

Public Opinion in Subnational Politics

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Abstract

Until recently, the study of representation at the subnational level was hobbled by the lack of high-quality information about public opinion. The advent of new data sources, however, as well as of new methods such as multilevel regression and poststratification (MRP), has greatly enhanced scholars' capacity to describe public opinion in states, legislative districts, cities, and other subnational units. These advances in measurement have in turn revolutionized the study of subnational representation. In this article, we summarize new approaches to the measurement of subnational opinion. We then review recent developments in the study of the role of subnational public opinion in the political process and discuss potentially fruitful avenues for future research.¹

Keywords: Public opinion, representation, state politics

1. Replication files for this article can be downloaded from the Harvard Dataverse, <https://doi.org/10.7910/DVN/4KFU8S>.

1 Introduction

The advent of new data sources and statistical techniques has led to a revolution in scholars' ability to examine public opinion and representation at the subnational level. The most important methodological development has been the development of regularization methods for subnational opinion estimation, particularly multilevel regression and poststratification, or MRP (Gelman and Little 1997). Thanks to these developments, the study of public opinion and representation in subnational politics has rapidly advanced in recent years. Multiple studies on public opinion and representation in American state governments and cities have appeared in each of the discipline's flagship journals over the past decade. In this article, we will provide an overview of how scholars can measure public opinion at the subnational level. We will illustrate the discussion through an application to public opinion and representation on gay rights. Next, we will discuss recent substantive advances in the study of representation at the subnational level. Finally, we will discuss where we see the study of public opinion in state and local politics going in the coming years.

2 New Data on Public Opinion

One of the most important reasons that the study of public opinion and representation in subnational politics has grown dramatically over the past decade has been the availability of new data sources. Much of this progress been due to the efforts of the Roper Center for Public Opinion (<https://ropercenter.cornell.edu>). The Center has collected over 20,000 polls from hundreds of survey firms going back to the 1930s and has made the individual-level data available for download by researchers from member institutions. These commercial polls offer an enormous wealth of data on a

huge variety of topics. For example, the archive contains over 100 polls from the past two decades that cover the topic of gay rights, our running example in this paper.

In addition, a number of large-scale academic surveys have been developed over the past two decades that examine public opinion on dozens of individual issues. In 2000, and then again 2004 and 2008, researchers at the University of Pennsylvania’s Annenberg School of Communications surveyed over fifty thousand people over the course of the presidential election campaign. In recent years, cooperative surveys have emerged that produce large national samples by aggregating numerous small sample surveys, most notably the Cooperative Congressional Election Study (CCES) and the Cooperative Campaign Analysis Project (CCAP). The combination of all these data sources means that scholars can now examine the causes and consequences of public opinion on hundreds of issues over the past three quarters of a century.

3 Estimating Subnational Opinion

Of course, new data sources have not been enough on their own. Rather, it has been the combination of new data and methods that has really kickstarted work on subnational opinion and representation. Through the end of the 20th century, political scientists’ primary approach to measuring subnational public opinion was to “disaggregate” one or more national surveys and take the average (possibly accounting for sampling weights) in each subnational unit (e.g., Miller and Stokes 1963; Erikson, Wright, and McIver 1993; Brace et al. 2002). Since the publication of Gelman and Little’s (1997) seminal MRP article, however, political scientists have increasingly turned to methods that combine model-based regularization with post-hoc weighting.

MRP and its relatives have been shown to perform well on samples as small as a few thousand people and to have lower cross-validated prediction error than disag-

gregation (Park, Gelman, and Bafumi 2004; Lax and Phillips 2009b; Warshaw and Rodden 2012; but see Buttice and Highton 2013). Indeed, some have gone so far as to call MRP the “gold standard” for estimating subnational opinion (Selb and Munzert 2011, 3). Our position is more nuanced. In some contexts, especially when public opinion is the dependent variable and unbiasedness is more important than efficiency, design-based disaggregation can be preferable to model-based methods such as MRP. In many others, the advantages of a model-based approach outweigh its drawbacks, but even then the form of regularization and other modeling choices must be carefully considered. In this section, we discuss various approaches to subnational opinion estimation and illustrate tradeoffs between them using the well-studied example of public opinion on gay rights.

3.1 Disaggregation and Other Design-Based Methods

The most straightforward estimator of subnational opinion is the sample average in a given subnational unit. The sample average is a “design-based” estimator in that its validity can be grounded solely in assumptions about the sampling design (e.g., that the data are a simple random sample) rather than in a model of the data-generating process in the population (e.g., that opinion is normally distributed conditional on a linear combination of covariates). By incorporating sampling weights, unbiased design-based estimators can be derived for almost any sampling design, including ones in which sampling probabilities are correlated or unequal across units (see, e.g., Lumley 2010).

