POLSCI.733
Maximum likelihood estimation

Term paper

Dag Tanneberg*

April 29, 2015

Contents

* dag.tanneberg@duke.edu

1. Introduction

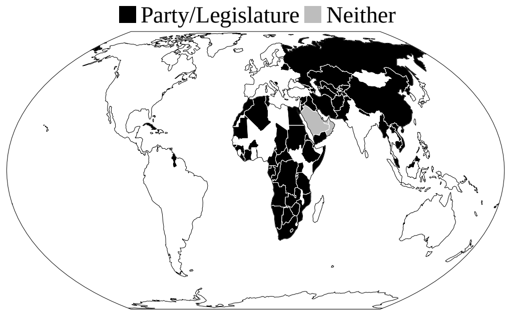

Figure 1: Parties and legislatures in authoritarian regimes, 2004

Research holds that co-optation and political repression are two mainstays of authoritarian regimes (Gerschewski, 2013, 21f.). Usually co-optation is defined as "the intentional extension of benefits to potential challengers to the regime in exchange for their loyalty" (Frantz and Kendall-Tylor, 2014, p. 333). Legislatures and political parties are said to simplify such exchanges, and after the end of the Cold War those nominally democratic institutions have sprung up in almost every authoritarian regime. By 2004 only Saudi Arabia, Oman, the United Arab Emirates, and Qatar sustained neither political parties nor a parliament. Yet, authoritarian regimes did not forget about political repression. Restrictions on core political liberties and violations of physical integrity rights are still pervasive in authoritarian politics. But little is know about how co-optation affects political repression.

This is the point of departure for Erica Frantz' and Andrea Kendall-Taylor's (2014) 'A dictators toolkit: Understanding how co-optation affects repression in autocracies'. Based on extensive quantitative analyses they argue that co-optation fundamentally changes the use of repression (ibid., p. 332): Increasing levels of co-optation lead dictators to reduce restrictions on empowerment rights, but simultaneously they increase physical integrity violations. The authors explain their key finding with the trade-offs involved in political repression. Restrictions on empowerment rights aim at the general public and characterize a diffuse approach to social control. Physical integrity violations in contrast target specific individuals and are attractive when the opposition is known. Nominally democratic institutions offer fora where regime opponents can raise demands and thus they generate knowledge on the political opposition. Under the bottom line, the institutions of co-optation generate knowledge on threats to the regime and lead dictators to prefer physical integrity violations over empowerment rights restrictions (ibid., p. 337).

This paper replicates the work of Frantz and Kendall-Taylor. It presents evidence on the violation of a key statistical assumption, it shows the weak predictive power of the original analysis, and it criticizes the use of over-parameterized statistical models. Moreover, my revision of the original analysis probes the interaction between the physical integrity violations and co-optation: As government respect for the integrity of person decreases the credibility of political parties and parliaments is diminished and their liberating effect on empowerment rights decreases. The following section describes design and data and design of the original publication, and section three presents the replication results. Section four discusses my modified model, and section five concludes.

2. Design & data

Based on Geddes et al.'s (2014) "Autocratic regimes" data Frantz and Kendall-Taylor analyze 154 dictatorships over the period from 1981 to 2004. The authors follow the example of J. R. Vreeland (2008) and run ordered logistic regressions (c.f. Fox, 2008; Fox and Weisberg, 2011) to account for the ordinal nature of their dependent variables. Consequently, their research design probes the effect of co-optation on either type of political repression, empowerment rights restrictions and physical integrity violations, based on pooled time-series cross-section data. Furthermore, as institutional changes might take years to impact government policies, Frantz and Kendall-Taylor use contemporaneous levels of co-optation (t_0) to predict future levels of political repression ($t+1$ to $t+5$). All models include a lagged dependent variable (t_0) to account for serial autocorrelation and standard errors are clustered at the country level as a remedy to heteroscedasticity (Beck and Katz, 1995). Finally, Frantz and Kendall-Taylor used multiple imputation to avoid inefficiency and biased estimates or inference (Honaker and King, 2010; Honaker, King, and Blackwell, 2011; King et al., 2001). This section introduces the three key variables involved, Appendix A provides summary information on all control variables.

