

Dynamic Comparative Public Opinion*

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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: October 23, 2019.

(Treier and Jackman 2008; Pemstein, Meserve, and Melton 2010, [Arel-Bundock and Mebane 2011])

Estimating Dynamic Comparative Public Opinion

The logic underlying DCPO's approach to estimating dynamic comparative public opinion starts at the individual level with the two-parameter logistic IRT model. In this model, the probability that individual i responds affirmatively to a dichotomous question q is a function of three parameters:

$$Pr(Y_{iq} = 1) = \text{logit}^{-1}\left(\frac{\theta'_i - \beta_q}{\alpha_q}\right) \quad (1)$$

First, the individual's score on the unbounded 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 50%. 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; in other words, the slope of the curve describing the relationship between the latent trait and the probability of answering affirmatively flattens out.

If scores on the unbounded latent trait are modeled as normally distributed within the population of country k at time t , then the population-level two-parameter logistic IRT model is:

$$\eta_{ktq} = \text{logit}^{-1}\left(\frac{\bar{\theta}'_{kt} - \beta_q}{\sqrt{\alpha_q^2 + (1.7 * \sigma_{kt})^2}}\right) \quad (2)$$

where η_{ktq} is the expected probability that a random person in country k at time t answers question q affirmatively and $\bar{\theta}'_{kt}$ and σ_{kt} are the mean and standard deviation of the unbounded latent trait θ' in the population of country k at time t (see Mislevy 1983, 280; see also, using the probit IRT model, McGann 2014, 120).

Further, many survey questions are not simply dichotomous, but instead measure respondents' attitudes on ordinal scales, assumed here to range from 1 to R . To take advantage of this additional information, the cumulative logit formulation is used, in which the probability to be estimated is not that individual i provided a simple affirmative response, as in Equation 2 above, but instead the probability that individual i provided a response at least as positive as response r for all r greater than 1 and less than or equal to R . This yields a population-level graded response model:

$$\eta_{ktqr} = \text{logit}^{-1}\left(\frac{\bar{\theta}'_{kt} - \beta_{qr}}{\sqrt{\alpha_q^2 + (1.7 * \sigma_{kt})^2}}\right) \quad (3)$$

The differences between Equation 3 and Equation 2 above are in the additional subscripts for η and β . Here, η_{ktqr} is the expected probability that a random individual in country k at time t replies to question q with a response at least as positive as response r . The additional subscript to β_{qr} indicates that this parameter represents the difficulty of response r of question q , constrained to be increasing for increasing r .

A final addition to the model of the probability η_{ktqr} takes into account differences in item response bias across countries. 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 acquiescence and extreme 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), denoted here as δ_{kq} .¹ In the context of the population-level graded response model presented in Equation 3, including country-specific item bias can be readily understood as a country-varying shift in the difficulty of each question:

$$\eta_{ktqr} = \text{logit}^{-1}\left(\frac{\bar{\theta}'_{kt} - (\beta_{qr} + \delta_{kq})}{\sqrt{\alpha_q^2 + (1.7 * \sigma_{kt})^2}}\right) \quad (4)$$

Before continuing, we pause to briefly review the relationships of the parameters in this equation. The numerator of Equation 4 implies first that η_{ktqr} , the expected probability of a response at least as positive as r , increases as the mean value of the latent trait in the population, $\bar{\theta}'_{kt}$, increases and second that η_{ktqr} decreases with more difficult questions and higher response categories, β_{qr} , and particularly so where the item-response bias, δ_{kq} , is positive. The equation’s denominator implies that η_{ktqr} is drawn closer to 50% as the geometric mean of the question’s dispersion, α_q , and the standard deviation in opinion in the population, σ_{kt} , increases: individuals sampled even from a population with a negative mean value on the latent trait and answering a difficult question will still be more likely to supply more positive responses—and those from a population with a positive mean score on the latent trait and answering an easy question will be more likely to supply more negative responses—if the question’s dispersion is greater or attitudes are more polarized in the population.

Given this expected probability η_{ktqr} , the total number of survey responses at least as positive as r to each question q in country k at time t , y_{ktqr} , out of the total number of respondents surveyed, n_{ktqr} , is then modeled using the beta-binomial distribution, which allows for an overall dispersion parameter, ϕ , to account for additional sources of survey error (see McGann 2014, 120; Claassen 2019, 4-5).

$$a_{ktqr} = \phi \eta_{ktqr} \quad (5)$$

$$b_{ktqr} = \phi(1 - \eta_{ktqr}) \quad (6)$$

$$y_{ktqr} \sim \text{BetaBinomial}(n_{ktqr}, a_{ktqr}, b_{ktqr}) \quad (7)$$

To estimate the dynamics of comparative public opinion, the change over time, the prior distribution for each of the public opinion parameters in Equation 4, $\bar{\theta}'_{kt}$ and σ_{kt} , is given by a simple local-level dynamic linear transition model:

$$\bar{\theta}_{kt} \sim N(\bar{\theta}'_{k,t-1}, \sigma_{\theta'}^2) \quad (8)$$

$$\sigma_{kt} \sim N(\sigma_{k,t-1}, \sigma_{\sigma}^2) \quad (9)$$

¹Claassen’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.

By treating these parameters' values at time $t - 1$ as their expected values at time t , these priors work to smooth estimates of both the mean and the standard deviation of the latent trait in the population of each country over time. If no survey data is available for a particular time, these models provide estimates based on the estimates for previous and subsequent periods. The variances $\sigma_{\theta'}^2$ and σ_{σ}^2 are estimated from the data.

Identification, Priors, and Estimation

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

To ensure that [...], the sum of δ_{kq} across all countries k is fixed to zero for each question q :

$$\sum_{k=1}^K \delta_{kq} = 0 \quad (10)$$

The dispersion parameters α are constrained to be positive.

One user-specified difficulty parameter *beta* is fixed to a value of 1.

The dispersion parameter ϕ for the beta-binomial model is given a $\Gamma(4, .01)$ prior.

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), and this is the scale of $\bar{\theta}'_{kt}$. 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, at a given time, 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) note, "bounding the latent variable may do little harm to the scale and produce more sensible estimates of uncertainty." DCPO therefore uses the standard cumulative normal distribution function to transform the unbounded estimates, $\bar{\theta}'_{kt}$, to the unit interval:

$$\bar{\theta}_{kt} = \Phi(\bar{\theta}'_{kt} - 1) \quad (11)$$

The resulting $\bar{\theta}_{kt}$ is the DCPO estimate of aggregate public opinion for country k at time t .

%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."

Conclusions

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

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

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	

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