### Appendix: Arms and Electoral Influence: Arms Deals with Autocracies and U.S. Presidential Elections

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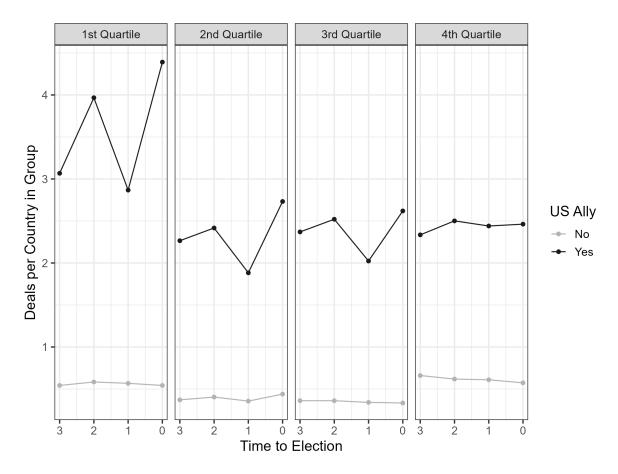
### 1 Arms Deals Count Model Check

In this section, I check the hurdle Poisson models of U.S. arms deals in three steps. First, I show similar patterns in raw data. Second, I demonstrate that OLS, Poisson, and zero-inflated Poisson models give similar inferences to the hurdle Poisson models in the manuscript. Finally,

I use posterior predictive checks to show that a hurdle Poisson outcome likelihood fits the observed data best.

### 1.1 Raw Data

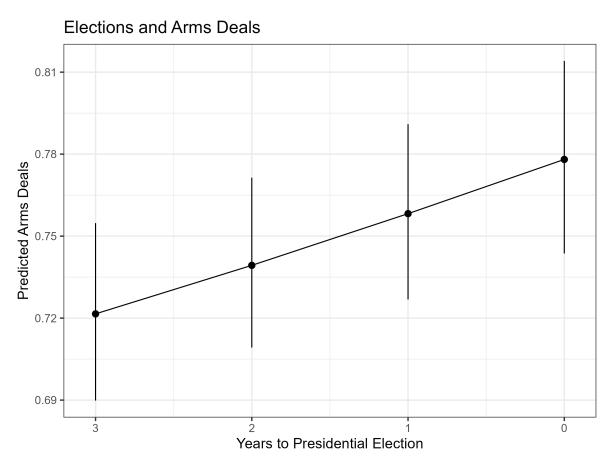
The pattern of increasing arms deals with autocratic allies as presidential elections approach is evident in raw data. Figure 1 plots the number of arms deals per country after dividing state-year observations based on years to a presidential election, four quartiles of polyarchy, and whether a country is U.S. ally. Autocratic U.S. allies average more than one additional deal in election years than in years immediately after an election. More democratic allies receive more arms deals than non-allied states, but deals with these countries do not track the electoral cycle.



**Figure 1.** Average arms deals with the United States per country in each quartile of democracy throughout U.S. presidential election cycles. Colors divide states based on whether they are U.S. allies.

### 1.1.1 General Arms Deal Cycles

In addition to the raw data, arms deal cycles are apparent even without interacting the time to presidential election measure with the autocracy indicator. I plot predicted arms deals as a function of years to a presidential election from a model that does not interact the election timing variable with anything else Figure 2. The increase of .05 deals across a presidential election cycle is small but distinguishable from zero.



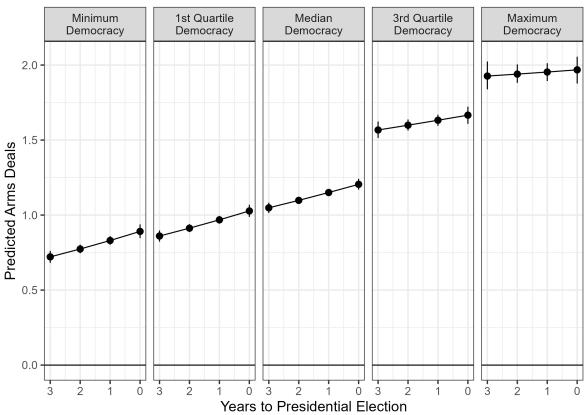
**Figure 2.** Predicted arms deals by the United States across the presidential election cycle, all else equal. Estimates from a hurdle Poisson model of arms deals between 1950 and 2014.