Design-based estimators have the advantage of being transparent and easy to calculate and of not relying on difficult-to-verify parametric assumptions. It is thus unsurprising that almost every study of subnational opinion conducted before the

2000s relied on design-based estimators, typically using data disaggregated from national surveys. Design-based estimators have important drawbacks, however. First, due to clustered sampling designs, nonresponse bias, and other factors, subnational survey samples were often unrepresentative, thus biasing nominally unbiased estimators. Second, disaggregating from national surveys often resulted in very small samples at the subnational level, yielding highly imprecise estimates. In principle, the first problem can be ameliorated with poststratification or other weighting methods (Särndal and Lundstrom 2005), and the second by pooling together surveys to increase sample sizes (Erikson, Wright, and McIver 1993). Ultimately, however, the goals of reducing bias and increasing precision are in tension with one another. Increasing the number of poststratification variables, for example, often increases the variance of estimators (Little and Vartivarian 2005) and, in the limit, leads inevitably to some population cells being absent from the sample. As we discuss later, MRP can be thought of as a model-based method for managing this tradeoff between bias and variance.

Despite these limitations, the usefulness of disaggregation should not be overlooked. When subnational samples are close to random and not too small, a design-based estimator, possibly combined with adjustment weighting, should be approximately unbiased and reasonably precise. Further, when analyzing opinion as an outcome variable, researchers might well prefer a somewhat noisy but unbiased design-based measure than a model-based one that trades off bias for lower variance.² In particular, we suggest that studies of causal effects on public opinion (e.g., policy feedback) should generally use disaggregation rather than a model-based method such as MRP.

2. Measurement error in a dependent variable inflates standard errors but does not usually bias regression estimates (Lewis and Linzer 2005).

To illustrate the trade-offs between methods, we examine the policy feedback effects of the Supreme Court’s decision in *Obergefell v. Hodges* to legalize same-sex marriage in 2015. There is evidence that exposure to gay people has driven changes in public opinion on gay rights. It thus stands to reason that observing same-sex marriages, or married gay couples, might lead people to change their views on same-sex marriage. On the eve of the Supreme Court decision, 13 states did not allow same-sex marriage (Movement Advancement Project 2018). Did the public in those states change their views on same-sex marriage in the wake of the Supreme Court decision? To examine this question, we use a simple difference-in-differences model that examines changes in state-level public opinion between 2015 and 2016 (Table 1).

In order to evaluate how data and modeling decisions affect substantive findings on policy feedback effects, we compare several measurement choices. First, we utilize a massive set of survey data from the Public Religion Research Institute’s American Values Atlas. In 2015 and 2016, they interviewed approximately 50,000 Americans in each year. This provides large scale samples in each state, and enables us to generate relatively precise estimates of public opinion on same-sex marriage in each state (though it’s important to note that their samples are unweighted within each state). In the left column of Table 1, we find that in states where same-sex marriage was legalized, public opinion shifted about 3 points in favor of same-sex marriage. Moreover, this effect is significant at the .05 level.

Next, we use a smaller set of public opinion data using surveys that we downloaded from the Roper Center. This provided a sample of approximately 9,000 Americans in 2015 and 10,000 in 2016. The second column of Table 1 shows the results using unweighted disaggregated estimates of opinion in each state. It indicates that the substantive size of the effect of the Supreme Court decision on public opinion is very similar to the effect in column 1. But the effect is estimated much more noisily. The

third column shows a similar result using weighted disaggregated estimates.

Finally, we used a dynamic MRP model to smooth public opinion across states.³ This model increased the accuracy of the estimates of public opinion in each state. But it also smoothed away most of the treatment effect. Indeed, the right column of Table 1 shows that MRP effect of the Supreme Court decision is estimated to be significantly smaller than the large-sample disaggregation estimate in the first column (though still distinguishable from 0). Note also that the model now explains essentially all the variation in the smoothed estimates.

This example illustrates the bias-variance tradeoff between disaggregation and smoothing models. Under the assumption of simple random sampling, the disaggregated samples in the first three columns yield unbiased estimates of the policy feedback effects of gay marriage policies. However, the point estimates from these models are imprecise—especially in the models in columns 2 and 3 that draw upon small disaggregated opinion samples from the handful of surveys available in those years via the Roper Center. In contrast, the estimate of policy feedback effects in column 4 that uses an MRP model is very precisely estimated. But the policy feedback effect has been attenuated to close to zero.

Table 1: Policy Feedback Effect of Legalization of Same-Sex Marriage on Opinion

	Disaggregation Large Sample (unweighted)	Disaggregation Small Sample (unweighted)	Disaggregation Small Sample (weighted)	MRP Small Sample (weighted)
SSM Legal	0.034** (0.013)	0.030 (0.017)	0.018 (0.018)	0.006*** (0.001)
State FEs	X	X	X	X
Year FEs	X	X	X	X
R ²	0.951	0.942	0.936	1.000
Num. obs.	100	100	100	100

Note: Standard errors are clustered by state.

