"Doctoral Dissertation Research in Political Science: Dynamic Policy Responsiveness in the US States"

Julianna Pacheco

4/13/2009

Project Summary

When public opinion changes, how closely do policies follow? The answer is central to democratic theory. The principal of popular sovereignty implies some degree of *dynamic* policy responsiveness; a new policy is enacted because mass opinion became supportive of that new policy. While dynamic models of policy responsiveness have been tested at the national level, much less is known about the American states. This is an important shortcoming, particularly in light of evidence that state public opinion is directly responsible for policy differences across the fifty states.

I advance our knowledge about dynamic policy responsiveness at the sub-national level by measuring the *longitudinal* variation in state public opinion on different policy areas and linking these measures to various policy outputs at the state level. The dissertation is divided into two parts. Part I concentrates on the measurement of state public opinion across a variety of domestic issues over time. I show that multilevel modeling coupled with imputation and post-stratification (Park, Gelman, & Bafumi 2004) can be used to measure public opinion over time when augmented by a small (three year) moving average. Part II uses these dynamic measures to test two models of policy responsiveness at the sub-national level: the thermostatic model and the simple responsiveness model. The *thermostatic model* of policy responsiveness suggests that public opinion and policy exist in equilibrium; small incremental changes in public opinion produce small shifts in policy and vice versa (Erikson, MacKuen, & Stimson 2002; Wlezien 1995). Small shifts in policy elicit small changes in public opinion as the public reacts to government activity. The *simple responsiveness model* posits that public opinion directly influences policy, not vice versa (Norrander 2000). I use incremental policy changes (such as those related to spending) to test the thermostatic model and episodic policy changes (such as the adoption of smoking bans) to test the simple responsiveness model.

The **intellectual merit** of the project is the explicit incorporation of state public opinion into models of policy adoption and policy change. State politics scholars have advanced our knowledge about how public opinion influences policy differences across the states. Yet, the bulk of this work has focused on the cross-sectional correlation between public opinion and policy instead of the dynamic relationship between state residents' preferences and policy outputs. My project is the first to (1) measure state public opinion over time, (2) incorporate dynamic measures of state public opinion to the study of policy responsiveness, and (3) consider how the model of responsiveness depends on the particular policy. Hence, the dissertation advances our understanding not only of whether dynamic policy responsiveness exists across the states, but also how the link between opinion and policy varies across policy types and institutional factors.

The **broader impacts** of the study are embodied in the original dataset that will be made publicly available, along with the details of the methodology used to generate and validate dynamic measures of state public opinion. The methods of estimation can be extended to measure other preferences at the state level over time, as well as other attitudes such as tolerance, trust, efficacy or confidence which may also exhibit over time change across states.

Project Description

How policy makers respond to the preferences of the mass public is fundamental to any understanding of democracy in practice. As a result, many empirical efforts have sought to measure, model, and explain policy responsiveness to public opinion. Cross-sectional efforts have shown moderate to high associations between constituent opinion and roll call votes (Miller & Stokes 1963; Ansolabehere et al. 2001) and policy outputs at the state (Erikson, Wright & McIver 1993) and local (Berkman & Plutzer 2005) levels. Because cross-sectional associations may be spurious, considerable attention has been given to *dynamic models of policy responsiveness* – how policy changes follow shifts in public opinion (Page & Shapiro 1992; Erikson, MacKuen, & Stimson 2002; Johnson, Brace, & Arceneaux 2005). Dynamic models also offer the potential to explain changes in the degree of responsiveness over time (Jacobs & Shapiro 2000).

The US states are ideal for examining the dynamic relationship between mass preferences and policy. Not only do states vary in their collective preferences and policies, they also differ in mediating factors—such as party competition, professionalization, and interest group activity—that may condition the effect of opinion on policy. States vary in the timing of policy adoptions too; some states adopt policies quickly, while others are laggards or do not adopt them at all. To date, however, most state-level research has been cross-sectional- focusing on the role of public opinion on policy at one point in time. More recent studies have compared across two or three points in time (Johnson et al. 2005; Camobreco & Barnello 2008; Norrander 2000).

