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DYNAMIC PUBLIC OPINION AND POLICY RESPONSIVENESS IN THE AMERICAN STATES

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by
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ABSTRACT
When public opinion changes, how closely do policies follow? Central to democratic theory, the principle of popular sovereignty implies some degree of dynamic policy responsiveness: new policies should be enacted when mass opinion becomes supportive of that new policy. But, for a successful democracy, public opinion must also be attentive to what government does; citizens have to react to policy changes otherwise there is little incentive for elected officials to respond to public opinion. 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. Moreover, because states differ in their institutional and political contexts, testing models of dynamic responsiveness at the state level provides many opportunities to specify the conditions when policy responsiveness is higher or lower.

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. Specifically, I show that multilevel regression coupled with imputation and post-stratification can be used to measure public opinion over time when augmented by a small (e.g., three year) moving average. I use this approach to estimate yearly state public opinion on global attitudes (e.g., party identification and ideology) as well as specific attitudes (e.g., the death penalty, abortion, education spending, welfare spending, and smoking bans).

I then use these measures to explore the dynamic properties of state public opinion and to test models of policy responsiveness at the sub-national level. In regard to the former, I find that the dynamic pattern of public opinion varies across issues. For instance, preferences towards the death penalty, welfare spending, and anti-smoking legislation are dynamic with heterogeneous
trends, preferences towards education spending are dynamic with homogeneous trends, and abortion attitudes are fairly stable.

Through various time series analyses, I find that state opinion plays a critical role in policy changes at the sub-national level for three issue areas: education, welfare, and anti-smoking legislation. Moreover, I provide additional evidence that the impact of public opinion on policy is causal. To give just one example, I estimate that if support for education spending increases by three percentage points, spending per classroom increases by over $500 immediately (assuming 25 students per classroom). State opinion also plays a large role in whether a state adopts a new policy, such as a smoking ban in restaurants.

I also find that the causal relationship between public opinion and policy is a two-way street, although how opinion responds to policy changes depends on the issue. For education and welfare, policy changes exhibited a negative relationship on public opinion, albeit, only in the long term. On the other hand, attitudes towards anti-smoking legislation become more supportive as states enact additional restrictions. These analyses suggest that state opinion responds in rational and reasonable ways to policy changes.

The broader impacts of the study are embodied in the original dataset that is 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.
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Chapter 1

Does Public Opinion Matter?

The question of whether public preferences matter in the policy decisions of politicians has been the topic of research for decades. Indeed, policy responsiveness—how closely policies are aligned with mass public opinion—is a central component of a successful democracy. We expect a democratic government to be in tune with the policy needs of the electorate and to respond in a timely manner. In fact, if public opinion played little or no role in the policy process, we might question the extent to which governments are “democratic”.

However, the idea of policy responsiveness is not a static one. Not only do we expect policy decisions to be in line with majority opinion, but we also expect policy changes to reflect opinion changes. If there is a shift in mass public opinion, for instance, then we expect for elites to (1) gauge this shift and (2) react to this shift by producing policies that are consistent with majority public opinion. Elections provide a link between the political preferences of the electorate and elite decision-making. If elites do not produce policies that are congruent with public opinion, then they risk losing their jobs in the next election. Inherent in this depiction of democracy is a dynamic relationship between mass public opinion and policies. Public opinion changes for some reason, elites catch wind of this change, and new policies are adopted.

Dynamic responsiveness also implies that policy changes influence changes in public preferences. Indeed, a functioning democracy also requires that the public responds in a rational way to policy changes. As Wlezien (1995) states “if the public did not notice and respond to changes in policy, then politicians would have little interest to represent what the public wants” (981-982).

The dynamic relationship between public opinion and policy across the states is the topic of this dissertation. While the dynamic relationship between mass preferences and policy has been explored at the national level (e.g., Wlezien 1995; Erikson, MacKuen, and Stimson 2002),
much less is known about how changes in public preferences influence policy changes in the American states. This is an important shortcoming, particularly in light of evidence that state public opinion is directly responsible for cross-sectional policy differences across the fifty states (e.g., Erikson, Wright, and McIver 1993). The first step in exploring the relationship between state opinion and policy over time is to develop a method that can be used to estimate state opinion over time. As I explain below, scholars have long struggled with how to accurately and reliably measure the public preferences of states and many of these challenges are intensified when adding a time component. Hence, a large portion of this dissertation is devoted to measuring state opinion over time.

The next step to understanding how policy changes reflect changes in state opinion is to describe the dynamic patterns of opinion across the states. Logically, policy changes across the states can only reflect opinion if there are large variations in how state citizens change their preferences. And at a more basic level, public opinion has to change in order to be reflected in policy changes. To this end, I explore (1) whether state opinion changes across time and (2) whether the patterns of change are homogeneous or heterogeneous across the states.

Finally, I explore the extent to which dynamic policy responsiveness exists at the sub-national level. As I explain, dynamic policy responsiveness is not just about the impact that opinion has on policy. Dynamic policy responsiveness also requires public opinion to respond to policy changes over time. Hence, not only do I consider how public opinion is related to policy changes over time, but also how public preferences respond to policy changes over time.

Why focus on the states? The states provide a prime laboratory for studying how public opinion is translated into policies and vice versa because of the variations in possible mediating factors, such as elite ideology (Erikson, Wright, and McIver 1993), party activists (Carmines & Stimson 1989), and political parties (Burstein 2003). Other aspects, such as issue salience, legislative and electoral characteristics, demographics, and interest group activity, also differ
across states; these factors allow scholars to identify variables that may condition the impact of public opinion on the policy process. In other instances, theories that have empirical support at the national level may have to be modified when applied to the states because of the unique political environment in which states governments operate. While these specific types of analyses are beyond the scope of this project, the results presented here offer scholars a baseline from which to develop additional theories and empirical projects.

How Should We Measure State Opinion Over Time?

Scholars have struggled with how to accurately measure state public opinion since at least the 1960s (Dye 1969; Hofferbert 1966). The primary problem is that few states have high quality polls. And, the states that do have high quality polls often have inconsistent question wording, modes, and survey designs making cross-sectional, and especially longitudinal, comparisons difficult. Recent methodological advances, however, make it possible to use national surveys, such as the General Social Survey or the National Election Survey, to obtain reliable and representative state estimates of public opinion across time.

Chapter 2 reviews the methodological literature on state public opinion and introduces the technique used in this dissertation to measure dynamic state public opinion from national surveys. I apply recent advances in aggregate opinion estimation to measure annual state public opinion from national polls. Specifically, I use multilevel modeling, imputation, and post-stratification (MRP) applied to a small pooled time frame. This technique was first introduced by Park, Bafumi, and Gelman (2006) and recently used by Lax and Phillips (2008, 2009). Yet, previous scholars have used this technique either on pooled surveys over decades or for one particular survey at a time. What is novel about the analyses presented in this dissertation is that I include a time component into the measurement strategy. As I show in Chapter 2 by using this technique to measure state partisanship and ideology over time, the MRP approach generates
reliable and valid measures of state public opinion across the fifty states and the District of Columbia over time when combined with a small moving average.

