	-0.0002^{***}		
			(0.0001)	(0.0001)		
t_{Riots}					-0.297^{***}	-0.288^{***}
					(0.036)	(0.036)
t^2_{Riots}					0.014^{***}	0.015^{***}
					(0.003)	(0.003)
t^3_{Riots}					-0.0002^{***}	-0.0002^{***}
					(0.0001)	(0.0001)
Constant	-1.946^{***}	-1.801^{***}	-0.992^{***}	-0.353^{*}	-1.009^{***}	-0.733^{***}
	(0.173)	(0.345)	(0.101)	(0.184)	(0.099)	(0.194)
Observations	2,800	2,800	2,800	2,800	2,800	2,800
Log Likelihood	-446.725	-434.860	-1,115.546	-1,096.245	-1,110.467	-1,093.737
Akaike Inf. Crit.	903.449	891.720	2,241.091	2,214.490	2,230.934	2,209.474

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: The Relationship Between Dictatorial Legislatures and Coups & Popular Dissent by Third Order Polynomial Time Counter (Matched)

	Dependent variables:					
	DV:Elite Coups		DV: Anti-Gov Demonstration		DV: Riots	
	(1)	(2)	(3)	(4)	(5)	(6)
Co-optation	-0.895^{***}	-0.862^{***}	0.102	0.130	0.180	0.213^{*}
	(0.264)	(0.267)	(0.120)	(0.122)	(0.124)	(0.126)
t_{Coups}	-0.124^{*}	-0.096				
	(0.064)	(0.065)				
t^2_{Coups}	0.007^{*}	0.005				
	(0.004)	(0.004)				
t^3_{Coups}	-0.0001^{*}	-0.0001				
	(0.0001)	(0.0001)				
GDPPC		-0.701		0.477^{**}		0.209
		(0.484)		(0.212)		(0.219)
GDPPC Growth		-0.048^{***}		0.007		0.008
		(0.018)		(0.011)		(0.012)
Trade Openness		0.003		-0.008^{***}		-0.008^{***}
		(0.003)		(0.002)		(0.002)
Military Leader		0.905^{***}		0.379^{***}		0.336^{**}
		(0.252)		(0.136)		(0.140)
Communist		0.528		0.152		-0.167
		(0.546)		(0.245)		(0.251)
Cold War		-0.429^{*}		-0.664^{***}		-0.247^{*}
		(0.254)		(0.136)		(0.138)
$t_{Demonstration}$			-0.345^{***}	-0.339^{***}		
			(0.042)	(0.043)		
$t^2_{Demonstration}$			0.020^{***}	0.020^{***}		
			(0.004)	(0.004)		
$t^3_{Demonstration}$			-0.0003^{***}	-0.0003^{***}		
			(0.0001)	(0.0001)		
t_{Riots}					-0.326^{***}	-0.318^{***}
					(0.043)	(0.044)
t^2_{Riots}					0.017^{***}	0.017^{***}
					(0.004)	(0.004)
t^3_{Riots}					-0.0003^{***}	-0.0003^{***}
					(0.0001)	(0.0001)
Constant	-2.236^{***}	-2.537^{***}	-0.626^{***}	-0.201	-0.696^{***}	-0.322
	(0.237)	(0.403)	(0.101)	(0.195)	(0.108)	(0.208)
Observations	2,800	2,800	2,800	2,800	2,800	2,800
Log Likelihood	-321.909	-306.694	-868.857	-845.463	-817.133	-802.403
Akaike Inf. Crit.	653.818	635.388	1,747.714	1,712.927	1,644.266	1,626.805
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 11: The Relationship Between Dictatorial Legislatures, Elite Coups & Popular Dissent with Clustered SEs (Matched)

	Dependent variables:					
	DV: Elite Coups		DV: Anti-Gov Demonstration		Dv: Riots	
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched	(5) Unmatched	(6) Matched
Co-optation	-0.894^{*}	-0.883^{*}	0.377	0.380	0.740^{***}	0.748^{***}
	(0.378)	(0.373)	(0.236)	(0.236)	(0.218)	(0.218)
GDPPC	-0.0297^{*}	-0.0304^{*}	−0.018	−0.0109	−0.00803	−0.00867
	(0.0135)	(0.0136)	(0.0106)	(0.0105)	(0.00960)	(0.00989)
GDPPC Growth	−0.554	−0.552	0.0556	0.0563	−0.105	−0.103
	(0.339)	(0.340)	(0.205)	(0.206)	(0.160)	(0.159)
Trade Openness	−0.00225	−0.00213	-0.00691^{*}	-0.00687^{*}	-0.00622^{**}	-0.00606^{**}
	(0.00258)	(0.00256)	(0.00271)	(0.00272)	(0.00189)	(0.00187)
Military Leader	0.616^{*}	0.622^{*}	0.135	0.138	0.169	0.179
	(0.304)	(0.305)	(0.229)	(0.233)	(0.225)	(0.226)
Communist	−0.487	−0.469	−0.367	−0.362	−0.101	−0.0837
	(0.356)	(0.357)	(0.425)	(0.421)	(0.291)	(0.287)
Cold War	−0.0616	−0.0166	-0.796^{***}	-0.790^{***}	0.0977	0.125
	(0.322)	(0.320)	(0.221)	(0.218)	(0.203)	(0.206)
Constant	-1.495^{***}	-2.681^{***}	-0.776^{***}	-1.808^{***}	-0.985^{***}	-0.874^{**}
	(0.149)	(0.503)	(0.159)	(0.517)	(0.149)	(0.435)
Observations	2800	2800	2800	2800	2800	2800
σ	-0.737 (0.524)	-0.738 (0.523)	0.450^{*} (0.216)	0.448^{*} (0.215)	-0.203 (0.250)	-0.217 (0.251)
Akaike Inf. Crit.	910.1	911.9	2139.4	2141.4	2279.2	2286.5

Note: Regression coefficients shown with robust standard errors in parentheses (standard erreors for the random effects models are clustered by country).
*p<0.1; **p<0.05; ***p<0.01

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