My dissertation will be the first state-level analysis to examine *yearly* change in both opinion and policy, which will allow me to address four broad questions: To what extent does dynamic policy responsiveness exist in the states? Why are some states quicker to respond than others? What role do changes in public opinion play in the timing differences in policy adoptions? How do the institutional and political environments mediate the effect of opinion on policy?

The answers to these questions require dynamic measures of state public opinion. Measuring state public opinion, even cross-sectionally, is a formidable task. Few states have regular high quality polls and even these may have inconsistent sampling designs, modes, and question wordings. In lieu of state polls, scholars have used national polls, broken down by state of residence. However, variation in state sample sizes and the potential for non-representative samples hinder valid and reliable measurement of opinion. In my dissertation, I apply recent advances in aggregate opinion estimation to measure annual state public opinion from national polls. These will be matched with time series data on several different policies in order to test hypotheses about policy processes and responsiveness.

Policy Responsiveness at the Sub-national Level

The vast literature on the role of public opinion on policy across the states can be divided into two traditions. The first looks at how state public opinion is related to the *general* ideological direction of state policies. In their influential book, *Statehouse Democracy*, Erikson, Wright, and McIver (1993) find a high correlation between state ideology (estimated from CBS/NYT surveys) and state policy liberalism (an index of eight policy measures). The authors conclude that "state opinion is virtually the *only* cause of the net ideological tendency of policy in the state" (1993 81). This approach leads to broad generalizations about the link between the political leanings of state electorates and policies. It is, however, difficult to make inferences about specific policy areas.

The second tradition explores how *policy-specific opinion* is related to *specific* policies, challenging and testing the assumption that public opinion is well captured by a summary liberal-conservative measure. For instance, state attitudes towards abortion are highly related to parental consent laws, funding for abortions, and spousal notifications across the states (Norrander & Wilcox 1999) as well as the restrictiveness of abortion policies (Arceneaux 2002). Johnson et al. (2005) find that state attitudes toward the environment are significantly related to state environmental policies. Brace et al. (2002) find that state policy preferences are related to AIDs research, the number of hate crime laws, welfare generosity, and state environment policies. In all of these studies, policy-specific opinion predicted policy outcomes *even after controlling for state ideology*, showing the value of measuring specific policy preferences. The size and significance of opinion tends to vary across issue areas, suggesting that issue characteristics, such as saliency, influence the link between public opinion and policy and, more generally, demonstrates the value of considering multiple issues (Burstein 2003).

Both traditions tend to look at how measures of public opinion *pooled across time* are related to policy outputs *pooled across time.* Such cross-sectional analyses do not allow scholars to test *dynamic* policy models (e.g., thermostatic processes, innovation models) or to raise even basic questions about causal order: does public opinion influence state policy or does state policy influence public opinion? As Brace et al. (2004) note "the issue of longitudinal variation [in public opinion] within the states is central to a comprehensive understanding of the process through which mass opinion and policy connect at the sub-national level" (529-530).

I will measure state public opinion and the corresponding policy on at least five specific issues including the death penalty, abortion, education spending, welfare spending, and smoking bans. I also measure global indicators of political orientation including party identification and political ideology. After exploring the dynamic patterns across the states for each issue (e.g. whether states trend together or differently on each issue), I consider two models of dynamic responsiveness. A thermostatic model—where public opinion and policy exist in equilibrium—is expected to fit recurring policies in which changes are matters of degree, such as spending (Erikson, MacKuen, & Stimson 2002; Wlezien 1995). A simple responsiveness model—where changes in public opinion directly influence policy (and not vice versa)—is expected to apply to episodic changes in policy such as the adoption of new policies or qualitative changes in prior policies, such as the elimination of the death penalty (Norrander 2000). The main distinction between these two models is the direction of causality. A thermostatic model implies a two way reciprocal effect of public opinion and policy while a simple responsiveness model implies a one way effect where opinion influences policy only. By linking dynamic measures of state public opinion to a range of policy changes, I not only explore *whether* dynamic policy responsiveness exists in the states, but also *how* the specific relationship between opinion and policy changes based on the specific policy output (recurring policy changes or episodic policy changes).

