Dynamic Comparative Public Opinion*

Frederick Solt *University of Iowa*

The study of public opinion in comparative context has been hampered by data that is sparse, that is, unavailable for many countries and years; incomparable, i.e., ostensibly addressing the same issue but generated by different survey items; or, most often, both. Questions of representation and of policy feedback on public opinion, for example, cannot be explored fully from a cross-national perspective without comparable time-series data for many countries that span their respective times of policy adoption. Recent works (Claassen 2019; Caughey, O'Grady, and Warshaw 2019) have introduced a latent variable approach to the study of comparative public opinion that maximizes the information gleaned from available surveys to overcome issues of missing and incomparable data and allow comparativists to examine the dynamics of public opinion. This paper advances this field of research by presenting a new model and software for estimating latent variables of public opinion from cross-national survey data that yield superior fit and more quantities of theoretical interest than previous works allow.

Keywords: public opinion, item response theory, measurement

A wealth of surveys provide information on the state of public opinion on various issues in different countries over the years, but scholars have faced significant hurdles to putting all of this information to use in any comparative study. The most challenging of these obstacles is that, across countries and over time, the questions asked regarding any given issue are rarely the same, making responses to these questions incomparable.

As a result, the most common approach to the study of comparative public opinion is to use a single cross-section, typically provided by a single cross-national survey (see, e.g., Dalton, Farrell and McAllister 2011, Ansell (2014)). Some works have captured some element of change over time by taking advantage of multiple waves of an ongoing cross-national survey (see, e.g., Inglehart 1997, Inglehart and Welzel (2005)) or, more rarely, drawing on multiple surveys that employed the same item (see, e.g., Solt 2011, Ezrow and Hellwig (2014)).

A growing body of work is taking a different tack, examining the dynamics of public opinion in single countries over time. These studies draw on

(Not using stimson: Hobolt2008, McGann2014, Stubager2015)

dynamic comparative: Hagemann2016

field of comparative public opinion lack of dynamics (in contrast to public opinion work in U.S.) Check out Thomassen2011 Russell Dalton's work Norris on trust (2011, 63-77)

problem: scarce data perennial problem of public opinion research: exact question wanted is rarely asked no (good) way to (fully) integrate what does exist

question of feedback: positive or negative? ("policies create constituencies" vs. thermostatic) under what conditions?

*The paper's revision history and the materials needed to reproduce its analyses can be found on Github here. I am grateful for comments received at the 2014 meetings of the European Political Science Association and American Political Science Association, the 2016 meeting of the Midwest Political Science Association, and at Princeton University, Oxford University, the University of Tennessee, the University of Iowa, Central European University, and the Polish Academy of Sciences. Corresponding author: frederick-solt@uiowa.edu. Current version: September 14, 2019.

solution: informed by recent efforts to improve data quality of cross-national time-series data on other latent concepts, such as democracy (Treier and Jackman 2008; Pemstein, Meserve, and Melton 2010, [Arel-Bundock and Mebane 2011]) and judicial independence (Linzer and Staton [2013]), I offer a Bayesian measurement model for comparative public opinion

priors for scarce data: Bailey (2001) Bayesian for missing data: Jackman (2000) random walk for flexibility: Linzer and Staton [2013] heteroskedastic ideal points: Lauderdale (2010) – actually not heteroskedastic (no gammas) no risk of outside raters doing a worse job with some countries because no outsiders: public opinion is what it is

Table 1: Comparing IRT Models of Aggregate Public Opinion

	McGann (2014)	**Claassen (2019)**	**Caughley, O'Grady, and Warshaw (2019)**	**DCPO**
Cross-National	No	Yes	Yes	Yes
Ordinal	No	No	Yes	Yes
Country-Varying Question Difficulty	No	Yes	No	Yes
Bounded	Yes	No	No	Yes
Country-Year Population Variance	Yes	No	No	Yes