### 1.2 Alternative Estimators

The same pattern is also apparent if I use three alternative likelihoods in the model of arms deals, election timing and autocracy. While the hurdle Poisson is the most theoretically appropriate specification, standard Poisson and zero-inflated Poisson models give similar inferences. Poisson results hold without controls as well. I plot predicted arms deals across recipient democracy and election timing from each of these models in Figure 3, Figure 4 and Figure 5. All

three estimators suggest increasing arms deals for autocratic allies as elections approach, and little change in deals with democratic allies near presidential elections.

### Elections, Democracy, and Arms Deals



**Figure 3.** Predicted arms deals between the United States and other states 1950 to 2014 by presidential election proximity and partner democracy based on a Poisson regression model with only those variables and no controls. Points mark the estimates and error bars summarize the 90% credible interval.

### Elections and Arms Deals: Poisson Minimum 1st Quartile Democracy Democracy

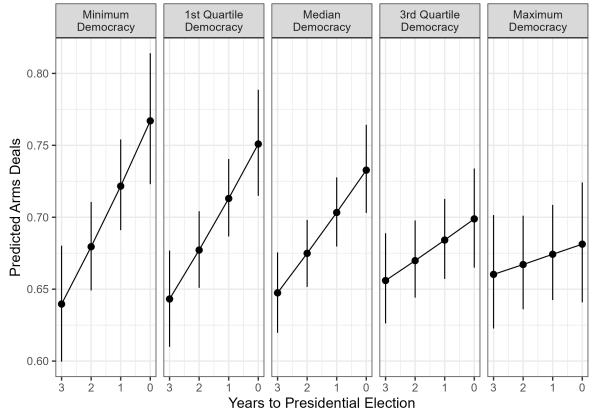
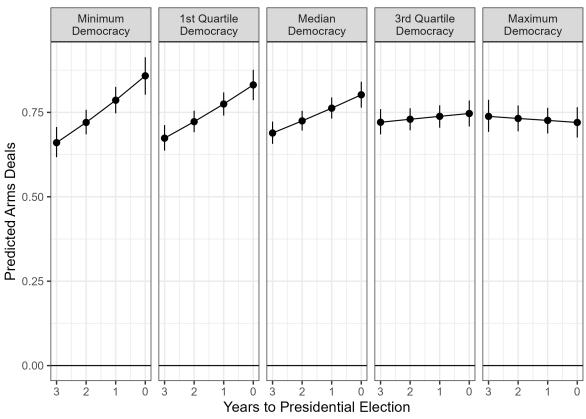


Figure 4. Predicted arms deals between the United States and other states 1950 to 2014 by presidential election proximity and partner democracy based on a Poisson model. Points mark the estimates and error bars summarize the 90% credible interval.

### Elections and Arms Deals: Zero-Inflated Poisson



**Figure 5.** Predicted arms deals between the United States and other states 1950 to 2014 by presidential election proximity and partner democracy based on a zero-inflated Poisson model. Points mark the estimates and error bars summarize the 90% credible interval.

### 1.3 Posterior Predictive Checks

This final check shows the predictive performance of the hurdle Poisson model, relative to a negative binomial likelihood. While neither model captures the lumpy outcome distribution, the hurdle Poisson is much better First, I show the posterior predictive check for the hurdle Poisson in Figure 6.

Both Figure 6 and Figure 8 are rootograms, which plot expected counts against observed counts. In both figures, the line gives the expected counts based on the model, and the bars mark observed counts. Bars that exceed zero are counts the model under predicts, while bars above zero show underpredicted values. As a result, the hurdle Poisson predicts zero values well, underpredicts some large values, and overpredicts a few small values.

Hurdle Poisson Posterior Predictive Check: Arms Deals

## Expected Observed

**Figure 6.** Posterior predictive check of the hurdle Poisson model of U.S. arms deals. The fitted line gives the expected counts and bars show the observed distribution.