3. This model is discussed in more detail below.

3.2 MRP and Other Model-Based Regularization Methods

As noted above, MRP was developed as a means of addressing the twin problems of bias and variance, which respectively derive from the unrepresentativeness and small size of many subnational survey samples. MRP entails two steps. First, a multilevel regression model is used to estimate opinion in population cells defined by the cross-classification of geographic and demographic variables (e.g., state, race, and gender). Second, opinion in each subnational unit is estimated by poststratifying (i.e., weighting) the cell estimates in proportion to their share of the subnational population. Because the multilevel model regularizes each cell estimate by “shrinking” its estimate towards observably similar cells, the model increases the estimates’ precision at the expense of some increase in bias.

Of course, MRP is only one possible way of combining regularized prediction and post-hoc weighting. An alternative regularization method, such as lasso or BART, could be used (e.g., Caughey and Hartman 2017; Goplerud et al. 2018; Bisbee 2018). Even within the multilevel regression framework, one must choose from which observations to “borrow strength.” In classic MRP, the smoothing is purely cross-sectional. Two other options are to borrow strength over time through a dynamic model or from responses to other survey questions through a latent-variable model. Since straightforward poststratification is not always feasible, an alternative approach to weighting the cell estimates may be used. Different approaches may be optimal for different purposes, and each of these choices is a subject of ongoing research.

3.2.1 Smoothing Cross-Sectionally

The first-generation MRP models developed by Park, Gelman, and Bafumi (2004) borrow strength cross-sectionally. That is, the estimate for a given population cell

is smoothed using data from similar states and/or demographic groups. For example, the opinion estimate for black women in Mississippi might be informed by the responses of other Mississippians as well as by those of women and African Americans in other states. Moreover, through a second-level model, the estimate for the average Mississippian might be influenced by the estimates from similar states, such as Alabama.

To illustrate, we use the MRP model developed by Lax and Phillips (2009b, 2009a). This model uses a multilevel logistic regression model to smooth state-level opinion on gay marriage and other gay rights issues cross-sectionally for a suite of demographic-geographic strata. The level-1 model for the response of individual i is

$$\Pr(y_i = 1) = \text{logit}^{-1}(\gamma_0 + \alpha_{r[i]}^{\text{race}} + \alpha_{g[i]}^{\text{gender}} + \alpha_{e[i]}^{\text{edu}} + \alpha_{a[i]}^{\text{age}} + \alpha_{s[i]}^{\text{state}} + \alpha_{p[i]}^{\text{poll}}), \quad (1)$$

for $r \in \{1, \dots, 4\}$, $g \in \{1, 2\}$, $e \in \{1, \dots, 5\}$, $a \in \{1, \dots, 4\}$, and $p \in \{1, \dots, \# \text{ polls}\}$. In the second-level of the model, the state effects α^{state} are modeled as a function of the region into which the state falls, the state's percentage of evangelical or Mormon residents, and the Democratic presidential vote share in the last election.

$$\alpha_s^{\text{state}} \sim N(\alpha_z^{\text{region}} + \beta_1 \times \text{pres}_p + \beta_2 \times \text{religion}_s, \sigma_s^2); \quad s \in \{1, \dots, 51\}. \quad (2)$$

We estimate a slightly simpler version of this model using the `dgo` package in R (Dunham, Caughey, and Warshaw 2016). In our model, we estimate public opinion in each state on same-sex marriage in 2012 using age and education as individual-level strata and religion, union membership, median income, and the percent of each state's residents in same-sex relationships as state-level predictors. The results are shown in Figure 1. In addition, in Figure 2 we replicate Lax and Phillips's (2009)

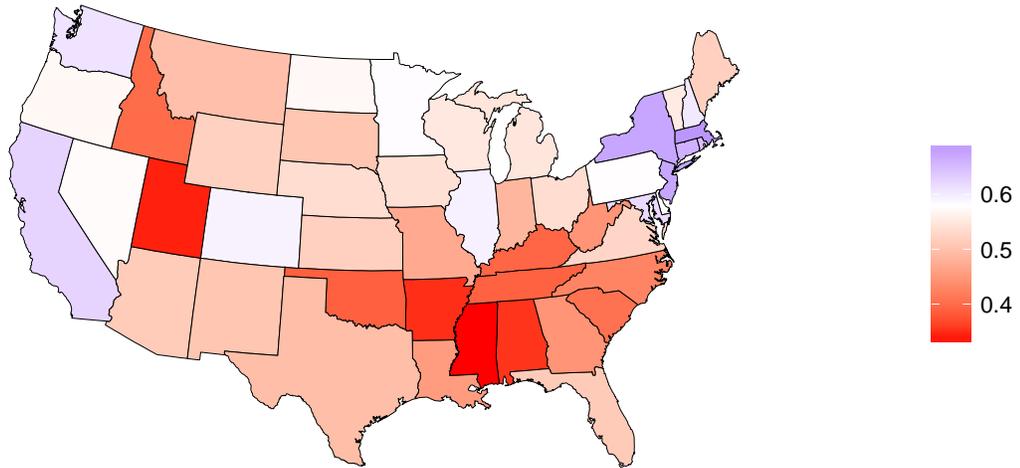


Figure 1: Mass Support for Same-Sex Marriage (2012)