While it is important to understand how the general tendencies of the states change, describing the partisan and ideological landscape of the fifty states is just part of the story. We also care about state public opinion on specific policy issues. Consequently, in Chapter 3, I apply the MRP approach to measure specific state opinion on five issues: the death penalty, abortion, education spending, welfare spending, and anti-smoking legislation. These five issues, while not representative, are asked frequently across time in surveys, have a strong precedent in the literature, and are issues over which the states have large jurisdiction. By having public opinion measures on specific policy issues, I can directly test how state opinion influences specific policy changes across the states and compare how the dynamic relationship between opinion and policy may differ across issue areas.

It is important to understand that the entire dissertation concentrates on state public opinion at the macro level. Explicit in this approach is the notion that aggregate public opinion—and corresponding changes in aggregate public opinion—is meaningful and rational despite low levels of political knowledge (Delli Carpini and Keeter 1996), political constraint (Converse 1964), or political consistency (Converse 1964; Campbell et al. 1960; Berelson, et al. 1954) at the individual level. Instability inherent in levels of public opinion at the individual level caused by question wording (Nelson, Oxley, and Clawson 1997; 1999), or question ordering (Zaller 1992) effectively “cancels out” once aggregated to the macro level.

The logic here is that there are various groups of individuals with differing levels of political knowledge and political predispositions that make them change political preferences across time differently. One group of individuals has little knowledge about politics and, thus, is random in how their political preferences change across time. Another group of individuals has high levels of political knowledge, but changes their political preferences in response to the
environment depending on their political predispositions. In some instances, this group of individuals will remain stable even amid changes in current events because of their political predispositions. For instance, Republican identifiers may not change their presidential approval for a Republican president during poor economic times as much as Democratic identifiers simply because of their party identification and biases that go along with that identification. If there is change among this group of highly informed citizens it will not be random; instead it will be a rational response to current times. When we aggregate public opinion across these three groups (those that change at random, those that remain stable, and those that change in response to current times), we will have a “signal” that arises almost wholly from those who are rational in their political preferences and who are changing in response to the political environment. This is because those who change at random will cancel out and those who are stable will continue to remain stable. Hence, due to the “magic” of aggregation, we can view a rational public at the macro level, which elites respond to even amid an uninformed citizenry at the individual level. Indeed this logic of macro public opinion has been used to study changes in public opinion at the national level (e.g., Page and Shapiro 1992) as well as dynamic policy responsiveness at the national level (e.g., Erikson, Wright, and McIver 2002).

We can extend the logic of aggregation to study mass public opinion at the state level over time. Hence, I measure the macro opinion for each of the fifty states and the District of Columbia over time. By thinking about state public opinion at the macro level, we can ask questions that have important implications for our models of dynamic policy responsiveness, as I explain in the next sections.

Patterns of State Opinion over Time

While previous research on state public opinion has shown that there are large variations in political preferences across the states (Erikson, Wright, and McIver 1993), less is known about how state public opinion behaves across time. Research at the national level, however, provides
insight. For instance, we know from Page and Shapiro (1992) that 58% of policy questions analyzed showed no significant opinion movement (defined as 6 or more percentage points of change) (Chapter 2; 45). In addition, domestic policy opinions (63%) are somewhat more stable than foreign policy opinions (51%). Moreover, of those changes in policy preferences, more than half—59%—moved gradually across time (Page and Shapiro 1992 60). We also know from Page and Shapiro (1992) that if public opinion changes, it does so in a rational way and in response to current events. The question, however, is should we expect state public opinion to follow the same dynamic properties as national public opinion? And, if state public opinion is dynamic, do states trend in parallel ways or do they trend differently across time?

In Chapter 4, I draw from research at the national and sub-national levels to develop theories on whether (1) state public opinion is stable or dynamic and (2) whether the dynamic patterns are similar or different across states. Knowing whether state public opinion is stable or dynamic provides insight about our models of policy responsiveness at the state level. If state public opinion is stable, then our theories of policy responsiveness need not have a dynamic component. Methodologically, the data requirements to investigate policy responsiveness in the states are quite small if state public opinion is fairly stable; we would only need cross-sectional data to investigate the degree of policy responsiveness at the state level. If state public opinion is dynamic, then we must have dynamic theories which link state public opinion to policy outputs. And, the methodological demands would be higher if state public opinion is dynamic; we would be required to have time series data to explore policy responsiveness at the state level.

If state public opinion is dynamic, there are two patterns of dynamism that we may see across the states. In the first pattern, state public opinion trends the same across time. This would occur if state public opinion changed in the same direction and at roughly the same rate on a particular issue across the states. States would maintain their relative ranking, regardless of the time point. The second scenario occurs when state public opinion trends differently across the
states. In this scenario, state public opinion may become more favorable in some states while in other states it becomes less favorable. Methodologically, the more patterns of state public opinion diverge across states, the less we can rely on state opinion data sets that pool surveys over many years.

To explore the dynamic properties of state opinion, I analyze the characteristics of state ideology and partisanship developed in Chapter 2 as well as the five specific public opinion measures developed in Chapter 3. Through both descriptive and complicated time series analyses, I find in Chapter 4 that issues differ in their longitudinal variations and their patterns across the states. State partisanship changes gradually over time with evidence of heterogeneous trends. On the other hand, state ideology is characterized by stability and when it does change, it does so in small increments. Preferences towards the death penalty and welfare spending are dynamic with heterogeneous trends, particularly across regions. Preferences towards education spending and anti-smoking legislation are also dynamic, yet with much more homogeneous trends compared to preferences towards the death penalty or welfare spending. Finally, abortion attitudes are quite stable across time in the states. These results provide insight into what causes shifts in state opinion as well as the consequences that these shifts have on policy changes.

**Putting Dynamics into Policy Responsiveness in the States**

The study of how state public opinion varies and how these variations result in policy differences has a long tradition in state politics research. Early scholars focused on socioeconomic and demographic characteristics, such as state wealth, the degree of industrialization, race, and ethnicity in describing state differences in policy preferences with the assumption that demographics are directly linked to macro public opinion (Dye 1969; Hofferbert 1966; Sharkansky 1967). Recent work uses more advanced methodological techniques to measure state public opinion and its effect on policy directly. In their influential book *Statehouse Democracy*, Erikson, Wright, and McIver (1993) aggregate individual level responses to national
level surveys across various years to measure state ideology. They find that state ideology statistically explains over 80% of the variance in state policy liberalism. The authors conclude that “state opinion is virtually the only cause of the net ideological tendency of policy in the state” (Erikson, Wright, and McIver 1993 81).

Scholars have also looked at how state public opinion on specific policies is related to specific policy outputs. Norrander and Wilcox (1999) find that state attitudes towards abortion are highly related to abortion policies, such as parental consent laws, funding for abortions, and spousal notifications, across the states. Johnson, Brace, and Arceneaux (2005) find that state attitudes toward the environment are significantly related to state environmental policies. Brace et al. (2002) find that state public opinion is related to various policies including AIDS Research, the number of hate crime laws, AFDC monthly payments, and state environment policies. Significant effects of public opinion have also been found on per capita state debt (Clingermayer & Wood 1995), state variation in Medicaid eligibility rules (Grogan 1994), pharmacy assistance programs (Gray, Lowery, and Godwin 2007), and gay-related policies (Haider-Markel & Kaufmann 2006). In short, there is strong evidence that states differ in policy preferences and that these differences account for policy differences across the fifty states.