Policy Innovation and Public Opinion

While the dissertation is broad, the bulk of the proposed research funds will be used to acquire a dataset that is central to exploring the degree of responsiveness on policy innovations that are episodic. Acquiring the *Gallup Poll Social Series on Consumption Habit*s will permit estimation of attitudes towards smoking bans, enabling me to analyze state adoptions of anti-smoking legislation. This important health policy has been explored empirically before, allowing me to build upon an established research program (Shipan & Volden 2006; 2008). In the interest of space, I will focus on that portion of the dissertation in this section before moving on to describe the methods for estimating annual, state level public opinion. An overview of the entire dissertation is included at the end of this proposal.

The adoption of new policies in the states —also called policy innovations (Walker 1969) – has been the focus of many studies. Most have focused on the political and economic determinants of policy innovation, largely ignoring the expressed preferences of state residents. Evidence suggests that innovations tend to start in states that are large, wealthy, and urbanized with the assumption that these states have the financial resources to adopt new policies (Walker 1969; Berry & Berry 1990). Interest groups provide information to state officials and encourage innovations (Shipan & Volden 2006). Policy entrepreneurs and professional associations also help officials overcome information obstacles because they decrease uncertainty about a new policy (Mintrom 2000; Balla 2001). In addition, officials use information from neighboring states with similar policies to learn about the problems and successes of new policies. A neighbor's policy has been found influential across a range of policy issues including Indian gaming (Boehmke & Witmer 2004), lotteries (Berry & Berry 1990), anti-smoking (Shipan & Volden 2006), school charters (Mintrom 1997; Mintrom & Vergari 1998), healthcare (Balla 2001), taxes (Berry & Berry 1992), enterprise zone programs (Turner & Cassell 2007), and welfare (Volden 2007). Finally, unified party control provides officials with the necessary consensus on specific policies, which increases policy innovation (Berry & Berry 1990).

Yet, if public opinion exerts an impact on policy innovation, many of these conclusions may need to be qualified. For instance, a neighboring state's policy may spur policy innovation not because of spatial proximity, but because state officials look toward other states with similar levels of public opinion when considering new policies (Volden 2006). In other cases, our interpretation of variables may be improved. For example, if the influence of demographic characteristics on policy innovation disappears once public opinion is included in the model (e.g., Berkman & Plutzer 2009), this would suggest that demographics influence policy adoption indirectly through state public opinion instead of directly or through some other variable related to demography, such as political mobilization. Hence, not only can focusing on policy innovation advance our knowledge about *how* the specific relationship between opinion and policy changes based on the policy output, but it can also give us a better understanding about the mechanisms through which other variables impact policy innovation.

Using Smoking Bans to Study Policy Innovation

Every year an estimated 438,000 Americans die from tobacco-related diseases (American Lung Association 2008) and health officials have declared secondhand smoke dangerous, suggesting that comprehensive smoke-free legislation can improve public health. Some states adopted smoking bans in specific areas (e.g., workplaces, restaurants) while others enacted comprehensive smoking bans. And still others have yet to pass any major restrictions on smoking in public places. More interesting, there is great variation in the timing of smoke-free adoptions. California was the first to adopt smoking bans in restaurants and workplaces in 1994.

Since then, 21 other states and the District of Columbia have approved comprehensive smoke free air laws. What role do public preferences towards smoking bans play in the longitudinal variation in the adoption of smoking bans across the states?