finding of a strong relationship between mass support for same-sex marriage in 2012 and whether a state sanctioned same-sex marriage in 2013.

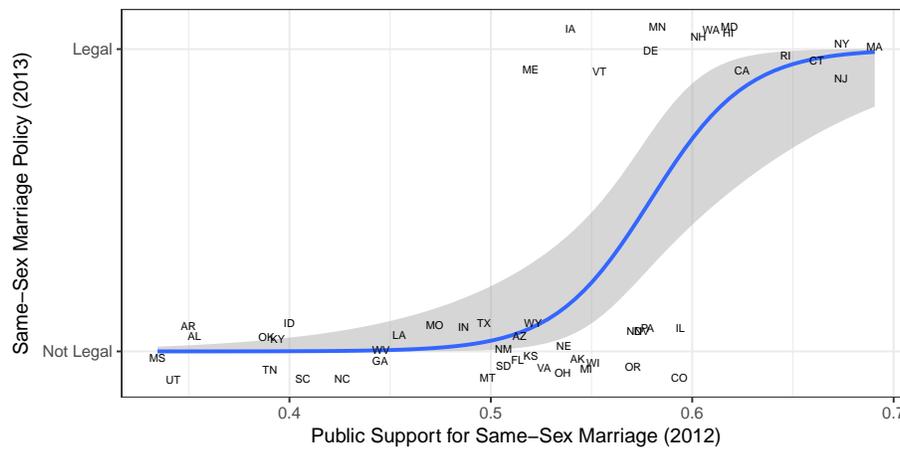


Figure 2: Policy Responsiveness to Opinion on Same-Sex Marriage (2012–2013)

We can do a similar analysis to show that public opinion on same-sex marriage is associated with municipal policies on same-sex marriage (Warshaw 2016). Figure 3 shows that there is a strong correlation between the rights that municipalities grant

to gay employees and public opinion on same-sex marriage.⁴ Cities with greater support for same-sex marriage are much more likely to provide strong protections to gay employees. This suggests that city governments are responsive to the views of their citizens on gay rights (see also, Palus 2010; Tausanovitch and Warshaw 2014; Einstein and Kogan 2016).

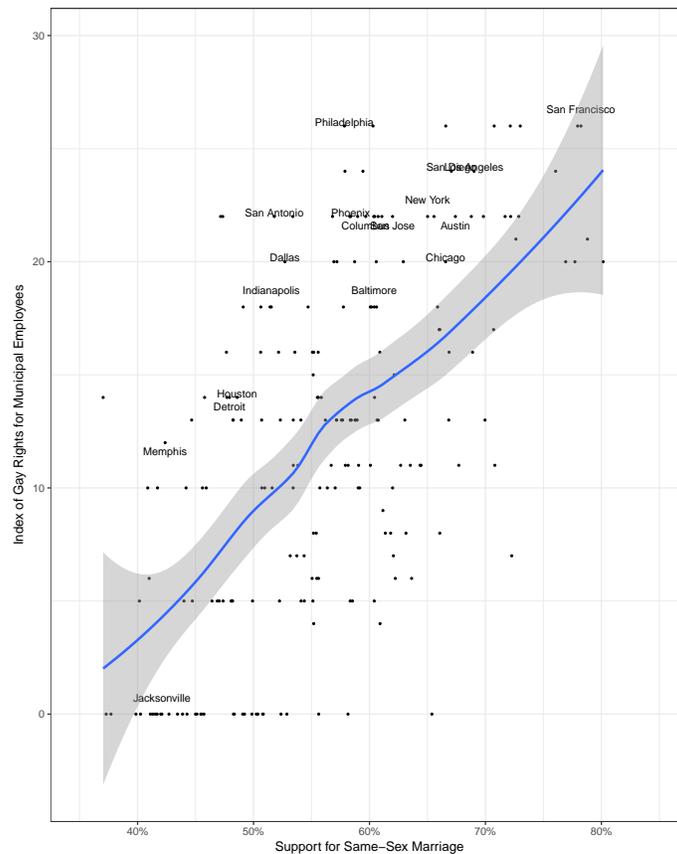


Figure 3: City responsiveness to public opinion on gay rights. This graph shows the association between public opinion on same-sex marriage in each city and an index of the rights that municipalities grant to gay employees.