Information on political repression is drawn from two different sources. To assess the level of empowerment rights restrictions the authors rely on Freedom House's civil liberties scale. It captures the extent to which citizens enjoy the "freedoms of expression and belief, associational and organizational rights, rule of law, and personal autonomy from the state" (Freedom House, 2010). In contrast to alternative measurements, Frantz and Kendall-Taylor argue, the Freedom House data is not endogenous to the existence of political parties and legislatures, i.e. their measurement of co-optation. The scale runs from 1 to 7, and higher values denote more restrictions on empowerment rights. Physical integrity violations are measured using the physical integrity index from the CIRI human rights dataset which provides "standards-based measures of government human rights practices" (Cingranelli and Richards, 2010, p. 402). It assesses the extent of torture, political imprisonment, extra-judicial killings, and disappearances on a scale from 0 to 8 whereby higher values denote more government respect for the sanctity of person. Frantz and Kendall-Taylor recode the index such that higher values denote more political repression.

The typology of political repression draws out meaningful differences between authoritarian regimes. This can be seen from Figure 2 which explores their relationship in the unimputed data. The full range of physical integrity violations is observed, but empowerment rights restrictions do not take their lowest possible value 1. Hence, all authoritarian regimes restrict civil and political liberties, but they do not always disrespect the sanctity of the individual at the same time. Moreover, Pearson's r between both repression types is only 0.31, and the LOESS smoother indicates that this already weak relationship disappears in certain regions of the data. More precisely, the smoother stays flat across the most densely populated interval of empowerment rights restrictions (4 to 6) and no inferences whatsoever may be drawn from changes in one type of political

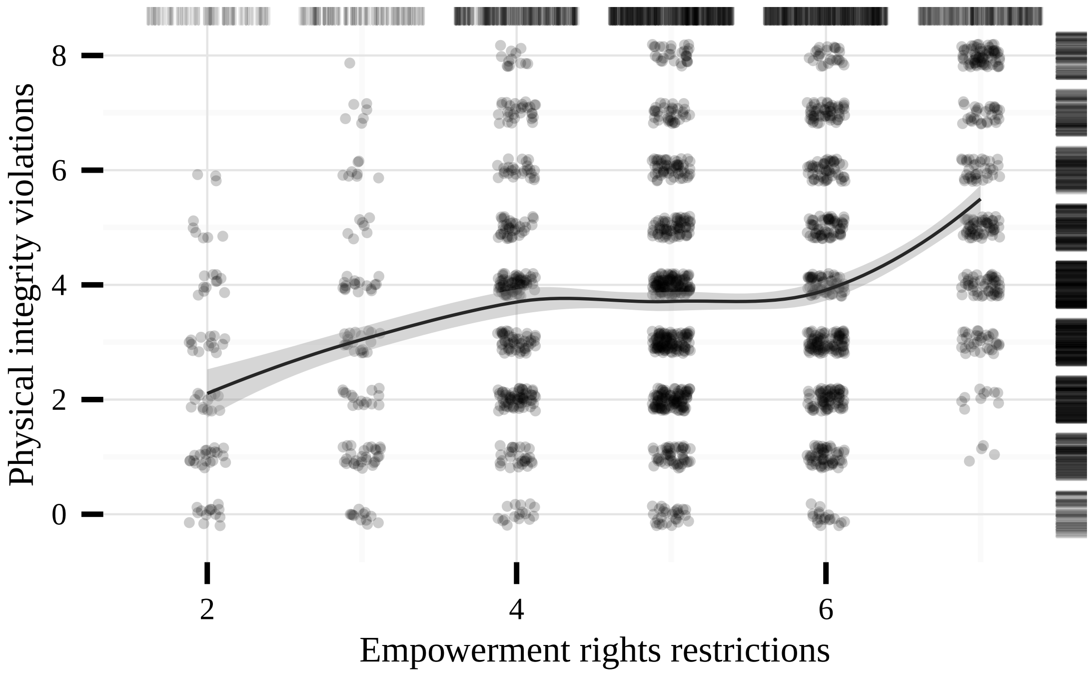

Figure 2: Political repression in authoritarian regimes between 1981 and 2004 with LOESS smoother and .95 per cent confidence envelope added.

repression on the other. Consequently, although authoritarian regimes use both types of political repression there is empirical reason to believe that they differ to "the extent to which they rely on one type more than the other" (Frantz and Kendall-Tylor, 2014, p. 336).