To measure state preferences towards smoking bans, I will combine individual survey data from the *Gallup Poll Social Series on Consumption Habits* 2001-2008 and the *Current Population Survey Smoking and Tobacco Supplement* 1992, 1993, 1995, 1996, 1998, 1999, 2000, and 2001 (CPS). In both surveys, respondents were asked their preferences towards smoking bans in workplaces, restaurants, bars, and hotels. After creating state level preferences towards smoking bans, state preferences will be linked to the adoption of smoking bans in restaurants, bars, and workplaces using data I have compiled from the National Cancer Institute's State Cancer Legislative Database (SCLD). The resulting series will span sixteen years, begin prior to the first state's adoption, and include a year of overlap to account for potential "house" and question effects that may influence expressed support for the policy.

Shipan and Volden (2006) conclude that preferences towards smoking do not significantly influence the adoption of anti-smoking legislation. However, they infer preferences based on the percentage of smokers in each state. The authors also include various measures of political ideology; however, none of these proxies significantly influenced the adoption of anti-smoking legislation. Using preferences on smoking bans in restaurants from the CPS, I find that the number of smokers only explains 28% of the variation in state opinion. I also find that states with similar levels of smoking prevalence can have varying opinions towards smoking bans. For instance, 22% of residents in Texas and Virginia are smokers, but Texas (μ=.52) and Virginia (μ=.45) have significantly different preferences towards banning smoking in restaurants ($p < 0.03$). This preliminary analysis suggests that inferring public opinion based on the percentage of smokers is problematic, leading to incorrect inferences in past research. By including direct measures of public opinion on smoking legislation, my project will provide stronger tests of the hypotheses examined by Shipan and Volden and policy innovation research generally.

Measuring Dynamic State Public Opinion

Using national surveys to obtain valid and reliable estimates of state public opinion is a challenge because national surveys use sampling designs aimed to accurately describe the nation, not individual states. Face to face national surveys, in particular, typically employ a multi-stage area (MSA) probability design whereby respondents are selected after primary sampling units (PSUs) are identified (Groves et al. 2002). These PSUs can include: counties, blocks, or other geographic units. The number of PSUs and the number of stages used to identify sampling units differ across surveys.

Multistage area probability designs present two problems for scholars measuring state opinion. First, there is no guarantee that the first stage selection of PSUs will be representative in each state. In the 2004 National Election Survey (NES), for example, only 1 MSA in the state of Missouri was selected. The design was unbiased in that each of the 8 MSAs in Missouri had a chance to be selected. But in any particular realization of the sample, it was possible that St. Louis may be included or excluded. The exclusion of St Louis results in an underrepresentation of Blacks and the potential for unrepresentative state estimates. As Brace et al. (2002) note, the risk of bias is greatest in the less populated states (*low population* coverage) and when a public opinion differs substantially across a state's geographical areas (*low population homology*). These would both be factors in medium size states that have substantial diversity in opinion (e.g., Wisconsin, Missouri, and North Carolina). At least risk of obtaining unrepresentative estimates are the largest states with many PSUs (e.g., California, Texas, Florida) and the smaller but homogeneous states (e.g., Maine, Wyoming). The crucial point is that while the design may be unbiased in terms of expected values, any particular implementation of the sampling design can produce a non-representative selection of PSUs for a particular state. All nationally representative sample surveys have the second problem: the amount of information per state is directly proportional to state population. Less populous states tend to have inadequate sample sizes, leading to imprecise estimates. Imprecision leads to larger variances and attenuated correlations and/or coefficients. One solution is to estimate models with just the 30-40 largest states. This is not always a viable option, such as when state size is a correlate of the dependent variable. In this case, omitting the small states from the analyses would lead to selection bias in addition to possibly decreasing the variance of other important independent variables.

Scholars have devised various strategies to overcome these challenges. These strategies include aggregation (Erikson et al. 1993; Brace et al. 2002) and multilevel modeling plus imputation and post-stratification, hereafter referred to as MLM-IPS (Park et al. 2004, 2006; Lax & Phillips 2009). As I show below, the MLM-IPS approach is better at measuring state public opinion than aggregation. By pooling surveys across a short time frame (for instance, across a three year window), we can obtain state samples large enough to generate reliable measures using the MLM-IPS approach. In addition, the MLM-IPS method uses post-stratification, which corrects for any under coverage bias that may have occurred due to the national sampling design or from differential non-response across demographic groups.