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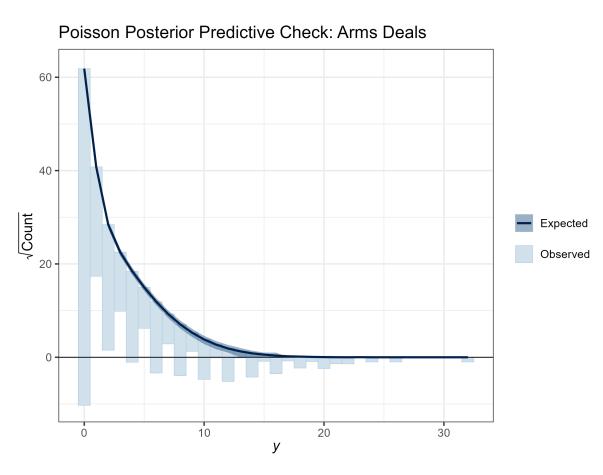
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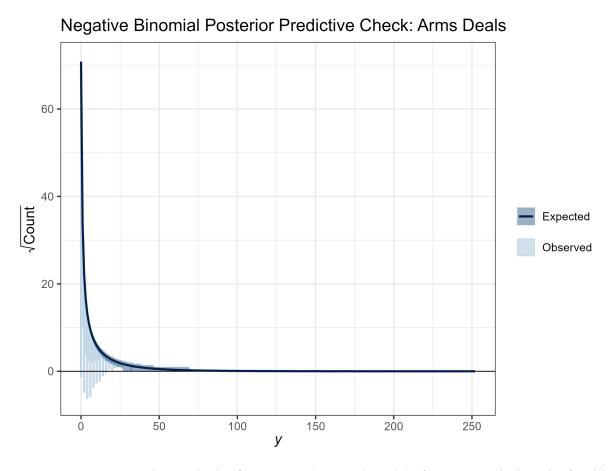
Relative to the hurdle, a regular Poisson model under-predicts zeros, as Figure 7 demonstrates. This also reduces predictive accuracy for non-zero deals.

While the lumpy distribution of deals complicates predictions with a Poisson likelihood, a negative binomial likelihood fits poorly. As Figure 8 demonstrates, the extra variance in a negative binomial results in underpredicting almost all observed values, as well as predictions



**Figure 7.** Posterior predictive check of a Poisson model of U.S. arms deals. The fitted line gives the expected counts and bars show the observed distribution.

that are far above the range of the observed data. I therefore rely on models with a Poisson likelihood.



**Figure 8.** Posterior predictive check of a negative binomial model of U.S. arms deals. The fitted line gives the expected counts and bars show the observed distribution.

### 2 Contracts Model Checks

This section checks the second analysis, which examines the interaction between arms deals and contract awards in the 50 states. First, I present additional estimates from the ordered beta regression- the state varying intercepts and lagged dependent variables. I then show that student-t and hurdle log-normal models of defense contract changes and levels also suggest that arms deals increase contract awards to swing states.

### 2.1 Additional Estimates

Figure 9 presents estimates from the ordered beta regression with transformed contracts. There is wide variation in contracting levels and temporal dependence across states. States with higher contracting levels also have more consistent temporal autocorrelation in contracts, while states such as North Dakota receive occasional arms contracts and thus have little temporal dependence.

### 2.2 Alternative Estimators

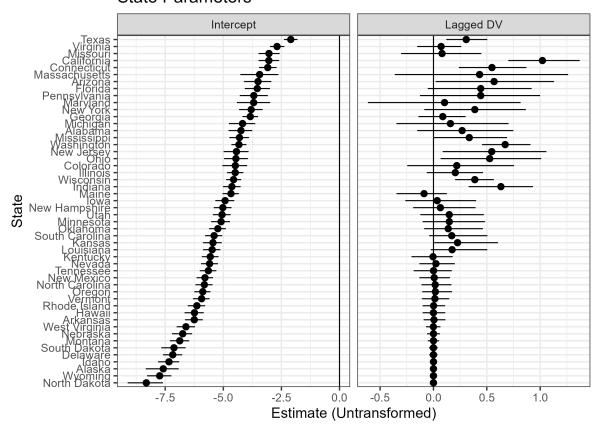
This section checks the results in the manuscript by adjusting the outcome measurement and estimation strategy in two ways.<sup>1</sup> First, I do not transform the contracts measure in any way, and fit a log-normal hurdle model, which assumes that the outcome has a zero process and observed values that are approximately normal after a log transformation. This approach does not model state-year observations with zero contracts well, but it fits non-zero contracts tolerably. As the top panel of Figure 10 shows, the interaction between arms deals and swing state status is almost entirely positive. At the same time, the association between deals and the level of contracts outside of swing states is almost entirely negative. This latter estimate is not part of the argument, and may be due to difficulties accounting for zeros in the log-normal hurdle.

A second approach uses the difference in contracts for each state in every year as the outcome. Because this measure is not normally distributed and has fat tails, I use a student-t outcome distribution. The student-t model also omits the state-specific lagged dependent variable, because using changes eliminates some of those dynamics.