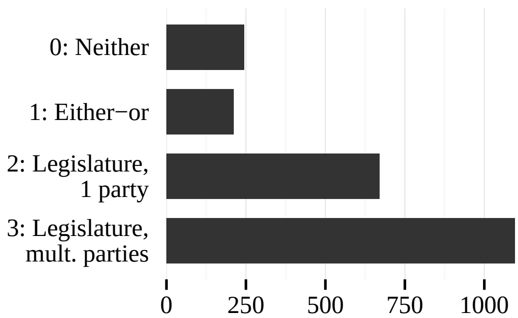

Figure 3: Co-optation, 1981-2004

Frantz and Kendall-Taylor assume that co-optation tips the scales of political repression. They measure this key explanatory variable by the existence of political parties and legislatures. Information on either institution is drawn from the 'Democracy & Dictatorship' data (Cheibub, Gandhi, and J. Vreeland, 2010) that map their de facto existence. Frantz and Kendall-Taylor create an index that takes the value of 3 if there is a multi-party legislature, 2 if there is a single-party legislature, 1 if there is no legislature but at least one political party or, equivalently, if there is a non-partisan legislature, and 0 if neither exists. The authors presume that their index behaves linearly, and they justify their coding scheme with an interest in the "interactive effect" of legislatures and political parties (Frantz and Kendall-Tylor, 2014, p. 338). Figure 3 explores the empirical picture in the unimputed data. The majority of $2,221$ non-missing country-year observations falls into the highest category. Accordingly, more than half of all authoritarian regimes in the data sponsored multi-party legislatures. Single-party regimes come in second, and only a minority of observations ranks lower than 2 on the index. In sum, the crucial empirical distinction is whether authoritarian regimes co-opt via single party or multiple parties.

3. Replication results

On first sight the key findings discussed by Frantz and Kendall-Taylor hold. However, critical evaluation of key statistical assumptions, predictive accuracy and model parsimony give reason to doubt their statistical adequacy and substantial significance. Following a brief recapitulation of the key results each point is briefly discussed in the remainder of this section.

Figure 5 summarizes all ordered logistic regressions presented in the original publication. Differences between the published and the replicated analyses are often negligible. With few exceptions coefficients and cluster robust standard errors agree up to two decimal places.[1] As can be seen from the top row in Figure 5 higher levels of co-optation concur with lower levels of empowerment rights restrictions, but they tend to go hand in hand with increases in physical integrity violations. Moreover, in line with the idea of inert government practices the attenuating impact of co-optation on empowerment rights restrictions increases in absolute size when moving from $t+1$ to $t+5$. The same time-dependent dynamic is not observable for physical integrity violations. Finally, all models speak to the staying power of political repression because all lagged responses are positively signed and statistically significant. In short, all key findings can be reproduced and a more detailed discussion of the original publication is possible.

Ordered logistic regression rests on the parallel-regressions assumption. It constrains differences between the cumulative distribution functions of any two categories to a constant, and thus all regression coefficients are assumed to be equal across categories (Fox, 2008, p. 476). One way to test the assumption is a χ^2-comparison between the constrained coefficients and their unconstrained alternatives from a multinomial regression. As shown in Table 1 only the $t+1$ and $t+2$ models reject the alternative hypothesis of non-constant

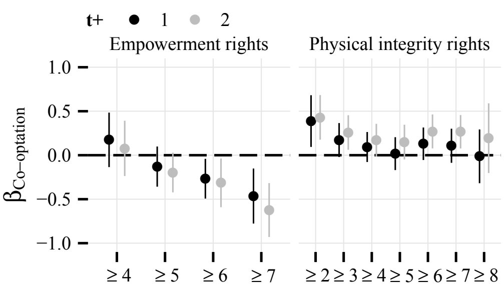

Figure 4: Separate logistic regressions

[1] A fundamental difference concerns the polynomials on tenure duration. The original models would not converge in *R* unless multicollinearity was reduced by using orthogonal polynomials.