Aggregation

Erikson et al. (1993) showed that reliable and unbiased measures of ideology and partisanship can be obtained for each state by pooling multiple years of national-level data, such as the CBS/NYT polls, and then aggregating to the state level. In a more recent article, Erikson et al. (2007) pool 27 years of national polls to obtain mean values of state ideology and partisanship across the fifty states. Brace et al. (2002) show that the pooling and aggregation technique can also be applied to state-level attitudes about specific policies; they pool 24 years of General Social Survey data to obtain mean values of state public opinion towards nine issues such as racial integration, abortion, homosexuality, welfare, and the death penalty. Formally, aggregation can be described by Equation 1, where j indexes states and i indexes individuals:

$$\hat{Y}_j = \frac{1}{n_j} \sum_{i=1}^{n} y_{ij} \qquad (1)$$

Multilevel Modeling, Imputation, and Post-Stratification (MLM-IPS)

The second approach uses imputation and post-stratification with Bayesian multilevel modeling. The MLM-IPS approach, first introduced by Gelman and Little (1997), can be divided into three steps: (1) estimation of a multilevel model with predictors, (2) imputation, and (3) post-stratification (see also Park et al. 2004, 2006; Lax & Phillips 2009).

We begin with a multilevel model to estimate state public opinion for individuals given demographics and state. The MLM-IPS approach includes various predictors to estimate state public opinion. Following Park et al. (2004; 2006), I use gender (0=male, 1=female), race (0=non-black, 1=black), age (four categories: 18-29, 30-44, 45-64, and 65+) and education (four categories: no high school degree, high school degree, some college, and college+). I model age and education with varying intercepts using non-nested models. Non-nested models for categorical variables are computationally easier because it eliminates including each dummy variable into the model directly (Gelman & Hill 2007). I write the model below using indexes *j,k,* and *l* for state, age category, and education category, respectively; the subscript *i* refers to individual respondents.

(2) **Level 1:** $\Pr(y_i=1) = \text{logit}^{-1}(\beta_0 + \beta_1\text{Female}_i + \beta_2\text{Black}_i + \alpha_{j[i]} + \alpha_{k[i]} + \alpha_{l[i]})$

(3) **Level 2:** $\alpha_j \sim N(0, \sigma^2_{state})$ for $j=1,\ldots,51$
$\alpha_k \sim N(0,\sigma^2_{age})$ for $k=1,\ldots,4$
$\alpha_l \sim N(0,\sigma^2_{education})$ for $l=1,\ldots,4$

Following Park et al. (2004; 2006) and Gelman and Hill (2007), I fit the model using the Bayesian software *WinBugs* (Spiegelhalter et al. 1999) as called from R (R Development Core Team 2003) using Gelman's (2003) *Bugs.R.* Bayesian multilevel models are especially useful for more complicated multilevel models, for example those with non-nested components, and also allow the estimation of uncertainty by using prior distributions, which are given to all parameters (Gelman & Hill 2007 345). Parameters can then be drawn from these distributions over a number of simulations. I assign normal distributions to the coefficients with means of 0 and standard deviations $\sigma^2_{state,}$ $\sigma^2_{age,}$ $\sigma^2_{educ,}$ estimated from the data given non-informative uniform prior densities (Park et al. 2004 378).

The next step is imputation. I define each combination of demographic characteristics and state (for instance, a non-black, female, aged 18-29, with a high school degree from Connecticut) as a "person type." Each of the 3,264 person types has an associated probability of supporting a particular policy, which is modeled in the multilevel regression as a function of state, gender, age, race and education. Imputation is conducted on each person type even if absent from the sample. After imputation, we have θ_c, which is the inverse logistic given the relevant predictors and their estimated coefficients (θ_c, is an average based on 1,000 simulations with *c* indexing the 3,264 unique combinations).