Results from the student-t model of contract changes also suggest that arms deals increase contract awards to swing states. 99% of the posterior mass in the interaction coefficient between deals and states is positive. While 92% of the posterior mass in the deals term is positive, which suggests increased deals lead to increased changes in contracts for other states as well, there is a 95% posterior probability that the relationship between arms deals and contracts in swing states is larger. As a result, arms deals increase changes in defense contracts more in swing states than in other states.

<sup>&</sup>lt;sup>1</sup>All models estimated with brms (Bürkner, 2017).

### **State Parameters**



**Figure 9.** Estimated state intercept and temporal autocorrelation from ordered beta regression of transformed defense contracts in U.S. states, 2001–2020. Estimates ordered by the magnitude of the varying intercept. Error bars summarize the 90% credible interval.

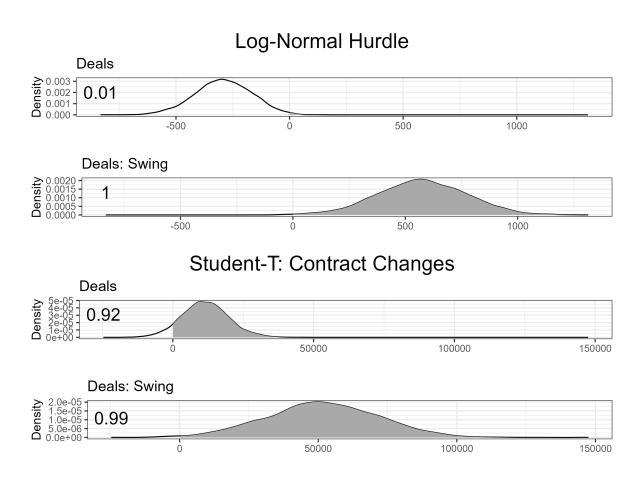


Figure 10. Shaded area and text give the positive posterior mass of each coefficient.

### 3 Additional Mechanism

Here, I document an additional check of the connection between deals and swing state contracts. The arms deals models show that deals with autocracies increase as presidential elections approach. If those deals go to swing state contracts, then the marginal impact of deals on contracts in swing states should increase as presidential elections approach.

To check this, I alter the model of contracts in the manuscript by interacting the time to election indicator with swing state dummy and arms deals. I then present the marginal effect of deals on defense contracts in Figure 11.

# Marginal Impact of Arms Deals by Swing State and Election Proximity Swing State No Years to Presidential Election

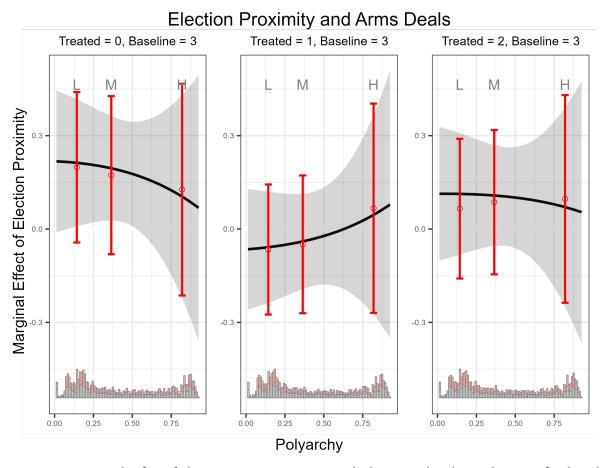
**Figure 11.** Marginal effect of arms deals on defense contract awards based on swing state status and presidential election proximity. Estimates in millions of dollars.

The marginal impact of arms deals on contracts increases as presidential elections approach, but only in swing states. After an election, deals do not increase contracts in any state. But as a presidential election approaches, the marginal impact of deals on swing state contracts increases and is clearly positive in the year before and year of a presidential election. There is no clear impact of deals non-swing state contracts at any point in the electoral cycle. This implies that arms deals with autocracies near elections feed increased swing state contracts.