There are a number of best practices that scholars have developed for cross-sectional MRP models. First, MRP often performs well with samples as small as a few

4. The data on the rights that municipalities grant to gay employees is derived from the Human Rights Campaign’s Municipal Equality Index (MEI), which scores how well approximately 300 cities support the LGBT people who live and work there.

thousand survey respondents (Lax and Phillips 2009b; Warshaw and Rodden 2012), but its performance is heterogenous across issues (Buttice and Highton 2013). MRP is almost always more accurate as sample sizes increase. Second, scholars should generally use at least one variable to help predict opinion at each geographic level in the multi-level model (Lax and Phillips 2013). Moreover, researchers should spend time making sure that these variables are good predictors of the variation in opinion across geography (Buttice and Highton 2013). Most of the performance gains in smoothing models come from the inclusion of good constituency-level predictors (Warshaw and Rodden 2012; Hanretty, Lauderdale, and Vivyan 2016). Finally, smoothing based on geographically proximate units can also improve predictive accuracy and compensate for weak constituency-level predictors (Hanretty, Lauderdale, and Vivyan 2016).

Future work is likely to use machine learning approaches to smooth public opinion based on a larger set of predictors than the handful of predictors leveraged in existing work (e.g., Caughey and Hartman 2017; Goplerud et al. 2018; Bisbee 2018). This work shows great promise at further improving the ability of scholars to develop accurate estimates of the cross-sectional variation in public opinion at the subnational level.

A more foundational limitation of cross-sectional public opinion models is that they are ill-suited for determining the causal effect of public opinion on public policy and other important outcomes (Lowery, Gray, and Hager 1989; Brace 2018). It is impossible to rule-out reverse causation whereby public opinion is influenced by a policy feedback process. For instance, Figures 2 and 3 show that public opinion and policy on same-sex marriage are correlated. But they cannot rule out the possibility that the order of causality is reversed, and the establishment of same-sex marriage leads to an increase in support for gay marriage in the mass public. In addition, some omitted variable could be confounding the relationship between public opinion and policy. For example, perhaps partisan turnover (e.g., the election of Democratic

governors) was the key factor that led to the legalization of same-sex marriage. One way to bolster causal inferences is to switch from a cross-sectional to a dynamic perspective and examine differences in public opinion across time.

3.2.2 Smoothing over Time

Examining subnational opinion over time raises new questions about whether to borrow strength cross-sectionally from other units at the same point in time or instead (or in addition) to do so dynamically, from data on the same unit at different points in time. At one end of the spectrum is the option of estimating separate cross-sectional MRP models in every year (e.g., Enns and Koch 2013; Lewis and Jacobsmeier 2017). The advantage of this approach is that it maximizes flexibility and variation over time. Its main disadvantage is the other side of the coin: years when data are thin will have imprecise estimates, and when data in a particular time period are missing altogether estimates cannot be produced.

The other extreme, smoothing across time only, is predicated on the often-reasonable assumption that the best guess for opinion in one year is opinion on the same question in the years immediately before or after. We would expect Democratic party identification (PID) in New Hampshire in 1957, for instance, to be strongly predicted by its PID in 1956—more strongly, perhaps, than by 1957 PID in similar states such as Maine or Vermont. Such substantive information can be encoded in various ways through a moving average (Pacheco 2011), a linear or quadratic time trend (Shirley and Gelman 2015; Gelman et al. 2016), or a Bayesian dynamic linear model (DLM; Linzer 2013; Caughey and Warshaw 2015, 2018).

In between these two extremes, models that smooth over time can be combined with cross-sectional information. Pacheco (2011), for example, first applies cross-sectional MRP in each year separately and then takes a moving average of the es-

timates over time. A disadvantage of this two-step approach is that it does not automatically propagate uncertainty in the first-stage estimates through to the second stage. An alternative is to estimate a unified Bayesian model in which the cross-sectional parameters are smoothed over time (Caughey and Warshaw 2015) or in which opinion is modeled with a DLM that incorporates both lagged opinion and cross-sectional covariates (Caughey and Warshaw 2018). Estimating a unified model properly accounts for uncertainty, though at the possible expense of tractability and computation time.

We use this last approach to estimate public opinion on same-sex marriage in each state-year from 1999–2016. Figure 4 shows that public support for same-sex marriage has increased in every state during this time period, though with some heterogeneity in the time trends across states. To examine whether these state-specific trends were associated with the adoption of same-sex marriage laws, we estimate a simple regression model in which the outcome takes a value of 0 in states that ban same-sex marriage and civil unions, 1 in states that allow civil unions, and 2 in states that allow same sex marriage.