Previous research, however, tends to look at how measures of state public opinion pooled across time are related to policy outputs pooled across time. Hence, while we know a lot about the correlation between opinion and policy at the sub-national level, we know little about the dynamic relationship between opinion and policy in the states. For instance, besides not knowing whether changes in opinion precede or follow changes in policy, we also do not know whether the effects of opinion on policy (or vice versa) are felt immediately or gradually over time. We do not know whether theories of dynamic responsiveness, which have empirical support at the national level, characterize the dynamic relationship between opinion and policy at the sub-national level. And, we do not know whether opinion plays a role in the innovation and diffusion
of policies across the states, which is an important policy process unique to the sub-national level. 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 test theories of dynamic responsiveness in the American states using two types of policy changes: incremental policy changes in Chapter 5 and policy innovations in Chapter 6. I start Chapter 5 by outlining various theories of dynamic responsiveness, most of which are drawn from studies conducted at the national level. I then use three issue areas: education, welfare, and anti-smoking legislation to test these theories. More specifically, I test whether the thermostatic model of policy responsiveness characterizes the dynamic relationship between state public opinion and policy for these three issue areas. The thermostatic model suggests that public opinion and policy exist in equilibrium; small incremental changes in public opinion produce small shifts in policy and small shifts in policy produce changes in public opinion (Erikson, MacKuen, and Stimson 2002; Wlezien 1995; Johnson et al. 2005). In particular, public opinion is theorized to respond to policy in the negative direction; as policy overshoots the public’s ideal, the public will respond by demanding policies in the opposite direction. I find that the thermostatic model of policy responsiveness best illustrates the dynamic relationship between state opinion and policy for education and welfare expenditures. The dynamic relationship between policy and opinion for anti-smoking legislation is consistent with traditional theories of responsiveness, but goes against what is predicted by the thermostatic model. While state opinion towards education and welfare spending respond in the expected negative direction to actual expenditures, state preferences towards anti-smoking legislation become more supportive after restrictions have been passed.

It is because of the unique results with anti-smoking legislation that I take an in-depth look at the role that public opinion plays in the adoption of particular anti-smoking state policies
in Chapter 6. Specifically, I test how state opinion towards smoking bans in restaurants is related to the adoption of smoking bans in restaurants across the states. I use the policy innovation and diffusion perspective, which allows me to model the policy changes as episodic and explore the role that public opinion has on these policy changes by using event history analysis. Via this approach, states adopt a new policy (in this case, smoking bans in restaurants), but at different times. By using event history analysis, I can explore the role that public opinion plays in the timing variations in state adoption of smoking bans. This is different from the analyses in Chapter 5 in which I explored the role of public opinion on a continuous measure of anti-smoking legislation that can (potentially) change every year.

As I show in Chapter 6, public opinion plays a large role in the probability that a state adopts a new policy superseding the effects of neighboring states, which is traditionally a key factor in policy adoption (Berry & Berry 1990). More specifically, the results in Chapter 6 suggest that states look towards neighbors when making decisions about innovating because it provides information about the level of public support within their own borders. State legislators view the adoption of policies in neighboring states as a resource through which to learn about the public support in their own state for similar policies. If neighboring states that are similar in culture, demographics, and ideology have enacted certain policies, then public support is ripe for similar policies in a legislator’s own state.

The analyses in Chapters 5 and 6 provide strong evidence that public opinion plays a large and causal role on state policies over time. As public opinion in a particular state changes, policy soon follows. Moreover, as public support for a particular new policy increases, a state is more likely to adopt that new policy. A major implication of these findings is that dynamic responsiveness is alive and well at the sub-national level. State attitudes perform remarkably well at explaining differences in state policies over time, even after controlling for other important factors. At the same time, differences in state policies help explain, at least somewhat, why there
are variations in how state residents change their attitudes over time. This suggests that previous cross-sectional studies that have identified a correlation between state policies and public opinion are not spurious; public opinion and policy exhibit a significant reactive relationship over time at the sub-national level.

**Concluding Remarks**

Seventeen years ago, Erikson, Wright, and McIver (1993) revolutionized the study of policy responsiveness at the sub-national level by showing scholars how to incorporate public opinion into their theories and models. They showed us how to accurately and reliably measure state opinion from national surveys and provided evidence that democratic governance is successful in the American states. And, in so doing, they reawakened scholars to the study of public opinion and policy at the sub-national level.

Erikson, Wright, and McIver’s (1993) study is largely the impetus for the current project. My hope is that the methodological approaches used here provide an avenue for future work on measuring state opinion over time across a variety of different issue areas, attitudes, and preferences. Moreover, the empirical analyses on the dynamic relationship between opinion and policy across the states presented here are simply the first steps to understanding the complex nature of democratic politics at the sub-national level. As explained in the concluding chapter, there is much to learn and the avenues for future research on how policy reflects public opinion and vice versa in the states are plentiful.
**References for Chapter 1**


Chapter 2

Measuring State Public Opinion across Time

Few concepts are more important to the study of politics and policy-making than public opinion. This may be even more evident at the sub-national level; Cohen (2006) has argued that the comparative study of state politics stalled during the 1960s and 1970s partly because scholars were without comparable data on public opinion. Recent statistical innovations on aggregate estimation, pioneered by Erikson, Wright, and McIver’s (1993) in their *Statehouse Democracy*, however, has reinvigorated state politics research on public opinion and its impact on policy. And, today, we have good data on many aspects of state-level public opinion, often for all fifty states. These datasets have allowed scholars to answer several questions about policy responsiveness at the sub-national level (Erikson, Wright, and McIver 1993; Norrander & Wilcox 1999; Brace et al. 2002; Arceneaux 2002; Johnson et al. 2005; Burstein 2003; Brace and Jewitt 1995).

Yet, there is work to be done. One of the most promising—and challenging—avenues of state politics research is the measurement of *dynamic* state public opinion. We are in need of estimates of state public opinion that are observed over time. Armed with dynamic measures of state public opinion, scholars can begin to understand more fully the complex relationship between public opinion and the policy process at the sub-national level. We can formally assess whether state public opinion is stable or dynamic—as I do in Chapter 4—which is a question that has interested state politics scholars recently (see the summer 2007 issue of *State Politics and Policy Quarterly* 2007 for a lengthy discussion; Brace et al. 2002). We can ask more complicated questions about policy responsiveness at the sub-national level involving time as I begin to do in Chapters 5 and 6. For instance how long do changes in state public opinion take to affect the policy process? Are some states quicker to respond to changes in state public opinion compared to others? What factors explain why some states respond to changes in state public opinion while
others do not? How do changes in state public opinion diffuse across the states? And, how does this diffusion affect the policy process? And, by measuring state public opinion on specific policy issues, we can explore how issue characteristics may condition the answers to these questions. Answering questions like these—which require dynamic measures of state public opinion—will advance our collective knowledge about democratic practice and politics at the sub-national level.

In this chapter, I apply recent advances in aggregate opinion estimation to measure annual state public opinion from national polls. Specifically, I use multilevel modeling, imputation, and post-stratification (MRP) applied to a small pooled time frame to estimate state partisanship and state ideology over time. As I will show, this method generates reliable and valid measures of state public opinion across the fifty states and the District of Columbia. In Chapter 3, I apply the MRP approach to the measurement of dynamic state public opinion on specific issues, such as the death penalty and abortion. In Chapter 4, I explore the dynamic properties of state public opinion across the various issues. The analyses in Chapters 2-4 lay the groundwork for our exploration of dynamic policy responsiveness in Chapters 5 and 6 where state public opinion is linked to various policy outputs across time at the sub-national level.