### 4 Interaction Robustness

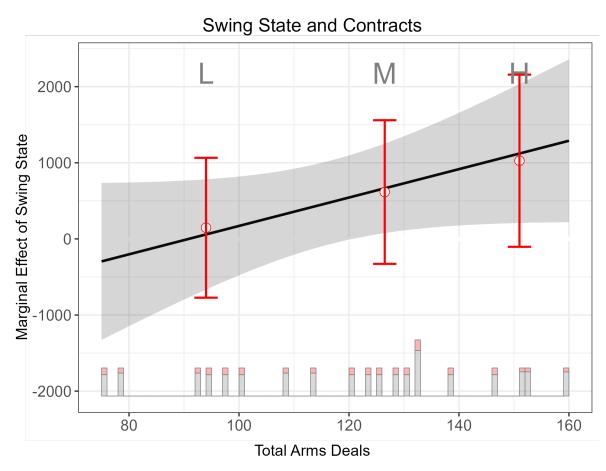
The models in the manuscript use interactions that assume a linear functional form. Violations of linearity and other issues can generate misleading inferences (Hainmueller, Mummolo and Xu, 2019). Here, I show that more flexible function forms give similar inferences about marginal effects. I do this by using binning estimators to examine the marginal impact of election proximity on arms deals and the marginal impact of swing state status on contracts.

First, I present the marginal effect of election proximity on arms deals in Figure 12. When time to election is 0, the marginal impact of this relative to the year after a presidential election is largest states with a low polyarchy score. This is consistent with the argument, although comparisons at the other two levels are less so.



**Figure 12.** Marginal effect of election proximity on arms deals across the observed range of polyarchy. Each comparison uses three years to the presidential election as a baseline.

Second, Figure 13 shows the same pattern in the marginal impact of swing state status as the manuscript. As deals increase, so does the marginal effect of swing state status. Each bin deviates minimally from the linear relationship.



**Figure 13.** Marginal effect of swing state status on defense contract awards based on arms deals. Estimates in millions of dollars.

### 5 Data Details

This section provides additional documentation, including tables of swing states, variables and sources, and coefficient estimates.

### 5.1 Swing State List

Table 1 lists the set of swing states and the years they are swing states. For this classification, I draw on Kriner and Reeves (2015).

 Table 1. : List of swing states.

State	Start	End	
Arizona	2017	2020	
Colorado	2009	2012	
Florida	2001	2020	
Georgia	2013	2020	
Iowa	2001	2012	
Michigan	2017	2020	
Minnesota	2005	2020	
Missouri	2005	2012	
Nevada	2001	2020	
New Hampshire	2001	2020	
New Mexico	2001	2008	
North Carolina	2005	2020	
Ohio	2001	2020	
Pennsylvania	2005	2020	
Tennessee	2000	2004	
Virginia	2001	2020	
Wisconsin	2001	2020	

### 5.2 Variables and Sources

### 5.3 Coefficient Estimates

The section presents tables with coefficient estimates. Table 2 summarizes the hurdle Poisson coefficient estimates for the aggregate deals model, while Table 3 summarizes the models of arms deals by type.<sup>2</sup>. Table 4 summarizes the three deals models and Table 5 gives ordered-beta coefficient estimates for the sectoral models of defense contracts.

<sup>&</sup>lt;sup>2</sup>All tables built with modelsummary (Arel-Bundock, 2022)

 Table 2. : Coefficient estimates from Poisson models of US arms deals.