Table 2 compares the results of this analysis with the same analysis using disaggregated estimates for each year. First, Columns 1 and 2 show the cross-sectional association between mass opinion on same-sex marriage and policy (averaged across the 1999-2015 period). Consistent with the findings in Lax and Phillips (2009a), both the disaggregated (column 1) and smoothed (column 2) estimates of public opinion on same-sex marriage have a strong cross-sectional association with policy. But the greater measurement error in the disaggregated estimates attenuates their relationship with policy compared to the smoothed estimates.

Next, in columns 3 and 4, we estimate models with fixed effects for state and year to account for state- and time-invariant confounders, thus leveraging only within-state

Support for Same-Sex Marriage by State

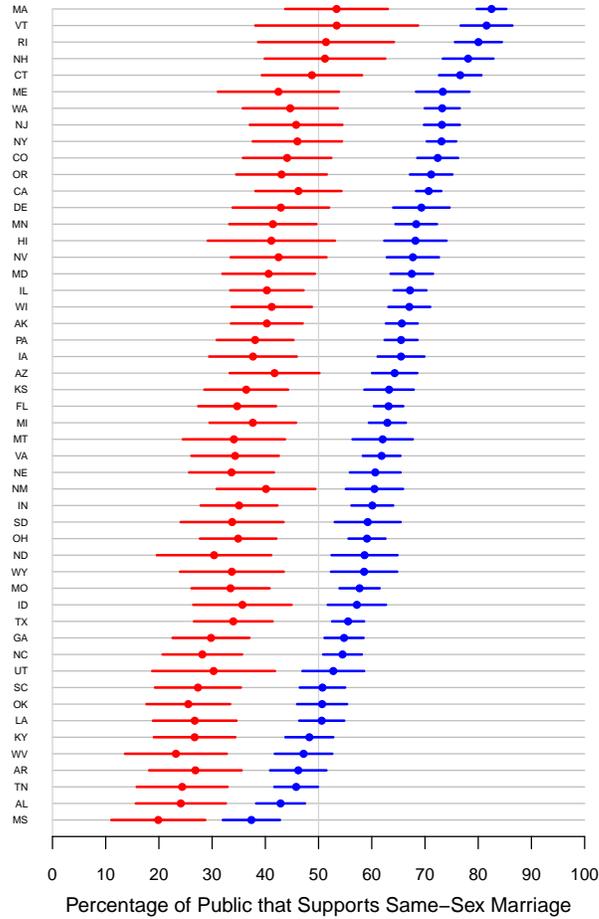


Figure 4: Change in Public Support for Same-Sex Marriage between 1999 and 2015

variation over time. Due to the measurement error in the disaggregated estimates, the regression estimate of their dynamic effect on policy is attenuated to essentially 0 (column 3). However, the smoothed estimates of opinion have a large and significant effect on public policy (column 4). This evidence is reassuring about the performance of statehouse democracy on same-sex marriage and reinforces the dynamic findings about responsiveness on same-sex marriage in Lewis and Jacobsmeier (2017).

Table 2: Dynamic Responsiveness on Same-Sex Marriage

	Disaggregated (CS)	Smoothed (CS)	Disaggregated (TSCS)	Smoothed (TSCS)
Percent Support for Same-Sex Marriage	0.013*** (0.003)	0.027*** (0.006)	0.001 (0.001)	0.113*** (0.025)
R ²	0.210	0.376	0.610	0.672
Num. obs.	584	584	584	584
State FEs			X	X
Year FEs	X	X	X	X

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Note: Standard errors are clustered by state.

3.2.3 Modeling Public Opinion as a Latent Variable

Latent-variable models (LVMs), which model multiple observed variables as functions of one or more unobserved ones, can be thought of as an especially elaborate form of model-based prediction. The advantage of an LVM is that it combines information not only from multiple units or time points, but also from multiple observed variables. In an item-response theory (IRT) model, for example, the probability of selecting the liberal response option to a given dichotomous question (e.g., favoring same-sex marriage) is modeled as function of a latent variable (e.g., gay-rights liberalism), the question’s “discrimination” with respect to that latent variable, and a “difficulty” parameter that reflects baseline support for the question.

LVMs can also be combined with other forms of smoothing. Tausanovitch and Warshaw (2013), for example, use an IRT model estimate the liberalism of thousands of geo-coded survey respondents, then apply cross-sectional MRP to the liberalism estimates to produce a measure of average liberalism in states, districts, and cities. Similarly, Caughey and Warshaw (2018) smooth IRT estimates of latent liberalism across time using a DLM.