Chapter 2 proceeds as follows. First, I explain the difficulties that scholars have had in measuring state public opinion generally and from national polls specifically. National polls present two challenges that scholars must overcome in order to produce “good” measures of state public opinion: small state sample sizes and the potential for non-representative estimates. I then present a method—multilevel modeling plus post-stratification (MRP)—that overcomes both of these challenges when applied to various small pooled time frames (Park et al. 2006). I use the MRP approach to measure global indicators of state public opinion—state ideology and partisanship—over time. The chapter ends with dynamic validity analyses.
The Challenges of Measuring State Public Opinion

Scholars have struggled with how to accurately measure state public opinion since at least the 1960s (Dye 1969; Hofferbert 1966). The primary problem is that few states have high quality polls. And, the states that do have high quality polls often have inconsistent question wording, modes, and survey designs making cross-sectional, and especially longitudinal, comparisons difficult. One solution to the lack of state data is to use substitutes that are easier to obtain for indirect measurements of public opinion.

The use of demographics as a proxy for public opinion grew out of early state research (Dye 1969; Hofferbert 1966). Yet, scholars continue to use demographics, such as the percentage of Catholics in each state, as proxies for public opinion (Norrander & Wilcox 1999; Boehmke & Witmer 2004; Mooney & Lee 1995). Another substitute for direct measurement is the simulation of state opinion from the demographic characteristics of the state residents (e.g., Weber et al. 1972). For this method, state political attitudes are simulated based on the distribution of demographic groups within a state (Weber et al. 1972). For example, scholars might estimate the likelihood that a type of person, such as a white, poor, female, would support the death penalty. Based on this estimation and the distribution of white, poor, females in a state (and other types of people), scholars would then estimate the state level opinion on the death penalty. An even more recent surrogate measure of state public opinion was developed by Berry et al. (1998; 2007). Berry et al. (1998; 2007) infer state ideology from interest group ratings of members of Congress and the distribution of votes for candidates in congressional elections. After estimating the ideology of citizens in each congressional district, scores are averaged across districts to yield a state-level measure of citizen ideology (Berry et al. 2007 113). Berry et al.’s (1998; 2007) measure of citizen ideology has been used in various papers (Schneider & Jacoby 2006) including those that look at whether state ideology is stable or dynamic (Berry et al. 2007; Brace et al. 2004).
Indirect measurement methods rest on various assumptions, which make them less than ideal for measuring state public opinion. For instance, although demography has a large influence over political preferences at the individual level, it is not determinative and often is a proxy for some other characteristic that has a direct influence over political attitudes. A large assumption of the simulation approach is that state residence in and of itself has no effect on political preferences. Current research suggests that this is an unlikely assumption (Lax and Phillips 2009; Leal 2006; Norrander and Wilcox 2006). And the Berry et al. (1998) measure, which infers public opinion based on interest group ratings of elected representatives, rests on the assumption that there is a strong correspondence between the ideological preferences of voters and elected officials. Though the correlation should be positive, the correspondence is not “perfect” because people vote for candidates for reasons beyond ideology including partisanship, incumbency, and policy positions (Cohen 2006). Officials, too, may cast votes for reasons of party loyalty, making them less centrist than their district and less in line with constituents (Jacobs and Shapiro 2000). In addition, scholars have argued that the interest group ratings used by Berry et al. (1998) are themselves biased indicators of the ideology of members of Congress (Groseclose, Levitt, and Snyder 1999).

At a more fundamental level, using surrogate measures makes it difficult for scholars to adequately explore the role of public opinion on the policy process at the state level. A poor correlation between surrogate measures and policy may be caused by poor measurement instead of a null relationship. A strong correlation, on the other hand, can be challenged on the grounds that the surrogate measure of public opinion actually measures something other than the expressed preferences of state residents. Hence, using proxies of state public opinion affects our understanding about the opinion-policy linkage at the sub-national level.

Because of these drawbacks, other scholars have focused on direct measurements of state public opinion. Some have cleverly found alternative sources that ensure that estimates are
representative, valid, and reliable. For instance, Cohen and Barrilleaux (1993) use exit polls to measure state-level abortion opinion as do Haider-Markel and Kaufman (2006) to measure attitudes about gay and lesbian issues. Norrander (2000; 2001) utilizes the Senate National Election Survey 1988, 1990, 1992 (SNES), which used states as its primary sampling units, to measure state opinion on a variety of issues including the death penalty, abortion, education and welfare spending as well as global indicators including party identification and ideology (see also Norrander & Wilcox 2006). The problem with these alternative sources, however, is their applicability across time. Unfortunately exit polls are not conducted on an annual basis, are not always available for all fifty states, and have variability in the issues for which respondents are asked. The SNES was only conducted during the elections of 1988, 1990, and 1992 and is too short to study movements of public opinion in the individual states.

Repeated national surveys, thus, provide the best source to measure state public opinion over time. More specifically, we can think of individual level data from repeated surveys at the national level as having the following structure:

\[
y_{i,j,t}, \quad i = 1 \ldots n_j; \quad j = 1 \ldots 51 (50 + DC); \quad t = 1 \ldots T
\]

where \( i \) indexes the individual in a particular state \( j \) with a total of \( n_j \) respondents for each state for a particular time unit \( t \).

Using national surveys with this data structure to measure state public opinion has a long tradition in state politics research (Erikson, Wright, and McIver 1993; 2007; Brace et al. 2002). There are two problems that scholars must overcome, however, when using national surveys to estimate state public opinion: variation in state sample sizes and the potential for non-representative estimates.
Using National Surveys to Measure State Public Opinion

Using national surveys to obtain valid and reliable estimates of state public opinion is a challenge to scholars because national surveys use a sampling design 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. 2004). These PSUs can include: counties, blocks, enumeration areas, or other geographic units. Commonly, national surveys have several stages whereby sampling units are indentified prior to interviews. The number of PSUs and the number of stages used to identify sampling units differ across surveys. For instance, the National Election Study (NES) employs a multi-stage area probability design where the sampling process is divided into four stages: a primary stage sampling of U.S. Metropolitan Statistical Areas (MSAs) or New England County Metropolitan Areas (NECMAs) and non-MSA counties, followed by a second stage sampling of area segments, a third stage sampling of housing units within sampled area segments and concluding with the random selection of a single respondent from selected housing units.

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 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 non-representative state estimates. As Brace et al. (2002) note, the risk of bias is greatest in

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1 Non-representative estimates can also be a consequence of survey design. For instance, women tend to outnumber men in telephone surveys however this tends to be true in all states. A uniform bias will not matter appreciably if the goal is to rank order the states. Hence, I focus mainly on bias stemming from cluster sampling, whose impact will differ across states.
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 more 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 could 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. To illustrate this, Table 2.1 uses CBS/NYT polls spanning 1977-2007 and reports sample sizes for those interviewed about their partisanship for the fifth largest state (Illinois), the median state (Kentucky), and the fifth least populous state (Delaware) for all years combined and for each year individually.\(^2\) In a typical year, there will be 436 respondents from Illinois, 180 from Kentucky, and only 32 from Delaware. In addition, some years (e.g., 2005) have less information than others, leading to very small samples for the less populous states. The amount of information we have at the state level also varies across issue, depending on how intensively the issue was polled.