The final stage is post-stratification. Post-stratification corrects for differences between state samples and state populations by weighting the predicted values of each person type in each state by actual Census counts of that person type in a state. For example, the 2000 Census reports that there were 581 people who were white, male, age 18-29, no high school degree, and living in Alabama: 1.7% of Alabama's population. The imputed opinion of each person type, θ_c, is then weighted by the corresponding population frequencies. In the final step, we calculate the average response over each person type (*c*) in each state (*s*) over the 1,000 simulations and summarize to get point predictions and uncertainty intervals:

(4) $$\hat{Y}_{state\ s} = \frac{\Sigma_{c\varepsilon s} N_c \theta_c}{\Sigma_{c\varepsilon s} N_c}$$

Feasibility Assessment and Validation Using Party Identification

To systematically compare the performance of both methods, I measure the proportion of individuals who identified with the Democratic Party from 1977-2007 using CBS/NYT polls. Respondents were asked the following: "Generally speaking, do you usually consider yourself a Republican, a Democrat, an Independent, or what?" I recoded this into a dummy variable so that a positive response indicates support for the Democratic Party with all else equaling zero. The final dataset consists of 324,862 respondents surveyed from 1977-2007 on party identification across all states.

Adding a Time Component

We can increase the amount of information, but still preserve a time component, by pooling across a small number of years. I compare estimates of state public opinion using each approach while employing a three year window. For instance, to get point estimates for 1979 using a three year pooled window, I combine estimates from 1978, 1979, and 1980. This process is repeated for each year after moving the time frame up a year at a time. By pooling and taking the median year, the first and last years are missing for the three year window. Hence, for the three year time frame, I have yearly estimates from 1978-2006.

Assessing the Problem of Small State Sample Sizes

The best method to measure state public opinion over time is one in which the predictive accuracy is optimal across various state sample sizes. It is not enough to have a method that performs well only in heavily populated states; we want to have accurate estimates across all states, regardless of size. I randomly select a subsample of respondents from a heavily populated state and use these subsamples to mimic other state sizes. I then compare estimates from these subsamples to estimates obtained from the full sample to cross validate. I use the largest state, California, to obtain four subsamples that mimic a large state (like Illinois), a medium state (like Kentucky), a less populated state (like Delaware), and a very small state. Specifically, I randomly draw a subset of 14,000 respondents without replacement from California across all years to create a simulated Illinois-sized state with an average N of about 466 per year. To get a simulated medium (Kentucky-sized) state, I randomly draw a subset of 6,000 respondents from California with an average of about 200 per year. I randomly draw a subset of 1,000 respondents to create a Delaware-sized state with an average of about only 33 respondents per year. Finally, I randomly draw a subset of 500 respondents to simulate a very small state with an average of about 17 respondents per year.

To cross validate these estimates with "true" measures, I compare them to yearly aggregated weighted estimates using the full sample of Californians (N=30,037 or an average of 1,000 per year). By using aggregated yearly estimates, I am able to assess the extent to which error is introduced by each estimation approach. Although others have used unweighted survey responses for both the baseline and sample data (Erikson et al. 1993; Brace et al. 2002; Lax & Phillips 2009), I use weighted responses since the "true" data are actually a manifestation of sample data. The survey weights correct for any non-response bias that may occur in the data and, consequently, return more accurate estimates. Accurate estimates are necessary, especially when comparing the predictive accuracy for MLM-IPS, which directly accounts for disparities between sample data and the population of interest.

I assess the predictive success of the aggregation and MLM-IPS methods by using criteria developed by Lax and Phillips (2009). I calculate the errors produced from each method by taking the absolute difference between the estimates for each state and the "true" measure. For each year, *t*, let $y_{t,s}^{true}$ be the true proportion of Democrats, let $y_{t,s}^{agg}$ be the proportion of Democrats measured via the aggregation method and let $y_{t,s}^{MLM-IPS}$ be the proportion of Democrats measured via the MLM-IPS approach using a three year pooled time frame. The absolute error is:

(5) $e_{t,s}^{agg} = | y_{t,s}^{agg} - y_{t,s}^{true} |$ $\qquad$ $e_{t,s}^{MLM-IPS} = | y_{t,s}^{MLM-IPS} - y_{t,s}^{true} |$