Modeling Dynamic Comparative Public Opinion

Group IRT

In the two-parameter logistic IRT model, the log odds of the probability that individual i respond affirmatively to a dichotomous question q is a function of three parameters:

$$log[\frac{p_i}{1-p_i}] = \frac{\theta_i - \beta_q}{\alpha_q} \tag{1}$$

First, the individual's score on the latent trait, θ_i; individuals with higher scores are more likely to give an affirmative response. Second, the *difficulty* of the question, β_q. As the question's difficulty increases, individuals are less likely to respond affirmatively, and vice versa. When θ_i and β_q are equal, the probability of an affirmative response is .5. Third, the *dispersion* of the question, α_q, which is proportional to the measurement error of the question. As the question's dispersion increases, individuals with lower scores on the latent trait become more likely to respond affirmatively and those with higher scores on the latent trait are more likely to respond negatively.

Mislevy (1983)

Ordinal

Cumulative logit

Country-Varying Question Difficulty

Responses to survey questions may vary across different countries not only as a result of differences in attitudes and preferences but also due to translation issues (see, e.g., Davidov and De Beuckelaer 2010), cultural differences in response styles (see, e.g., van Herk, Poortinga and Verhallen 2004), or other idiosyncrasies—recall Tarrow's (1971, 344) famous observation that the French understood survey questions regarding their "interest in politics" as inquiring about the strength of their partisan affiliations. Rather than simply allowing such problems of equivalence to contribute to the error of the model, they can be addressed explicitly by modeling the country-specific item bias (Stegmueller 2011), δ_{kq}. Claassen's (2019, 5-6) work employs this technique, and because estimating δ_{kq} requires data from repeated administrations of question q in country k, it discards survey data that does not meet this requirement. DCPO also incorporates δ_{kq} to capture country-specific item bias, but it takes a slightly different approach that aims to maximize the incorporation of available survey data: when responses to question q are observed in country k in only a single year, δ_{kq} is set to zero by assumption. This means that incorporating these 'one-shot' surveys will come at the cost of increasing the error of the model by any country-item bias that is present.

Bounded

Previous efforts to measure cross-national aggregate public opinion as a latent variable have generated estimates on an unbounded scale with mean zero and unit variance (see Claassen 2019, 14; Caughey, O'Grady and Warshaw 2019, 8). However, like many other concepts in political science (see Linzer and Staton 2015, 229), many aspects of public opinion are conceptually bounded, that is, it make sense to think of them as lying along a scale from fully absent to fully present in the relevant public. Take attitudes toward immigration as an example. One hypothetical country's citizens are absolutely opposed to any immigration, while another's are completely welcoming to migrants. Actual countries' levels of public opinion toward immigration are better understood not as unbounded but as falling somewhere between the bounds described by these two hypothetical countries. It is not surprising, then, that earlier works aggregating public opinion within a single country presented results on bounded scales (see Stimson 1991; McGann 2014). Even if the issue in question is less easily viewed as bounded, bounding is still a good idea because it reduces the uncertainty for the estimates for countries at the extremes, that is, those countries that should in fact be easier to estimate. As Linzer and Staton (2015, 229) write, "bounding the latent variable may do little harm to the scale and produce more sensible estimates of uncertainty." DCPO therefore bounds estimates of aggregate public opinion to range between zero and one.

Country-Year Population Variance

The probability of an individual i in country k at time t giving a response at least as positive as response r to question q is:

$$Pr(Y \geq r) = logit^{-1}(\frac{\bar{\theta}'_{kt} - (\beta_{qr} + \delta_{kq})}{\sqrt{\alpha_q^2 + \sigma_{kt}^2}}) \quad (2)$$

%McGann2014, 125: "the IRT model has the added advantages of being better justified in terms of individual-level behavior and the additional parameters (the polarization of the population in terms of policy mood) are substantively interesting."

Adding Dynamics

Random walk priors for $\bar{\theta}_{kt}$ and σ^2_{kt}

Identification, Priors, and Estimation

For each question q, δ_{kq} are constrained to have mean equal to zero.

