**Overview of Extant Literature**

In comparison to PTAs and BITs, economic sanctions appear far more frequently as an object of analysis in human rights (HR) literature. Dursen Peksen is perhaps the most prolific (and oft-cited) researcher to have investigated the impact of US- or Western alliance-led sanctions on HR outcomes (see [2009](https://journals.sagepub.com/doi/10.1177/0022343308098404), [2011](https://academic.oup.com/fpa/article-abstract/7/3/237/1790636?redirectedFrom=fulltext), [2021](https://journals.sagepub.com/doi/10.1177/1065912920941596), [2022](https://academic.oup.com/isagsq/article/2/2/ksac013/6561777), etc.), but others have lent their energies towards the topic as well (for example, see [Clay, 2018](https://academic.oup.com/jogss/article-abstract/3/2/133/4964800?redirectedFrom=fulltext); [Gutmann et al., 2020](https://academic.oup.com/jogss/article-abstract/3/2/133/4964800?redirectedFrom=fulltext); etc.). These works all deploy regression models of some form, and the preponderance thereof find a negative connection between sanctions and human rights, with Gutmann et al. (2020) supplying the most notable instance of an alternative assessment.[[1]](#footnote-1) About two weeks ago, a new contribution emerged: Anton Peez’s [“Re-examining the Effects of Western Sanctions on Democracy and Human Rights in the 21st Century” (2024)](https://osf.io/preprints/osf/ge7at). It is not only the most recent work, but also the most methodologically interesting, in my view, hence why I wish to engage with it most directly.

**Peez (2024)**

*Overview*

The *raison d’être* of Peez’s “re-examination” is effectively threefold:

1. To determine whether the findings of previous studies, which mainly relied on data covering the 20th century, hold in the presence of more recent observations, given the rise of “targeted” sanctions in the 21st century;
2. To bring newer, more reliable measures of HR respect and quality of governance to bear on the matter; and
3. To reduce selection bias by introducing as covariates “trigger events” (e.g., coups and fraudulent elections), which naturally predict the onset of sanctions.

Peez selects as his outcomes Fariss’s HR Scores (2014) and V-Dem’s main measure of electoral democracy, v2x\_polyarchy. The treatment, on the other hand, is a simple binary indicator of “whether a given country was sanctioned by either the UN, US, or the EU in a given year” (p. 10), as recorded from the [International Sanctions Termination (IST) Dataset (2022)](https://www.giga-hamburg.de/en/publications/research-data/international-sanctions-termination-dataset). Among the covariates are not only the aforementioned “trigger events,” but also measures of “target vulnerability and instability” (e.g., the presence of pro-democracy protests), intrastate conflict, and “political proximity” to the senders as measured by the extent of conformity to UN General Assembly votes cast by the US and EU (pp. 14-15). With these variables, Peez leverages [*PanelMatch*](https://cran.r-project.org/web/packages/PanelMatch/index.html)—an R package developed by [Imai et al. (2023)](https://onlinelibrary.wiley.com/doi/abs/10.1111/ajps.12685) to obviate the problem of two-way fixed effects (see [Imai and Kim, 2020](https://www.cambridge.org/core/journals/political-analysis/article/abs/on-the-use-of-twoway-fixed-effects-regression-models-for-causal-inference-with-panel-data/F10006D0210407C5F9C7CAC1EEE3EF0D))—to compute the Average Treatment Effect on the Treated (ATT) through matching, weighting, and implementing a difference-in-differences analysis. Ultimately, for each outcome, the ATT yielded is negative, meaning Peez’s findings generally comport with those of the extant literature.

*Analysis*

Peez’s is clearly an impressive and important contribution. Indeed, it is easy to feel an affinity for the paper since it adopts many steps I myself would have recommended—from predicating models on HR Scores and V-Dem indicators, to eschewing two-way fixed effects in favor of more reliable methods of minimizing selection bias arising from temporal and spatial factors. Nevertheless, the number of points of concern that remain are sufficient, in my view, so as to warrant a renewed examination of the relationship between sanctions and human rights:

1. In each case, the reported ATT, though negative, is actually rather small in “typological” terms. For example, Peez observes that, for the year 2022, the estimated drop in polyarchy is approximately the same as going from a Norway to a UK, while the fall in HR Scores is similar to going from a Germany to a Taiwan (pp. 20-21). In my estimation, the differences between these cases are marginal, ones about which even experts are sure to disagree. The negative effects’ qualitative import is therefore unclear, and their quantitative import is, too, for Peez doesn’t appear to report the confidence intervals of the ATTs.[[2]](#footnote-2)
2. To his credit, Peez acknowledges that the “treatment dosage” of sanctions implementation, as opposed to whether or not sanctions are implemented in a binary sense, may be a salient factor for researchers to consider, but that he was unable to do so given that the *PanelMatch* package is presently only compatible with dichotomous treatments (p. 10). Indeed, sanctions may exist along several continua, from the number of individuals targeted (e.g., select individuals to all of society), to the amount or proportion of a country’s economic activity being targeted, and effects on human rights may vary according to where the “prescription” at issue lies on these continua; however, the limitations of *PanelMatch* preclude the testing of such theories. Fortunately, there exist other novel procedures for rendering causal inferences from panel data, meaning it may yet be possible to take up Peez’s exhortation to “revisit” the question of treatment dosage (p. 10).
3. A throughline in my proposals for Chapters 1 and 2 is the use of machine learning methods to automate covariate selection and minimize researcher bias. Peez depends on his background knowledge and intuition to choose his variables, which is helpful in the case of “trigger events,” but doing so obviously leaves open the opportunity to make a contribution resting partly on automation.

**Preliminary Plan**

To answer these shortcomings, I may readily construct a new model hewing to the following steps:

1. In addition to finding the effect on the original, continuous outcomes, find the effect on “ordered” versions thereof, such that it may be possible to determine whether sanctions cause countries to drop “tiers” on the human rights and democracy continua. Ordinal versions of V-Dem’s polyarchy measure already exist (e\_v2x\_polyarchy\_\*3C, 4C, 5C); ones for HR Scores can be easily constructed by dividing the observations into specified quantiles.
2. Allow for non-binary treatment variables. This may be accomplished through the following:
   1. Locate and/or construct the non-binary treatments themselves. The IST dataset contains a three-point, ordinal measure of the costs of the sanction(s) to a country’s economy (costtarget), which may be seen as a decent proxy for the level of treatment “dosage.”[[3]](#footnote-3) The dataset also contains a variable enumerating the specific actions (measures) carried out by the sanctions, which may reasonably be organized from most targeted (e.g., asset freeze) to least targeted (e.g., comprehensive trade embargo).
   2. Select an approach compatible with continuous treatments. Currently, I’m most intrigued by the Spatiotemporal Autoregressive Distributed Lag (STADL) Model set forth by [Cook et al. (2023)](https://www.cambridge.org/core/journals/american-political-science-review/article/stadl-up-the-spatiotemporal-autoregressive-distributed-lag-model-for-tscs-data-analysis/ED58D5D44BC75671EA938CA59E865D19), which simply synthesizes any number of spatial models (i.e., those discussed in the proposal for Chapter 2) and time fixed effects. Helper functions for the procedure, as well as a useful primer thereon, are to be found in the R package [tcscdep](https://github.com/judechays/STADL), though it should be noted that STADL models need not necessarily rely on this package.[[4]](#footnote-4)
3. Use an automated method of selecting the covariates, such as lasso regression. Such an approach is especially justifiable for the Spatial Lag Model (SLX), into which panel data and machine learning methods may be “seamlessly integrated” [(Rüttenauer, 2024, p. 23)](https://arxiv.org/abs/2402.09895).

At the very least as a robustness check, I also aim to execute the model(s) on the era preceding 1990 and inclusive of it; Peez limits his universe of cases to the post-1989 era, theorizing that the end of the Cold War heralded the advent of targeted sanctions, but it may be interesting to see whether the effects of sanctions vary meaningfully across these spans of time.

1. Namely, they find a mixed connection between sanctions and human rights outcomes. [↑](#footnote-ref-1)
2. That is, absent the confidence intervals, it is difficult to evaluate whether the effects can be regarded as negative with a reasonably high degree of confidence. [↑](#footnote-ref-2)
3. The levels, specifically, are “minor,” “major,” and “severe.” See [IST Codebook](https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/SVR5W7) (2021, p. 21). [↑](#footnote-ref-3)
4. The package is helpful in constructing KNN spatial-weight matrices, but STADL models can technically be implemented by incorporating lagged time fixed effects into spatial-econometric models native to other packages. [↑](#footnote-ref-4)