	Generic Cycle	Regime Cycle (No Controls)	Regime Cycle	Regime and Ally Cycle
Hurdle: Intercept	6		5	5
•	(4, 7)		(3, 6)	(3, 6)
Intercept	-1.0	-0.13	-0.8	-0.66
•	(-1.5, -0.4)	(-0.19, -0.06)	(-1.4, -0.2)	(-1.28, -0.04)
Years to Election	-0.03	-0.07	-0.09	-0.17
	(-0.05, -0.01)	(-0.11, -0.03)	(-0.13, -0.06)	(-0.24, -0.09)
US Ally	0.8	·	0.8	0.6
,	(0.7, 0.8)		(0.8, 0.9)	(0.4, 0.7)
Polyarchy	-0.07	0.9	-0.2	-0.6
, ,	(-0.15, 0.01)	(0.8, 1.0)	(-0.3, -0.1)	(-0.9, -0.3)
Cold War	0.2	, ,	0.2	0.2
	(0.1, 0.3)		(0.1, 0.3)	(0.1, 0.3)
Global War on Terror	-0.15		-0.15	-0.15
Global War on Terror	(-0.23, -0.07)		(-0.23, -0.07)	(-0.23, -0.07)
EU Member	0.2		( 0.23, 0.07)	( 0.23, 0.07)
Le Member	(0.1, 0.3)			
Republican President	-0.009		-0.02	-0.02
Republican i resident	(-0.053, 0.037)		(-0.06, 0.03)	(-0.06, 0.03)
L CDD			, ,	, ,
Log GDP	-0.04		-0.030	-3e-02
O MID	(-0.06, -0.01)		(-0.056, -0.003)	(-5e-02, -7e-04)
Ongoing MID	-0.23		-0.3	-0.3
T D 1 :	(-0.42, -0.05)		(-0.5, -0.1)	(-0.5, -0.1)
Log Population	0.2		0.2	0.2
	(0.2, 0.2)		(0.1, 0.2)	(0.1, 0.2)
Log Distance	-0.07		-0.12	-0.11
	(-0.10, -0.04)		(-0.15, -0.09)	(-0.14, -0.08)
ommon Language	0.03		4e-02	0.048
	(-0.01, 0.08)		(5e-05, 9e-02)	(0.006, 0.091)
Hurdle: US Ally	-2		-2	-2
	(-2, -2)		(-2, -2)	(-2, -2)
Hurdle: Polyarchy	0.5		0.4	0.4
, ,	(0.3, 0.7)		(0.2, 0.6)	(0.2, 0.6)
Hurdle: Ongoing MID	0.7		0.6	0.7
	(0.3, 1.1)		(0.2, 1.1)	(0.3, 1.1)
Hurdle: Log GDP	-0.2		-0.16	-0.16
8	(-0.3, -0.1)		(-0.23, -0.08)	(-0.23, -0.08)
Years to Election:Polyarchy	, , ,	0.068	0.11	0.17
		(0.009, 0.129)	(0.05, 0.17)	(-0.01, 0.35)
Log Petrol Revenue		(*****, ***=*/	0.010	0.009
20g retror revenue			(0.007, 0.013)	(0.006, 0.012)
Years to Election:US Ally			(0.007, 0.013)	0.10
rears to Election. C5 rany				(0.01, 0.19)
US Ally:Polyarchy				0.5
O5 Thiy.1 Organity				(0.1, 0.8)
Voors to Electional IS Allya Delvo ash				-0.09
Years to Election:US Ally:Polyarchy				
				(-0.28, 0.10)

 Table 3. : Coefficient estimates from hurdle Poisson models of U.S. arms deals by sector.