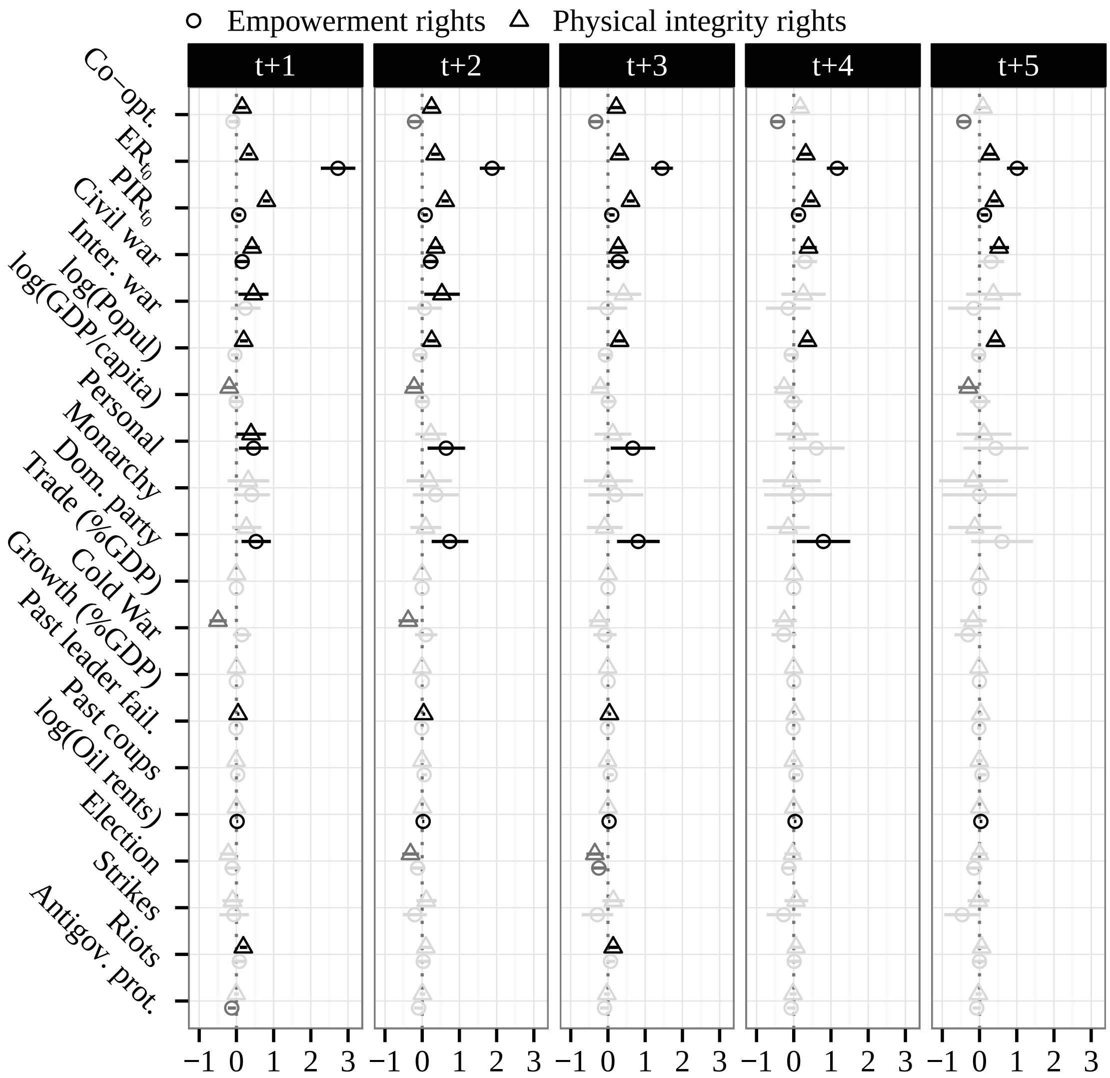

Figure 5: How co-optation affects political repression. Confidence intervals at the .95 level, positive coefficients black, negative estimates dark grey, statistically insignificant results faded. Cubic polynomials and cut points not shown.

coefficients and thus support the choice of statistical method. However, since very conservative Bonferroni adjusted P-values save the null an additional inspection seems justified. To that end $j-1$ separate logistic regressions were fit to the set of binary responses $\mathbb{1}_y(y_i \geq j)$.[2] If the parallel-regressions assumption holds the coefficients should differ little as j increases. Figure 4 shows the results for the key regressor co-optation with 95 per cent confidence intervals added. While the right-hand panel raises little reason for concern, coefficients in the left-hand panel exhibit a clear trend. As the level of empowerment rights restrictions increases co-optation develops more of a punch. In sum, the

Table 1: Parallel-regressions assumption: χ^2-comparisons

		$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Empowerment rights	Unadj. P-value	1.000	0.499	0.000	0.000	0.000
	Bonf. adj. P-value	1.000	0.833	0.000	0.000	0.000
Physical integrity	Unadj. P-value	0.003	0.002	0.000	0.000	0.000
	Bonf. adj. P-value	0.077	0.052	0.001	0.000	0.000

Note: P-values were averaged over all imputed models.

majority of models fails the parallel-regressions assumption and even if it is not rejected further scrutiny yields reason for concern.