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

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\(^2\) This time series trend uses the CBS/NYT polls. Respondents were asked “Generally speaking, do you usually consider yourself a Republican, a Democrat, an Independent, or what?” Respondents could answer Republican, Democrat, Independent or don’t know. I recoded this variable so that a positive response indicates support for the Democratic Party out of Republicans, Democrats, and Independents.
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 regression plus imputation and post-stratification, hereafter referred to as MRP (Park et al. 2004, 2006; Lax & Phillips 2009a, 2009b), which I describe in detail below.

**Aggregation**

Erikson et al. (1993) showed that reliable and unbiased measures of mass 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 level data 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 tolerance, racial integration abortion, homosexuality, religiosity, feminism, environmentalism, welfare, and the death penalty.\(^3\) Formally, aggregation can be described by Equation 1, where \(j\) indexes states and \(i\) indexes individuals:

\[
Y_j = \frac{1}{n_j} \sum_{i=1}^{n_j} y_{ij}
\]

The pooling and aggregation technique is by far the most popular approach to measuring state public opinion from national surveys. The aggregation approach is fairly straightforward to implement; researchers simply need to pool several national surveys across time and calculate means or proportions by state of residence. Furthermore, the estimates obtained from the

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\(^3\) Brace et al. (2002) uses the term disaggregation to refer to what others call aggregation. Brace et al. (2002) see one national survey being disaggregated to fifty subunits. On the other hand, aggregation refers to hundreds of respondents being aggregated into fifty large groups. The two terms are identical, though I use the term aggregation throughout the dissertation.
aggregation method are unbiased because we are simply taking the average value of all individuals on some public opinion measure in a given state.

The aggregation method, however, also has several disadvantages that make it less than ideal to measure dynamic state public opinion. First among these is that it can be difficult to generate enough cases for reliable yearly estimates for the less populous states. It is precisely because of these reliability issues that the aggregation method must be coupled with the pooling of many years of polls in order to produce reliable estimates of state public opinion. Another reason the pooling method has not been used to measure state public opinion over time is because it is best suited for opinions that change slowly over time. A large assumption of the pooling technique is that attitudes do not change over time; otherwise short-term dynamics would be completely washed out (Cohen 2006). Hence, scholars have been limited to using the pooling and aggregation method for certain attitudes that are assumed to be fairly stable across time, such as ideology, as opposed to those attitudes that can change rapidly, such as presidential approval or reactions to events and government actions. This assumption limits the number of issues to which the pooling method can be applied. Finally, the aggregation method does not address non-representative samples due either to design or differential non-response bias. Hence, the aggregation approach is not very good at addressing the issue of non-representativeness.

**Multilevel Regression, Imputation, and Post-Stratification (MRP)**

The MRP 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 2009a, 2009b). Multilevel regression is an extension of the OLS regression in which data are structured in groups and coefficients can vary by group. The 51 state level intercepts are then estimated as a weighted average of the mean of the observations in a state (i.e. the estimate that would be obtained by performing a fixed effects regression with state dummies only as independent variables) and the
mean over all states (i.e. the estimate that would be obtained by pooling all of the states together; this is also called the grand mean).

Raw values from states with smaller sample sizes (such as Delaware) carry less information with low reliability; consequently, these estimates are pulled toward the overall state average or grand mean (also called “shrinkage towards the mean”). On the other hand, raw values from states with large sample sizes (such as California) carry more information and have high reliability. Therefore, the estimates for large states are closer to the individual state average and nearly identical to estimates that would be obtained via the aggregation technique. In the intermediate case where states lie somewhere between these two extremes, the estimates are somewhere between the overall state average and the individual state average (Gelman and Hill 2007 254).

Unlike the aggregation approach, the MRP method allows for the inclusion of various demographic predictors to estimate state public opinion. Following previous research, 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 write the model below (ignoring time for the moment) in Equations 3 and 4 using indexes $j, k,$ and $l$ for state, age category, and education category, respectively; the subscript $i$ refers to individual respondents. For now, the dependent variable is some

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4 Park et al. (2004, 2006) also include region in their models. I do not include region, however, because I do not want to arbitrarily impose homogeneous trends within regions onto the measurement strategy. Imposing homogeneous trends has theoretical implications related to dynamic policy responsiveness; hence I only include individual level predictors.

5 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. Bayesian multilevel models 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 $\sigma^2_{\text{state}}, \sigma^2_{\text{age}}, \sigma^2_{\text{educ}},$ estimated from the data given non-informative uniform prior densities (Park et al. 2004 378).
dichotomous measure of public opinion. The terms after the intercept are modeled effects for the various groups of respondents.\textsuperscript{6}

\textbf{Eq. 3} \textbf{Level 1}: \( \Pr(y_i=1) = \text{logit}^{-1}(\beta_0 + \beta_1 \text{Female}_i + \beta_2 \text{Black}_i + \alpha_{j[i]} + \alpha_{k[i]} + \alpha_{l[i]}) \)

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

The next step is imputation. We can think of each combination of demographic characteristics and state as a “person type.” We have a total of 3,264 person types based on demographics and state. We would expect for each person type to have different probabilities of having a certain opinion given their demographic characteristics and state, which we have modeled above in the multilevel regression. To estimate these varying propensities, the coefficients are used to impute public opinion across each person type. Imputation is conducted on each of the 3,264 person types even if absent from the sample. After imputation, we have \( \theta_c \), which is the inverse logistic given the relevant predictors and their estimated coefficients for each of the 3,264 person types (\( c \)).\textsuperscript{7}

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 frequencies of each person type in a state obtained from the Census. In the final step, I calculate the average response over each person type (\( c \)) in each state (\( j \)) over the posterior

\textsuperscript{6} All of the demographic variables are modeled as fixed effects. That is, their slopes do not vary across states.

\textsuperscript{7} Because the multi-level model uses Bayesian statistics, there are actually 1,500 estimates for each coefficient from which these probabilities are calculated for each person type. Recall that Bayesian statistics samples parameters from the distributions, which are assigned in the measurement strategy (see ft. 5). I use 3 chains, with 1,000 simulations per chain and discard the first half of the simulations per chain, which leaves 1,500 estimates for each coefficient sampled the posterior distribution. Predicted probabilities are calculated for each person type using each of these 1,500 estimates. The probabilities are then averaged for each person type across the 1,500 simulations prior to post-stratification.
distribution to get point predictions; I also use the variance of the posterior distribution to calculate uncertainty intervals:

\[ Y_{state} = \frac{\sum_{c} N_c \theta_c}{\sum_{c} N_c} \]

The use of multilevel regression and post-stratification helps overcome the two major problems that arise when trying to measure state public opinion from national surveys. Multilevel modeling increases the reliability of less populous states via “shrinkage towards the mean”. Indeed the MRP approach has been shown to be superior to the aggregation method in terms of reliability, particularly when sample sizes are small, for instance, when \( N \) is less than 2,800 across all states (Lax and Phillips 2009). Post-stratification adjusts estimates so that they are more representative of state populations by using Census information.