The target of inference in LVMs is typically the latent variable itself rather than any one of its indicators. Predictions for individual indicators, however, can easily be generated using the estimated values of the latent variable and the parameters

of the model. Alternatively, latent-variable scores can be included in a multilevel model predicting individual question responses (e.g., Kestellec 2018). In either case, the estimates for specific survey questions could well be improved by the information from related questions (e.g., for same-sex marriage, questions on anti-discrimination protections for homosexuals). The LVM could even be used to impute the margins on a specific question for years or subnational units in which that specific question was not asked. Though as yet rare, the use of LVMs to improve subnational estimates for specific questions is a promising area for future research.

3.2.4 Weighting

The canonical smoothing (MRP) models developed by Park, Gelman, and Bafumi (2004) use simple poststratification weights to sum the predictions for each geographic-demographic strata and develop estimates of public opinion in each geographic area. These models typically assume that the population targets used to generate poststratification weights for each geographic-demographic are known with certainty, usually based on Census data. Moreover, they implicitly assume that respondents are sampled randomly within demographic strata. Of course, these two requirements are often unfulfilled in real-life applications.

In regards to the first issue, the canonical MRP models require scholars to have poststratification weights for each geographic-demographic strata. In the United States, it is often straightforward to obtain this information at the state level. But it is difficult to obtain these types of detailed population breakdowns below the state level. And in other countries, this kind of detailed census micro-data is often completely unavailable (Leemann and Wasserfallen 2017). The only available census data is often just the marginals of different groups in the state population (e.g., the percentage of people that are women). This has made it difficult for comparative politics scholars

to deploy smoothing models such as MRP to study representation and opinion.

There are a number of possible approaches to address this problem. In situations where population margins are available, Leemann and Wasserfallen (2017) show that it is possible to generate poststratification weights based on aggregate-level census data using an approach similar to raking. In situations where population margins are not even known with certainty, such as the distribution of partisans across states, scholars could use more complicated modeling approaches to generate population targets that combine different sources of available information (Kastellec et al. 2015; Jonge, Langer, and Sinozich 2018; Caughey and Wang 2018).

Recent work has also begun to address several other lingering issues related to weighting the estimates of a smoothing model. First, sampling in surveys is often not random within strata, such as in cluster-sampled surveys.⁵ In many cases, this requires analysts to either generate their own within-strata weights or weight the data using weights provided by the survey firm (see Ghitza and Gelman 2013; Caughey and Warshaw 2015). There is also a question about how many poststratification cells to use. A tentative lesson of recent work is that scholars usually don't need to use a complicated first-stage model with a large number of demographic strata (groups) when the substantive goal is to estimate public opinion at the geographic-level (Lax and Phillips 2013). However, more complicated first-stage models can be useful when the goal is to model the opinion of small demographic groups within states or other geographic units (Ghitza and Gelman 2013).

5. Many surveys use area-sampling designs in which respondents are clustered within geographic areas. In this approach, researchers sample a set of "primary sampling units" (PSUs), such as cities or census tracts. Then they interview a sample of people within each PSU. This approach yields samples that may be unbiased at the national level. But they could produce a nonrepresentative selection of PSUs for any particular geographic subunit. For instance, the PSU for Wyoming could be centered around Jackson Hole. Cluster sampling was standard practice in commercial polls before the 1970s, and it continues to be used by many high-quality academic surveys, including General Social Survey and the American National Election Survey.

3.3 Uncertainty in Public Opinion Estimates

A final important issue in the measurement and usage of public opinion at the sub-national level is that scholars need to be mindful that there is always uncertainty in public opinion estimates.⁶ It is important for scholars to take this uncertainty into account in any substantive analysis (Achen 1978; Lax and Phillips 2013; Kastellec et al. 2015). It is particularly crucial when the estimates of public opinion are used as a predictor in a regression model (see Gelman and Hill 2006, 542). In addition to traditional errors-in-variables corrections, two helpful frameworks for propagating measurement error into substantive inferences is the “method of composition” (Treier and Jackman 2008, 215–6), which entails drawing samples from the joint posterior distribution of the measurement and analysis models, and “multiple overimputation” (Blackwell, Honaker, and King 2017), which applies a correction to the sampling variance analogous to that used for multiple imputation. Several recent papers have used such approaches to propagate the uncertainty in their estimates of public opinion into their substantive models (Kastellec et al. 2015; Caughey and Warshaw 2018).⁷

4 Public Opinion and Representation

4.1 The Geography of Subnational Public Opinion

One of the most important tasks of public opinion research is to describe geographic variation in the mass public’s views. There is a large literature that has used recent methodological advances in our ability to measure subnational public opinion to examine geographic variation in public opinion. In many cases, this work forms the

6. This is true whether the estimates are generated using disaggregation, MRP, or some other model-based approach.

7. In our experience, correcting for measurement error often attenuates the estimated effects of public opinion relative to the unadjusted estimates.

foundation for substantive projects. For instance, Lax and Phillips (2009a) use MRP to measure state-level public opinion on gay-rights issues in the 2000s and examine the association between public opinion and policy. In other cases, however, public opinion is presented for purely descriptive purposes. Tausanovitch and Warshaw (2013) develop estimates of the policy ideology of every city and legislative district in the country. Elmendorf and Spencer (2014) estimate the average level of racial prejudice in every state and county in the country. They find the highest levels of racial prejudice in southern states such as Mississippi and South Carolina. However, they also find high levels of racial prejudice in several other states, such as Wyoming, Pennsylvania, and Ohio. Their findings provide policymakers with information about contemporary levels of racial prejudice in the United States that could be useful for future revisions to the Voting Rights Act and other laws protecting minorities.