How well do Frantz' and Kendall-Taylor's analyses predict the political repression in their sample? Since the consequences of failing the parallel-regressions assumption are not well understood predictive accuracy might be more important than fulfilling statistical technicalities. Using separation plots Figure 6 probes this possibility for the four models that did not immediately fail statistical technicalities (**Greenhill.2011**). Their implications are unsettling. With regard to physical integrity violations the statistical models are seemingly unable to discriminate between category members ● and non-members ●. Furthermore, the line of predicted probabilities stays flat in all but the extreme categories. Turning to empowerment rights restrictions the state of things seems slightly better. Either model, $t+1$ and $t+2$, tends to predict higher probabilities for category members than for non-members. Furthermore, the line of predicted probabilities visibly increases across all levels of empowerment rights restrictions. Nonetheless, the one-year lead model clearly fits the data best. In sum, decrying statistical significance co-optation offers little leverage on physical integrity violations, and only the one-year lead model for empowerment rights restrictions discriminates clearly between members and non-members of every response category.

However, as shown in Figure 5 co-optation is not even a statistically significant predictor of empowerment rights restrictions at $t+1$. What variable then accounts for the separation just described? Figure 7 probes this question. It compares BIC values from each full model to stripped down versions that include only the lagged response. If the latter accounts for serial autocorrelation only, then the full set of independent variables adds explanatory power and the BIC should decrease. Consequently, the differences shown on the vertical axis in Figure 7 should be negative.[3] The results are again unsettling. On the one hand the difference in BICs for physical integrity violations are always negative and large in absolute value. Nonetheless, those sizeable improvements in model fit do not add any predictive power at all and are thus inconsequential (c.f. Figure 6.[4] On the

[2] The marginal categories of all responses variables are sparsely populated and perfect separation occurred. The affected categories were disregarded.

[3] Note that BIC values were averaged over all imputations.

[4] Predictive accuracy declines with every additional lead. Results are available from GitHub.