**Adding a Time Component**

The MRP approach can be modified to obtain yearly estimates of public opinion by including a small moving time frame. I can increase the amount of information, but still preserve a time component, by pooling across a small number of years. In this illustration, I employ three year and five year moving averages, pooling surveys from the specified time frame to get point estimates in the median year. For instance, to get estimates in a particular year, \( t \), using a five year pooled window, I pool responses from \( t-2, t-1, t, t+1, \) and \( t+2 \), estimate the multilevel regression, impute, and post-stratify for each state using Census information from year, \( t \), for each state, \( j \). For the three year pooled window, I pool responses from \( t-1, t, \) and \( t+1 \), estimate the multilevel regression, impute, and post-stratify for each state using Census information from year, \( t \), for each state, \( j \). By pooling and taking the median year, the first and last years are missing for the three year window and the first two and last two years are missing for the five year window.

While pooling over a small time frame increases the amount of information we have, especially for the less populous states, it could smooth over important dynamics that may exist in time series data. Empirically, by pooling several years, we are introducing error into our yearly
estimates by pooling and averaging across several years. Thus there is a tradeoff between the reliability of estimates and sensitivity to very short-term shocks. Below I test whether the efficiency benefits of pooling over a small time period outweighs the costs of biasedness.

**Model Comparisons 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 (out of Republicans, Democrats, and Independents). The final dataset consists of 324,862 respondents surveyed from 1977-2007 on party identification across all states.

U.S. Census information obtained from IPUMS was used to post-stratify the estimates for the MRP approach (Ruggles et al. 2008). Data were gathered for demographic variables for all states from the 1950, 1960, 1970, 1980, 1990, and 2000 Censuses. To get annual estimates, I estimate the change in person types for each year by dividing the numerical difference between the current Census estimates and the future Census estimates by 10. I then add a portion of this difference to each estimate to get a smooth change in population for each state across the time. For instance, to get state estimates for 1981, I take the estimates from the 1980 Census minus the estimates from the 1970 Census divided by 10. This figure then gets added to the 1980 figure to measure figures for 1981. For 1982 this figure gets added twice, and so forth.

**Assessing the Problem of Small State Sample Sizes**

My goal is a measure of state public opinion in which the predictive accuracy is optimal across various state sample sizes. In order to assess the amount of error for states with different

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8 For detailed information about the CBS/NYT survey see Appendix A.
populations, 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). I assess the predictive success of the aggregation and MRP methods by using criteria developed by Lax and Phillips (2009a). 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 (again, measured yearly via the aggregation method), let \(y_{t,s}^{agg3}\) be the proportion of Democrats measured via the aggregation method using a three year pooled time frame and let \(y_{t,s}^{MRP3}\) be the proportion of Democrats measured via the MRP approach using a three year pooled time frame. In addition, let \(y_{t,s}^{agg5}\) be

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9 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 2009a), I use weighted responses since the “true” data are actually a manifestation of sample data. The survey weights are intended to 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 MRP, which directly accounts for disparities between sample data and the population of interest.
the proportion of Democrats measured via the aggregation method using a five year pooled time frame and let $y^\text{MRP5}_t,s$ be the proportion of Democrats measured via the MRP approach using a five year pooled time frame. The absolute error is:

$$e_t^{agg3} = |y_t^{agg3} - y_t^{true}| \quad \quad e_t^{agg5} = |y_t^{agg5} - y_t^{true}|$$

$$e_t^{MRP3} = |y_t^{MRP3} - y_t^{true}| \quad \quad e_t^{MRP5} = |y_t^{MRP5} - y_t^{true}|$$

This produces four absolute errors for the four pseudo states across twenty-eight years (1978-2006) for the three year pooled time frame and across twenty-six years (1979-2005) for the five year pooled time frame. For every state, $s$, I then calculate the average absolute error for each method across time, thus creating one summary measure for each method and time frame for each state. For instance, to get the summary measure for the aggregation method using the three year pooled time frame, I calculate the following:

$$\bar{e}_t^{agg3} = \frac{\sum_t e_t^{agg3}}{28}$$

Equation 7 is performed for each of the methods across pooled time frames with the denominator changing based on whether the pooled time frame is three or five years. The absolute errors are reported in Figure 2.1, where the solid dots represent estimates from the aggregation method and the open circles represent estimates from the MRP approach.

The upper panel of Figure 2.1 shows that MRP outperforms aggregation in terms of error across all state sizes for the random sampling design for both pooled time frames. For large states with random sampling, both approaches produce nearly identical results. We see, however, that the MRP approach produces much less error compared to the aggregation approach for small and very small states with random samples. We also see the five year pooled time frame generally has lower amounts of error compared to the three year pooled time frame, regardless of method or sampling design. This is directly attributed to the fact that including more years increases the amount of information that we have across states. Hence, even though we are averaging over
more years, estimates from the five year pooled time frame actually have less error associated with them compared to the three year pooled time frame. This suggests that pooling over a small time frame to increase information, but still preserve a time component is a valid modification to measure state public opinion over time.

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 2.2, where the solid dots represent estimates from the aggregation approach and the open circles represent estimates from the MRP approach. The upper panel of Figure 2.2 shows that the MRP approach outperforms the aggregation approach in terms of precision across state sizes for random samples. The MRP estimates have smaller standard deviations compared to the aggregation approach, especially for the less populous states. From the results presented in Figures 2.1 and 2.2 I conclude that the MRP—because of the use of multilevel modeling and covariates—helps overcome the problem of small state sample sizes that is inherent 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 MRP 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 under-sampling African Americans. I then calculate the mean absolute error and standard deviation for each under-sampled pseudo state across each method. The results for the absolute error for the under-sampled states are reported in the lower panel of Figure 2.1 and the results for the standard deviations are reported in the lower panel of Figure 2.2.

The lower panel of Figure 2.1 shows that the MRP model is especially superior in terms of error when a major demographic group is under-represented in the sample data. Even for a large state that undersamples African Americans, the MRP approach produces less error compared to aggregation. Similarly, the lower panel of Figure 2.2 shows that the MRP method is also better in terms of precision compared to the aggregation approach. Hence, the MRP approach helps overcome the problem of non-representative estimates through the use of post-stratification.

**How Complicated a Model for MRP?**

The relative superiority of MRP is due in part to Bayesian shrinkage and to the added information from the demographic covariates. The question then is which demographic covariates should be included in the model? Though theory should always guide a scholar’s decisions, this is often easier said than done when measuring state public opinion. If a scholar only includes the most theoretically important variable without much prior knowledge, s/he may actually risk biasing the estimates if other important variables are accidentally left out. Intuitively, the model specification with the most covariates should be less biased compared to other specifications primarily because we are using more information to measure state public opinion. In classical statistics, however, including irrelevant covariates increases the standard errors of the coefficients; in this case, including unnecessary covariates may artificially inflate the standard deviation—and decrease the precision—of our measures.
In addition to these issues, we also do not know how different model specifications influence the error and precision of estimates when applied to samples that undersample a major demographic group. Certainly, it seems that it would be most important to include those covariates that are related to the variable of interest and which are affected by the sampling methods. But, how biased are our estimates if we leave out an important demographic characteristic that is also related to the sampling methods? Answering these questions is important particularly as I apply the MRP approach to measure dynamic state public opinion on other issues.