This produces absolute errors for each method for the four pseudo states for each year. For state, *s*¸ I then calculate the average absolute error for each method over the 28 year time span thus creating one summary measure for each method and pseudo state:

(6) $$\bar{e}_{t,s}^{agg} = \frac{\sum_t e_{t,s}^{agg}}{28}$$

For each method, I also calculate the average standard deviation in the estimates for each state across time to assess precision. These are reported in Figure 1, where the solid dots represent estimates from the aggregation approach and the open circles represent estimates from the MLM-IPS approach.

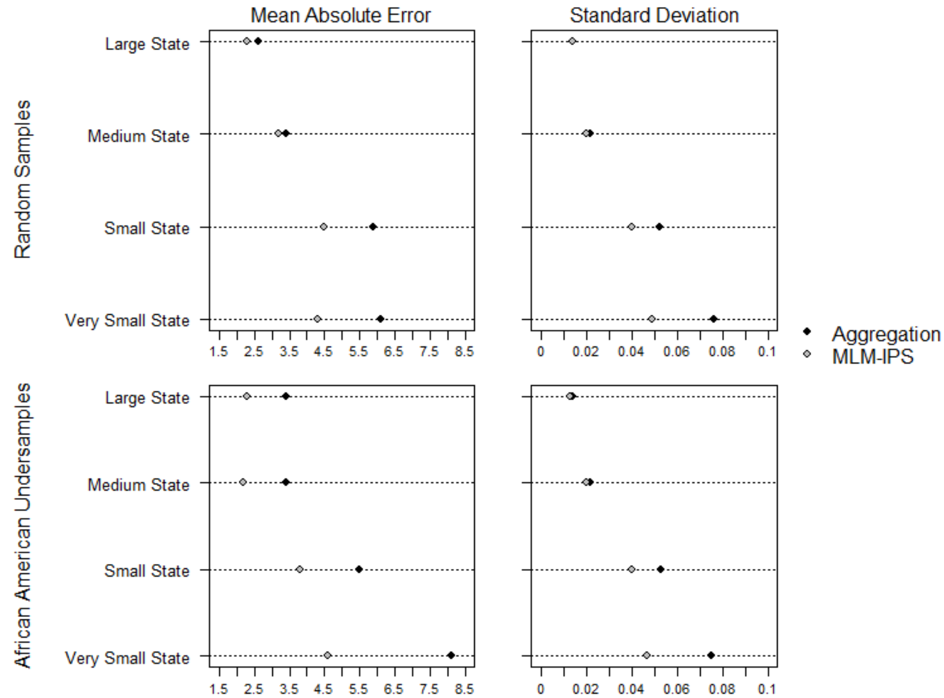
The upper panel of Figure 1 shows that MLM-IPS outperforms aggregation—in terms of error and precision—across all state sizes for the random sampling design. The differences between the aggregation and MLM-IPS approaches are especially noteworthy for the less populous states. Hence, the MLM-IPS—because of the use of multilevel modeling and covariates—helps overcome the problem of small state sample sizes that is unavoidable when using national polls.

Assessing the Problem of Non-Representativeness

Scholars must also overcome the possibility that state estimates may be unrepresentative of state populations due to the chance that a state could get a non-representative selection of PSUs employed by the sampling design. The under-coverage of certain demographic groups within a state is particularly problematic to measuring state public opinion when those same demographic characteristics are related to the outcome measure. For instance, we know that African Americans are more likely to identify with the Democratic Party compared to whites. If, by chance, we happen to under sample African Americans in a state (for instance, in Missouri because St. Louis was excluded from the sampling design), then our estimates would be unrepresentative of the state population on party identification.

To empirically test the gains from the MLM-IPS approach, I again obtain four subsamples from California, but deliberately under-sample African Americans. Although African Americans make up about 7% of the state population in California, I adjust the data so that only 2% of the sample is made up of African Americans. As before, I create four pseudo states across four sample sizes each undersampling African Americans. I then calculate the mean absolute error and standard deviation for each under-sampled pseudo state across each method.