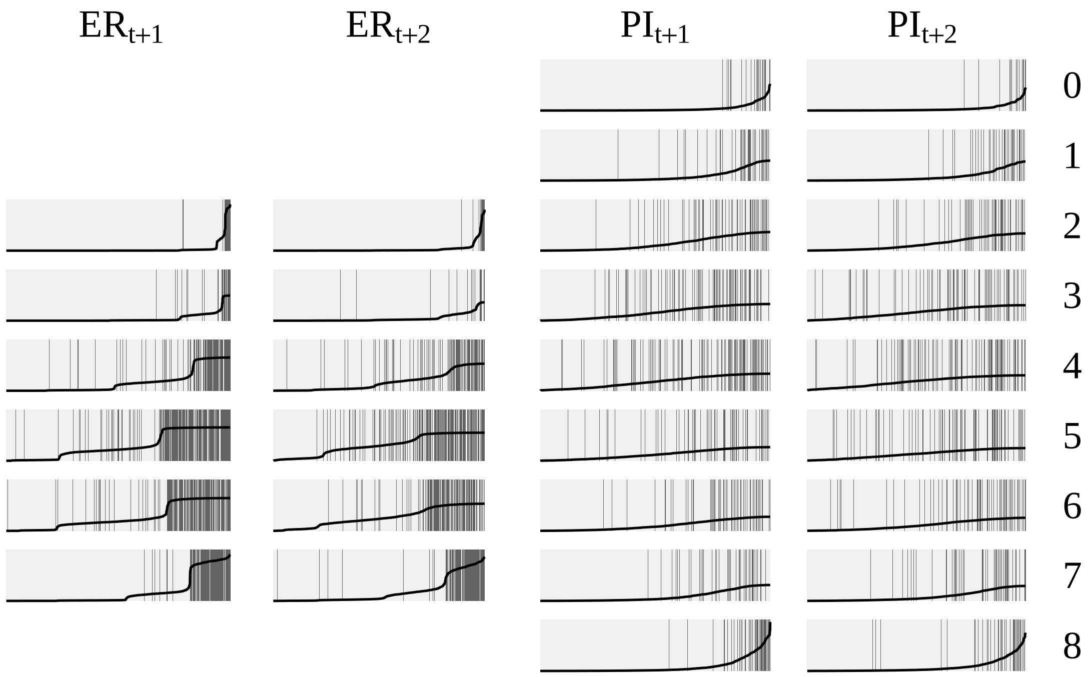

Figure 6: Predictive accuracy of supported models

other hand, differences in BIC for empowerment rights are always non-negative. While the one-year lead performed best in terms of prediction it performs worst in terms of parsimony. The corresponding difference in BICs is larger than 100 points! Hence, the improvement in fit over the stripped down model does not justify the inclusion of the full set of covariates at all. More generally, the single best predictor of empowerment rights restrictions at $t + 1$, $t + 2$, $t + 3$, and $t + 4$ is a lagged version of the response. In one sentence: Frantz and Kendall-Taylor likely overfit their data.[5]

In sum, Frantz' and Kendall-Taylor's results can be reproduced without noteworthy deviations. However, more nuanced assessements show most models presented in the original publication fail a key statistical assumption of ordered logistic regression. Moreover, it turns out that their key findings go hand in hand with weak predictive accuracy and strong signs of overfitting. It is thus open for debate what can be learned about the interaction of political repression and co-optation from the Frantz' and Kendall-Taylor's analyses.

[5] To remove more than 20 predictors from a model is somewhat dramatic and inhibits more nuanced assessments. Nonetheless, the results are too unequivocal to be mere drama.