To answer these questions, I re-estimate the MRP measures under various model specifications using both the random and African American under-sampled simulated states with a three year window. I then compare these estimates to the “true” measures using the mean absolute error and standard deviation similar to the analyses reported in Figures 2.1 and 2.2. I estimate four different model specifications predicting support for the Democratic Party at the state level: (1) a gender only model, (2) a race only model, (3) a gender, age, and education model, and (4) a full, standard model as reported above in Figures 2.1 and 2.2.\textsuperscript{10}

The results in Figure 2.3 show that the “standard” model, which includes all four demographic covariates, is the most unbiased model compared to the other model specifications. To be fair, the age, gender, and education model does outperform the standard model in terms of mean absolute error for the large, medium, and very small states with random sampling. However, in these instances the standard model is a close second. And, in all other cases the standard model has less error compared to other model specifications. The most biased model

\textsuperscript{10}It is important to note that not only do the models differ in the first stage of analyses they also differ in the variables used for the imputation and post-stratification. Imputation and post-stratification are only conducted on the variables that are included in the model. In the example where party identification is modeled by race only, race is also the only variable included in the imputation and post-stratification. In this example, instead 3,264 person types based on state of residence, gender, race, age, and education, there are only 102 person types based on state of residence and race.
specification, especially for the under-sampled states, is the gender only model. Figure 2.3 also shows that the loss of precision potentially associated with the full model specification is unfounded. All model specifications produce roughly identical standard deviations across state sample sizes and sampling designs.

The results in Figure 2.3 suggest that a scholar is on safer grounds by conducting a standard model when using MRP to measure state public opinion compared to other model specifications. For my purposes, I will be using the same model specification shown in Equations 2 and 3 to measure state public opinion across time using the MRP approach, regardless of the underlying variable of interest to be measured.

To summarize, the MRP approach is better suited than the aggregation approach to overcome the problems inherent with national surveys when estimating state public opinion over time. The MRP approach produces more reliable estimates than the aggregation approach, particularly for the less populous states, because of its use of multilevel modeling and demographic and geographic covariates (Lax and Phillips 2009a). The MRP approach also produces more representative estimates compared to the aggregation approach because of its use of post-stratification. We see that pooling over a small time frame, such as with a three or five year window, does not introduce a large amount of error into the estimates. Hence, either pooled time frame can be used to measure state public opinion while still preserving a time component. Finally, there is no risk for including all major demographic covariates into the model specification when measuring state public opinion using the MRP approach. In fact, the least biased and most precise estimates across state sample sizes and sampling designs were those from a “standard” model that included age, gender, race, and education.

In the remainder of this chapter, I apply the MRP approach to the measurement of dynamic state preferences on global indicators of public opinion including party identification and political ideology. These measures are used in subsequent chapters to characterize a state’s
general political tendencies. These will be important to include, particularly since the majority of
past research has included these measures into their empirical studies.

**Global Measures of State Public Opinion: Party Identification and Political Ideology**

When scholars and pundits make comparisons of the preferences of state residents, they
usually do so in the form of party identification and political ideology. Measuring the general
tendencies of state residents has a long tradition in state politics research, beginning with Key
(1949) and continuing today (Berry et al. 1998, 2007; Erikson, Wright, and McIver 1993, 2007;
Brace et al. 2004; 2007). Because party identification and ideology are strong determinants of the
vote, the distribution of these opinions across the states also have important electoral
implications, which is why scholars have often focused on party identification and state ideology
in describing the US States. Consequently, scholars have learned much about the partisan and
ideological makeup of the US states.

For instance pooling data from 1976-1988, Erikson, Wright, and McIver (1993) find that
the most Democratic states are clustered in the South and Border regions while the most
Republican states are generally found throughout the rural West and Midwest. The ideological
makeup of the states is much different than the partisan landscape. Erikson, Wright, and McIver
(1993) find from 1976-1988 the most conservative states are in the Deep South and the rural west
while the most liberal states cluster along the Pacific Rim and the Northeast. The ideological
makeup today seems to be relatively unchanged, while the partisan landscape has shifted since
Erikson, Wright, and McIver’s (1993) original analysis. Aggregating state partisanship to four
year intervals corresponding to presidential regimes since the Carter administration, Erikson,
Wright, and McIver (2006) find evidence that party identification has been moving Republican
with the Southern states moving the most. This more recent work, while preliminary,
underscores the need for dynamic measures of the general tendencies of state residents. With
reliable and valid dynamic measures of the political leanings of state electorates, scholars can
describe both the political landscape of the United States at any one point in time as well as how that political landscape has changed (or not) over time relative to national trends and partisan alignments.

I will return to a more rigorous analysis of the dynamic patterns for state partisanship and state ideology in Chapter 4. For the current chapter, I measure state partisanship and state ideology using the MRP approach from CBS/NYT surveys 1977-2007. For party identification, 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 (out of Republicans, Democrats, and Independents). For ideology, respondents were asked “How would you describe your views on most political matters? Generally, do you think of yourself as liberal, moderate, or conservative?” I recoded this into a dummy variable so that a positive response indicates liberal political views with all else equaling zero (out of liberals, moderates, and conservatives). A total of 324,862 respondents were interviewed on party identification and 329,452 respondents were surveyed on ideology from 1977-2007.

For both party identification and state ideology, I use the MRP approach on a three year pooled time frame using the full model specification as reported in Equations 2 and 3. Census information was used to post-stratify the estimates on the basis of gender, race, education, and age, similar to that reported above. The final dataset consists of 49 observations per year from 1978-1993 (no respondents from Alaska or Hawaii were interviewed prior to the 1995 survey) and 51 observations per year from 1994-2006 for both state partisanship and state ideology.

Figures 2.4 and 2.5 present maps of the proportion of Democrats and the proportion of liberals for the 48 contiguous states in 1978 and 2006, respectively. ¹¹ Consider first the state

¹¹ Alaska and Hawaii are not shown in these maps, although they are included in the analyses from 1994-2006.
partisanship measures reported in Figure 2.4. Based on the 1978 scores, we see that the most Democratic states are clustered in the South and border regions whereas the least Democratic states are found in the Midwest. In 2006, however, we see a shift in partisanship with the Southern states declining in Democratic support and the states in the Northeast increasing in support of the Democratic Party. This suggests that state partisanship is dynamic. Consider next Figure 2.5 on state ideology. The least liberal states in 1978 are found in the Deep South and rural West while the most liberal states are found in the Northeast and West. In 2006, some states in the Midwest shift slightly more liberal while other states in the South appear to have shifted less liberal. This suggests that state ideology is much slower to move compared to state partisanship, something that is echoed in Erikson, Wright, and McIver’s work (1993; 2007).

How valid are these dynamic measures of state partisanship and state ideology? A measure is valid if it measures the concept that it is intended to measure. There is an added challenge compared to traditional validity tests because our measures need to not only be valid overall but also across time; our measures must be valid at any one point in time. Figures 2.4 and 2.5 suggest that our measures have face validity, that is, state partisanship and state ideology seem reasonable and consistent with our accumulated understanding about the partisan and ideological makeup of the US states over time. Moreover, there is a long tradition in political science research that party identification can be measured by asking respondents whether they consider themselves Democrat, Republican, or Independent and that ideology can be measured by asking respondents whether they consider themselves liberal, conservative, or moderate.