Figure 1. Summary Models for Aggregation and MLM-IPS Approaches Pooled Across Years



The lower panel of Figure 1 shows that the MLM-IPS model is especially superior—in terms of error and precision—when a major demographic group is under-represented in the sample data. Hence, the MLM-IPS approach also helps overcome the problem of non-representative estimates through the use of post-stratification. The MLM-IPS estimates also correlate at higher levels with the true estimates across state sample sizes and designs compared to the aggregation estimates. Though preliminary, I conclude that the MLM-IPS approach is appropriate to measure dynamic state public opinion across time using three year pooled time frames. Later analyses will assess the relative costs and benefits of using a longer (e.g., 5 year) window for the moving average. I will also test the predictive accuracy of MLM-IPS under other model specifications (for instance, if only race was included as a covariate).

Conclusion: Intellectual Merit and Broader Impacts

My dissertation makes both methodological and theoretical contributions to the study of American politics. By augmenting the MLM-IPS approach with a simple moving average, I have demonstrated the feasibility of reliably measuring dynamic state opinion. I will use the resulting measures to extend the thermostatic model to the study of sub-national politics and enrich the study of policy innovation by explicitly incorporating public opinion into our models. Financial support to acquire the Gallup data on smoking bans will help ensure that my empirical analyses cover a broad array of policy types. It will also permit a direct extension of recent work on an important policy domain. I further hope that my approach will serve as a model for other scholars interested in measuring state opinion over time or provide a foundation for further improvements. I have also requested a small amount of support for archiving the data and the eventual placing of these state opinion data sets in the public domain for other scholars. I hope this original dataset will be a useful public good for other scholars studying American politics.

Dissertation Outline and Progress to Date

Chapter 1 introduces the dissertation and reviews the contents of each chapter. **Chapter 2** is a variant of a conference paper titled "Measuring Dynamic State Public Opinion: A Comparison of Three Approaches." I introduce the MLM-IPS technique and measure state public opinion on various issues including the death penalty, abortion, education spending, welfare spending, smoking bans, party identification, and political ideology. **Chapter 3** is an extension of a conference paper titled "Dynamic Properties of State Public Opinion." Three questions drive this chapter: (1) Is state public opinion dynamic or stable? (2) If dynamic, are states trending together or separately?, and (3) Do the answers to these questions depend on the issue? **Chapter 4** explores the role of public opinion on policies across all the issues generally with an attempt to empirically determine which issues characterize a thermostatic or simple responsive relationship with policy. Using education and welfare spending specifically, I further test under what political and institutional conditions thermostatic responsiveness is enhanced at the state level. **Chapter 5** uses the smoking data to test whether the simple responsiveness model explains responsiveness for policy innovation. **Chapter 6** concludes the dissertation, reviews the substantive conclusions and results, and presents direction for future research.

Research Schedule

Already completed: Generation of state opinion for abortion, death penalty, party identification, welfare spending and education spending. Validation tests, as reported in this proposal. Acquisition and creation of policy output data sets for smoking bans, spending issues, and the death penalty.

January-June 2009: Validity checks using external data. Generate opinion on political ideology. Continue writing Chapters 2 & 3. Revise and submit article that is a variant of Chapter 2.

Summer 2009: Acquire Gallup data and measure opinion for smoking bans. Explore policy responsiveness via the thermostatic model using spending preferences. Write paper for American Political Science Association (APSA) Conference to be presented in September 2009. Revise article, which is a variant of Chapter 3, for submission to a scholarly journal.

Fall 2009: Train undergraduate research assistant to organize datasets and documentation. Explore role of smoking preferences on the adoption of smoking bans. Draft Chapter 5. Rework the paper presented at APSA into Chapter 4.

Spring 2010: Re-work introductory and concluding chapters in light of findings. Continue revising the dissertation in preparation for doctoral defense in May 2010.