(3.0, 6.6) (3.7, 10.5) (4.4, 11.1) (1.1, 7.2) (3.0)  Intercept -0.23 -0.058 0.13 -0.066 -0.000  (-0.99, 0.54) (-1.009, 0.924) (-0.82, 1.05) (-1.035, 0.939) (-1.2)  Years to Election -0.044 -0.106 -0.153 -0.058 -0.000  (-0.103, 0.012) (-0.311, 0.091) (-0.292, -0.016) (-0.247, 0.129) (-0.258)  Polyarchy 0.219 0.436 -0.11 0.74	6.1 3.8 .6, 8.6) (1.4, 6.4)
(3.0, 6.6) (3.7, 10.5) (4.4, 11.1) (1.1, 7.2) (3.6)  Intercept -0.23 -0.058 0.13 -0.066 -0.000 (-0.99, 0.54) (-1.009, 0.924) (-0.82, 1.05) (-1.035, 0.939) (-1.2)  Years to Election -0.044 -0.106 -0.153 -0.058 -0.000 (-0.103, 0.012) (-0.311, 0.091) (-0.292, -0.016) (-0.247, 0.129) (-0.258)  Polyarchy 0.219 0.436 -0.11 0.74	(1.4, 6.4)
(-0.99, 0.54) (-1.009, 0.924) (-0.82, 1.05) (-1.035, 0.939) (-1.2 Years to Election -0.044 -0.106 -0.153 -0.058 -0.000 (-0.103, 0.012) (-0.311, 0.091) (-0.292, -0.016) (-0.247, 0.129) (-0.258) Polyarchy 0.219 0.436 -0.11 0.74	
Years to Election	-0.33 -0.22
(-0.103, 0.012) (-0.311, 0.091) (-0.292, -0.016) (-0.247, 0.129) (-0.258) Polyarchy 0.219 0.436 -0.11 0.74	24, 0.56) (-1.15, 0.69)
Polyarchy 0.219 0.436 -0.11 0.74	0.1270 -0.1259
, ,	84, 0.0059) (-0.2489, -0.0045)
(0.042, 0.410) $(-0.018, 0.926)$ $(-0.58, 0.36)$ $(0.28, 1.22)$ $(0.11)$	0.43 0.42
	1, 0.78) (0.06, 0.78)
Cold War 0.39 0.50 0.56 0.207 0.	0.095
(0.31, 0.47) $(0.28, 0.72)$ $(0.28, 0.85)$ $(-0.042, 0.455)$ $(0.098)$	08, 0.362) (-0.073, 0.263)
Republican President -0.0742 -0.08 0.215 -0.058 -0	0.049 0.0034
(-0.1418, -0.0042) $(-0.29, 0.14)$ $(0.034, 0.394)$ $(-0.280, 0.155)$ $(-0.18)$	80, 0.084) (-0.1565, 0.1569)
Log GDP -0.0418 -0.121 -0.061 -0.046 -0	0.040 -0.0043
	92, 0.013) (-0.0630, 0.0564)
Ongoing MID -0.225 -0.32 -0.056 -0.22 -0	0.025 -0.13
	61, 0.441) (-0.64, 0.29)
Log Petrol Revenue 0.0120 -1.5e-02 -0.0150 0.0086 0.0	.0139 0.0112
(0.0077, 0.0164) $(-2.8e-02, -1.2e-05)$ $(-0.0278, -0.0021)$ $(-0.0054, 0.0238)$ $(0.0054, 0.0054)$	54, 0.0229) (0.0016, 0.0207)
Log Population 0.058 0.0923 -0.0022 0.031 0	0.119 0.0097
(0.027, 0.088) $(-0.0035, 0.1879)$ $(-0.1020, 0.0981)$ $(-0.074, 0.136)$ $(0.058)$	(-0.0670, 0.0844)
Log Distance 0.063 0.209 0.238 0.012 -0	0.155 0.017
(0.017, 0.107) $(0.068, 0.355)$ $(0.091, 0.393)$ $(-0.124, 0.149)$ $(-0.232)$	32, -0.077) (-0.081, 0.112)
Common Language 0.35 0.15 0.105 0.119 -0	0.024 0.098
(0.28, 0.42) $(-0.06, 0.36)$ $(-0.082, 0.296)$ $(-0.095, 0.337)$ $(-0.15)$	57, 0.108) (-0.052, 0.247)
Years to Election:Polyarchy 0.028 0.044 0.194 -0.0024 0.	.1833 0.252
(-0.073, 0.127) $(-0.230, 0.320)$ $(-0.066, 0.441)$ $(-0.2745, 0.2704)$ $(-0.001)$	19, 0.3668) (0.063, 0.453)
Hurdle: US Ally -2.1 -1.4 -2.7 -1.3 -	-1.7 -1.6
(-2.2, -2.0) $(-1.6, -1.1)$ $(-3.0, -2.4)$ $(-1.5, -1.1)$ $(-1.5, -1.1)$	.9, -1.5) (-1.8, -1.4)
Hurdle: Ongoing MID 0.64 0.60 1.47 0.24	0.36 0.35
	29, 1.15) (-0.22, 1.04)
Hurdle: Log GDP -0.142 -0.136 -0.176 -0.025 -0.	0.1160 -0.051
	93, -0.0017) (-0.167, 0.060)
	-0.73
	03, -0.43) (0.82, 1.43)

 Table 4. : Coefficient estimates from models of defense contract awards.

	Rescaled Ordered Beta	Log-Normal Hurdle	Student-T: Contract Changes		
Intercept	-5.1	6.3	0.31		
•	(-5.6, -4.6)	(5.7, 6.8)	(-3.56, 4.15)		
Arms Deals	-0.00026	-0.00209	0.081		
	(-0.00155, 0.00103)	(-0.00389, -0.00041)	(-0.033, 0.205)		
Swing State	-0.290	-0.56	0.079		
	(-0.535, -0.034)	(-0.92, -0.21)	(-3.901, 4.106)		
Core State	0.0424	0.079	0.016		
	(-0.0041, 0.0906)	(0.012, 0.146)	(-3.667, 3.806)		
Global War on Terror	0.013	0.26	0.76		
	(-0.058, 0.082)	(0.18, 0.35)	(-3.14, 4.62)		
Time to Election	0.00092	-0.045	0.05		
	(-0.01649, 0.01748)	(-0.068, -0.022)	(-3.52, 3.57)		
Republican President	0.029	-0.0082	1.2		
1	(-0.024, 0.079)	(-0.0762, 0.0582)	(-2.7, 5.1)		
Population (Rescaled)	0.098	-0.011	-0.35		
,	(-0.011, 0.207)	(-0.127, 0.106)	(-4.18, 3.52)		
Log GDP	-0.082	0.37	-0.24		
8	(-0.181, 0.019)	(0.25, 0.49)	(-4.15, 3.59)		
Arms Deals:Swing State	1.9e-03	0.0041	0.367		
8	(6.1e-06, 3.9e-03)	(0.0013, 0.0068)	(0.083, 0.647)		
$\phi$	629	, ,	,		
•	(565, 698)				
Hurdle: Intercept	, ,	-2.9			
		(-3.2, -2.6)			
Hurdle: Log GDP		-0.659			
		(-1.228, -0.065)			
$\sigma$		0.38	135		
		(0.37, 0.40)	(121, 151)		