Conclusions

strengths: makes maximum use of available data permits testing hypotheses regarding change over time incorporates uncertainty

weaknesses: data collection demands challenges at individual level (but subsets)

Single-country studies of public opinion have flourished since the release of Stimson's (1991) algorithm for identifying the common trends in any collection of survey questions that have been repeatedly asked over many years. By extending this work to allow the creation of cross-national pooled time series that identify how public opinion varies both across countries and over time, DCPO has the potential to trigger a new wave of research on the causes and consequences of public opinion that will take into account the experiences of many countries.

Further, this allows a broadly comparative approach that is new to work on the relationship between opinion and policy. Existing studies on that examine this topic over time investigate only a single country or, much more rarely, a handful of countries. By examining a broad sample of democracies, DCPO helps researchers avoid conclusions based on the idiosyncrasies of any given political setting and provide a firmer grounding for our understanding of how democracies work and the threats to representation that they face.

model	**mae**	**improv_over_cmmae**
claassen	0.032	70.9
country means	0.11	
dgirt	0.055	70.4
country means	0.186	
dcpo	0.031	83.3
country means	0.186	

References

Ansell, Ben. 2014. "The Political Economy of Ownership: Housing Markets and the Welfare State." *American Political Science Review* 108(2):383–402.

Caughey, Devin, Tom O'Grady and Christopher Warshaw. 2019. "Policy Ideology in European Mass Publics, 1981–2016." *American Political Science Review* pp. 1–20.

Claassen, Christopher. 2019. "Estimating Smooth Country–Year Panels of Public Opinion." *Political Analysis* 27(1):1–20.

Dalton, Russell J., David M. Farrell and Ian McAllister. 2011. *Political Parties and Democratic Linkage: How Parties Organize Democracy.* Oxford: Oxford University Press.

Davidov, Eldad and Alain De Beuckelaer. 2010. "How Harmful are Survey Translations? A Test with Schwartz's Human Values Instrument." *International Journal of Public Opinion Research* 22(4):485–510.

Ezrow, Lawrence and Timothy Hellwig. 2014. "Responding to Voters or Responding to Markets? Political Parties and Public Opinion in an Era of Globalization." *International Studies Quarterly* 58(4):816–827.

Inglehart, Ronald. 1997. *Culture Shift in Advanced Industrial Society.* Princeton: Princeton University Press.

Inglehart, Ronald and Christian Welzel. 2005. *Modernization, Cultural Change, and Democracy.* Cambridge: Cambridge University Press.

Linzer, Drew A. and Jeffrey K. Staton. 2015. "A Global Measure of Judicial Independence, 1948–2012." *Journal of Law and Courts* 3(2):223–256.

McGann, Anthony J. 2014. "Estimating the Political Center from Aggregate Data: An Item Response Theory Alternative to the Stimson Dyad Ratios Algorithm." *Political Analysis* 22(1):115–129.

Mislevy, Robert J. 1983. "Item Response Models for Grouped Data." *Journal of Educational Statistics* 8(4):271–288.

Solt, Frederick. 2011. "Diversionary Nationalism: Economic Inequality and the Formation of National Pride." *Journal of Politics* 73(3):821–830.

Stegmueller, Daniel. 2011. "Apples and Oranges? The Problem of Equivalence in Comparative Research." *Political Analysis* 19(4):471–487.

Stimson, James A. 1991. *Public Opinion in America: Moods, Cycles, and Swings.* Boulder: Westview Press.

Tarrow, Sidney. 1971. "The Urban-Rural Cleavage in Political Involvement: The Case of France." *American Political Science Review* 65(2):341–357.

van Herk, Hester, Ype H. Poortinga and Theo M. M. Verhallen. 2004. "Response Styles in Rating Scales: Evidence of Method Bias in Data From Six EU Countries." *Journal of Cross-Cultural Psychology* 35(3):346–360.