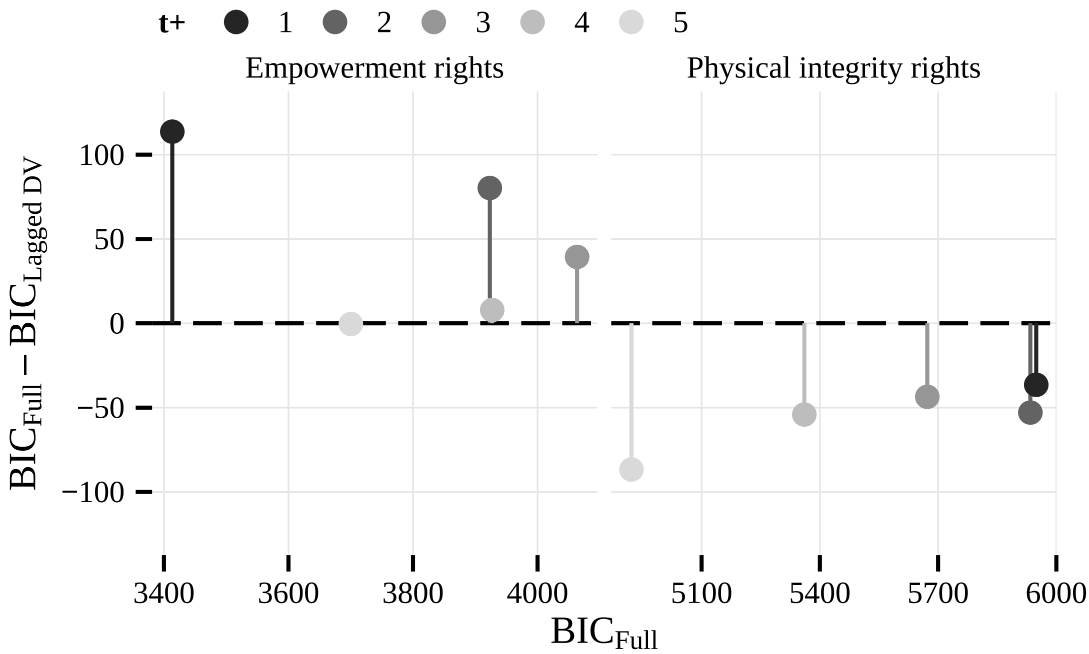

Figure 7: Model fit as measured by differences in BIC

A. Summary statistics of controls

To account for alternative explanations of political repression Frantz and Kendall-Taylor include a large set of controls (c.f. Frantz and Kendall-Tylor, 2014, 338f.). Among these are counts of ongoing civil and interstate war as well as domestic political dissent in the form of riots, general strikes, and anti-government demonstrations. Moreover, the authors include counts of past leadership turnovers and attempted coups under the assumption that authoritarian regimes with a history of leadership instability are more willing to repress. Other controls map the socio-economic status and historical context of the regime. For instance, assuming that oil-revenues offer alternative ways of co-optation Frantz and Kendall-Taylor control for oil rents per capita. Moreover, since size and growth of the population have been discussed as potential causes for state repression in the past the authors control for those as well. Moreover, they add indicators on trade and economic well-being as well as regime type. Moreover, to account for its considerable geopolitical repercussions a Cold War dummy is added to the model. Finally, following the advice of Carter and Signorino (2010) cubic splines of leadership duration are added.

Table 2: Summary statistics of control variables

Statistic	Min	Mean	Max	St. Dev.	N
Civil war	0	0.240	5	0.601	2,386
Interstate war	0	0.063	2	0.250	2,386
log(population)	4.215	8.777	14.074	1.712	2,352
log(GDP per capita)	5.139	7.913	10.807	1.058	2,352
Personal regime	0	0.292	1	0.455	1,857
Monarchy	0	0.097	1	0.297	1,857
Dominant party regime	0	0.489	1	0.500	1,857
Trade (Cold War	−50.046	1.003	90.470	7.694	2,049
Growth (Leadership duration	0	4.379	43	6.471	2,386
Past leadership fails	0	2.264	22	3.004	2,386
Past coups	−11.513	−3.867	10.811	8.328	2,250
Oil rents	0	0.090	5	0.442	1,857
Election year	0	0.358	23	1.378	1,857
Strikes	0	0.634	26	2.034	1,857

References

Beck, Nathaniel and Jonathan N. Katz (1995). "What to do (and not to do) with Time-Series Cross-Section Data". In: *The American Political Science Review* 89.3, pp. 634–647.

Carter, David B. and Curtis S. Signorino (2010). "Back to the Future: Modeling Time Dependence in Binary Data". In: *Political Analysis* 18.3, pp. 271–292.

Cheibub, José Antonio, Jennifer Gandhi, and James Vreeland (2010). "Democracy and Dictatorship Revisited". In: *Public Choice* 143.1/2, pp. 67–101.

Cingranelli, David L. and David L. Richards (2010). "The Cingranelli and Richards (CIRI) Human Rights Data Project". In: *Human Rights Quarterly* 32.2, pp. 401–424.

Fox, John (2008). *Applied Regression Analysis and Generalized Linear Models*. 2nd ed. Thousand Oaks and CA: Sage Publications.

Fox, John and Sanford Weisberg (2011). *An R companion to applied regression*. 2nd ed. Thousand Oaks and Calif: Sage Publications.

Frantz, Erica and Andrea Kendall-Tylor (2014). "A dictator's toolkit: Understanding how co-optation affects repression in autocracies". In: *Journal of Peace Research* 51.3, pp. 332–346.

Freedom House (2010). *Freedom in the World 2010: Methodology.*

Geddes, Barbara, Joseph Wright, and Erica Frantz (2014). "Autocratic Breakdown and Regime Transitions: A New Data Set". In: *Perspectives on Politics* 12.2, pp. 313–331.

Gerschewski, Johannes (2013). “The Three Pillars of Stability: Legitimation, Repression, and Co-optation in Autocratic Regimes”. In: *Democratization* 20.1, pp. 13–38.

Honaker, James and Gary King (2010). “What to do about missing values in time-series cross-section data”. In: *American Journal of Political Science* 54.2, pp. 561–581.

Honaker, James, Gary King, and Matthew Blackwell (2011). “Amelia II: A program for missing data”. In: *Journal of Statistical Software* 45.7, pp. 1–47.

King, Gary et al. (2001). “Analyzing Incomplete Political Science Data: An Alternative Algorithm for Multiple Imputation”. In: *American Political Science Review* 95.1, pp. 46–69.

Vreeland, James Raymond (2008). “Political Institutions and Human Rights: Why Dictatorships Enter into the United Nations Convention Against Torture”. In: *International Organization* 62.01.