 Table 5. : Coefficient estimates from models of defense contract awards by sector.

	Aircraft	Arms	Electronics	Missile and Space	Ships	Vehicles
Intercept	-5	-5	-5	-6	-5	-5
	(-6, -5)	(-5, -4)	(-6, -5)	(-6, -5)	(-6, -5)	(-5, -5)
Aircraft Deals	-3e-04					
0	(-3e-03, 2e-03)			0.00	0.4	0.00
Swing State	-0.37	-0.23	-0.08	0.23	0.1	0.08
C S	(-0.66, -0.09)	(-0.50, 0.03)	(-0.22, 0.05)	(-0.02, 0.49)	(-0.1, 0.4)	(-0.17, 0.35)
Core State	-0.01 (-0.07, 0.04)	0.08 (-0.01, 0.18)	0.02 (-0.03, 0.08)	-0.02 (-0.10, 0.05)	0.08 (-0.01, 0.16)	0.3 (0.1, 0.4)
Global War on Terror	0.06	(-0.01, 0.18)	0.002	0.07	(-0.01, 0.16) -0.04	-0.004
Giodai wai oli Terror	(-0.02, 0.15)	(-0.02, 0.22)	(-0.072, 0.075)	(-0.04, 0.17)	(-0.15, 0.07)	(-0.132, 0.125)
Republican President	-0.02	0.01	-0.02	-0.06	0.04	-0.113
republican i resident	(-0.10, 0.05)	(-0.07, 0.10)	(-0.06, 0.03)	(-0.15, 0.04)	(-0.04, 0.12)	(-0.229, 0.004)
Log GDP	0.10	0.12	0.15	0.02	-0.2	0.01
Log GD1	(-0.03, 0.22)	(-0.07, 0.31)	(0.04, 0.28)	(-0.18, 0.21)	(-0.4, -0.1)	(-0.19, 0.21)
Population (Rescaled)	-0.002	-0.03	-0.12	-0.008	0.178	-0.09
(	(-0.149, 0.144)	(-0.23, 0.17)	(-0.24, -0.01)	(-0.221, 0.196)	(-0.002, 0.353)	(-0.26, 0.07)
Time to Election	0.007	0.005	0.003	0.008	-0.003	0.02
	(-0.016, 0.030)	(-0.025, 0.037)	(-0.015, 0.020)	(-0.021, 0.036)	(-0.035, 0.029)	(-0.02, 0.05)
Aircraft Deals:Swing State	3e-03	, ,	, ,	, , ,	, ,	, , ,
8	(-8e-04, 7e-03)					
$\phi$	402	185	662	269	169	102
	(359, 444)	(165, 206)	(598, 730)	(240, 301)	(151, 189)	(89, 115)
Arms Deals		-0.004				
		(-0.010, 0.001)				
Arms Deals:Swing State		0.004				
_		(-0.006, 0.015)				
Electronics Deals			-2e-04			
			(-5e-03, 4e-03)			
Electronics Deals:Swing State			0.004			
			(-0.003, 0.011)			
Missile & Space Deals				0.002		
				(-0.002, 0.006)		
Missile & Space Deals:Swing State				-0.006		
				(-0.013, 0.002)		
Ships Deals					0.002	
oti pito i o					(-0.013, 0.018)	
Ships Deals:Swing State					0.01	
**1:1 5 1					(-0.01, 0.04)	
Vehicles Deals						-6e-03
W1:1 D 1 C : C :						(-1e-02, 6e-04)
Vehicles Deals:Swing State						0.004 (-0.007, 0.014)
						(-0.007, 0.014)

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