The growing availability of thousands of surveys over the entire span of the last half century has revolutionized scholars' ability to study variation in public opinion in earlier time periods. Caughey (2018), for example, combines data from hundreds of polls from the 1936–52 period to estimate support for New Deal liberalism in each state (see also Krimmel and Rader 2016). More generally, scholars have taken advantage of the lengthening time span of available survey data to examine trends in subnational opinion over many years. Examples include Pacheco's (2014) 1977–2004 study of state-level support for spending in various policy areas, Shirley and Gelman's (2015) 50-year study of state opinion on gun control, and Enns and Koch's (2013) and Caughey and Warshaw's (2018) estimates of ideological trends in the states over the past 75 years.

4.2 Policy Representation

The recent advances in our ability to model public opinion have led to three major advances in the study of representation. First, it has enabled scholars to study representation at new geographic levels. Table 3 shows a sample of the recent studies that have used smoothing models to examine representation at various geographic levels in both the United States and other countries. A number of studies have examined representation at the state-level, while a smaller number have examined representation below the state level. We expect much work in the coming years to focus on local governments in the United States (e.g., school districts), and increasingly to focus on comparative politics outside the United States.⁸ We also expect more work to focus on dyadic representation in legislatures. Second, the recent advances in opinion estimation have enabled scholars to study representation on many individual issues. For instance, Lax and Phillips (2012) estimate state-level public opinion on dozens of individual issues in the 2000s, and examine whether public policy on these issues is responsive and congruent with public opinion. Overall, they find a strong link between public opinion and policy. Finally, the availability of models that smooth opinion over time has enabled scholars to examine the dynamic effects of public opinion on public policy and other important outcomes. Given the move toward causal inference in the discipline, we expect that the study of dynamic responsiveness is going to increasingly dominate the study of representation.

8. However, data limitations are likely to continue to complicate the ability to scholars to study representation in new contexts. For example, substate geographic identifiers are often unavailable in survey data in the United States prior to about the year 2000. Moreover, subnational geographic identifiers are only sparsely available in surveys outside the United States.

Table 3: Selection of Studies Studying Representation at Subnational Level

Study	Level of Public Opinion	Topic	XS/Dynamic
Tausanovitch and Warshaw (2014)	American Cities	Policy Representation	XS
Berkman and Plutzer (2005)	American Schools	Policy Representation	XS
Lax and Phillips (2009b)	American States	Policy Representation	XS
Lax and Phillips (2012)	American States	Policy Representation	XS
Pacheco (2013)	American States	Policy Representation	Dynamic
Caughey and Warshaw (2018)	American States	Policy Representation	Dynamic
Pacheco (2012)	American States	Policy Representation	XS
Lewis and Jacobsmeier (2017)	American States	Policy Representation	Dynamic
Canes-Wrone, Clark, and Kelly (2014)	American States	Judicial Representation	XS
Kastellec, Lax, and Phillips (2010)	American States	Leg. Representation	XS
Kastellec et al. (2015)	American State Parties	Leg. Representation	XS
Shor (2017)	American State Leg. Districts	Leg. Representation	XS
Broockman and Skovron (2018)	American State Leg. Districts	Elite Perceptions	XS
Leemann and Wasserfallen (2016)	Swiss States	Policy Representation	XS

4.3 Policy Feedback

There is a smaller literature that has examined policy feedback effects on subnational public opinion. For example, Sances and Clinton (2017) examine whether the Medicaid expansion in the Affordable Care Act (ACA) affected public opinion. They find that the ACA had only small effects on opinion. But it is hard to know whether Sances and Clinton (2017)’s findings represent the modal effect of policy on public opinion, or whether the effects of the ACA are unusually small. The growing availability of historical opinion data and the recent development of large-scale cooperative surveys enable scholars to study policy feedback effects in a variety of new contexts.

5 Conclusion

Until recently, the lack of high-quality information about public opinion at the subnational level was an important barrier that hindered the study of representation in Congress, state government, and local government. In recent years, the availability of new data sources and the advent of smoothing models to characterize mass opinion at the subnational level has revolutionized scholars’ ability to describe public opinion and examine its influence on the political process in a variety of important contexts.

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