Yet, we can put our dynamic measures to more stringent tests of validity. If state partisanship and ideology are valid, they should (1) be related to concepts that are theoretically linked to partisanship and ideology (i.e., convergent validity) and (2) be correlated with outcomes of measurement approaches that are generally accepted as valid (i.e., criterion validity).
Convergent Validity

If state partisanship and state ideology reflect the expressed partisan and ideological preferences of state residents, then they should be related to the behavior of state electorates. State preferences on party identification and ideology should be reflected in state level differences in electoral voting. Macropartisanship—or party identification at the aggregate level—predicts aggregate electoral results at the national level, irrespective of economic conditions and candidate characteristics (Erikson, MacKuen, and Stimson 2002).

Extending this logic to the state level, we would expect a degree of dynamic correlation between the global indicators and the presidential vote. States showing a significant increase in Democratic identification or liberalism should show a corresponding increase in the presidential vote for the Democratic candidate. Table 2.2 tests dynamic validity directly by predicting the percentage of Democratic vote using a two way fixed effects model, i.e., fixed effects are included for both year and states to account for unit heterogeneity and time dependence. Recall, however, that our measures are estimated from a three year moving average. Hence, in order to be completely exogeneous in time to the dependent variable, the proportion of Democrats and proportion of liberals measured at $t-2$ are included. The models in Table 2.2 are not meant to be exhaustive, but are intended to provide a simple test of dynamic validity. The results provide evidence of dynamic validity. An increase in the proportion of Democrats at $t-2$ corresponds to an increase in the Democratic vote share in subsequent years. The same can be said about an increase in the proportion of liberals at $t-2$.

Criterion Validity

State partisanship and state ideology, if valid as I have measured them, should correlate with other variables that attempt to measure these same concepts. As explained at the beginning of the paper, measuring partisanship and ideology at the state level is not without its challenges. Still, there are generally agreed upon sources of measurement on party identification and ideology
are valid. One such source of measurement is state exit polls. From 1982-1988, CBS News conducted Election Day exit polls in selected states. Since then, the Voter News Service has taken over the responsibility of disseminating the state exit polls during each election year. State exit polls overcome the measurement challenges of national surveys by (1) typically interviewing hundreds of state residents, regardless of state size, and (2) employing sampling designs based on precinct. When used with the proper weights, aggregate estimates are representative of state populations. While exit polls capture the political preferences of the active state electorates, we would, nonetheless, expect a high correspondence between my dynamic measures of state partisanship and state ideology with similar measures from exit polls.

Table 2.3 presents more stringent tests of dynamic validity between the MRP estimates and those obtained from state exit polls by predicting the exit poll data using a two way fixed effects model, similar to the analyses reported above. The results, again, provide evidence of dynamic validity. An increase in the proportion of Democrats at $t-2$ corresponds to an increase in the proportion of Democrats in state exit polls. The same can be said about an increase in the proportion of liberals at $t-2$ and the proportion of liberals in state exit polls.

To summarize this section, I applied the MRP technique to the measurement of global preferences of state residents including partisanship and ideology. I also assessed the validity of the measures in several independent tests. The maps presented in Figures 2.4 and 2.5 provide face validity for the measures. State partisanship and state ideology also correlate well with other accepted measures of global preferences of state residents. Overall, I feel that these measures provide reasonable estimates of state partisanship and state ideology over time.

**Summary**

The main goal of this chapter was to devise a measurement strategy to estimate dynamic state public opinion using national surveys. I showed that multilevel modeling, imputation, and post-stratification (MRP) coupled with a simple moving average is a valid method for reliably
measuring state public opinion over time. Moreover, through the use of post-stratification, estimates are representative of state populations. Compared with aggregation, the MRP approach has less error and is more reliable, particularly for the less populated states. I then showed the applicable of the MRP approach by measuring and validating state partisanship and state ideology over time. In Chapter 3, I use the MRP method to measure dynamic state public opinion on specific issues, such as the death penalty, abortion, education spending, welfare spending, and smoking bans. Public opinion towards specific issues will be used in later chapters to explore dynamic policy responsiveness in the fifty states.
References for Chapter 2


Table 2.1 State Sample Sizes Across Time and State Size for Party Identification using CBS/NYT Polls 1977-2007

<table>
<thead>
<tr>
<th>Year</th>
<th>Large State (IL)</th>
<th>Medium State</th>
<th>Small State (DE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1977</td>
<td>208</td>
<td>96</td>
<td>8</td>
</tr>
<tr>
<td>1978</td>
<td>111</td>
<td>61</td>
<td>8</td>
</tr>
<tr>
<td>1979</td>
<td>163</td>
<td>93</td>
<td>11</td>
</tr>
<tr>
<td>1980</td>
<td>406</td>
<td>127</td>
<td>19</td>
</tr>
<tr>
<td>1981</td>
<td>203</td>
<td>55</td>
<td>10</td>
</tr>
<tr>
<td>1982</td>
<td>295</td>
<td>76</td>
<td>20</td>
</tr>
<tr>
<td>1983</td>
<td>215</td>
<td>61</td>
<td>16</td>
</tr>
<tr>
<td>1984</td>
<td>848</td>
<td>287</td>
<td>55</td>
</tr>
<tr>
<td>1985</td>
<td>385</td>
<td>128</td>
<td>27</td>
</tr>
<tr>
<td>1986</td>
<td>320</td>
<td>119</td>
<td>24</td>
</tr>
<tr>
<td>1987</td>
<td>419</td>
<td>163</td>
<td>37</td>
</tr>
<tr>
<td>1988</td>
<td>384</td>
<td>117</td>
<td>33</td>
</tr>
<tr>
<td>1989</td>
<td>166</td>
<td>64</td>
<td>13</td>
</tr>
<tr>
<td>1990</td>
<td>383</td>
<td>172</td>
<td>38</td>
</tr>
<tr>
<td>1991</td>
<td>634</td>
<td>281</td>
<td>52</td>
</tr>
<tr>
<td>1992</td>
<td>776</td>
<td>354</td>
<td>52</td>
</tr>
<tr>
<td>1993</td>
<td>428</td>
<td>150</td>
<td>33</td>
</tr>
<tr>
<td>1994</td>
<td>441</td>
<td>151</td>
<td>26</td>
</tr>
<tr>
<td>1995</td>
<td>315</td>
<td>121</td>
<td>20</td>
</tr>
<tr>
<td>1996</td>
<td>702</td>
<td>253</td>
<td>52</td>
</tr>
<tr>
<td>1997</td>
<td>514</td>
<td>209</td>
<td>35</td>
</tr>
<tr>
<td>1998</td>
<td>827</td>
<td>335</td>
<td>54</td>
</tr>
<tr>
<td>1999</td>
<td>812</td>
<td>377</td>
<td>59</td>
</tr>
<tr>
<td>2000</td>
<td>378</td>
<td>157</td>
<td>23</td>
</tr>
<tr>
<td>2001</td>
<td>481</td>
<td>198</td>
<td>35</td>
</tr>
<tr>
<td>2002</td>
<td>471</td>
<td>238</td>
<td>25</td>
</tr>
<tr>
<td>2003</td>
<td>768</td>
<td>388</td>
<td>61</td>
</tr>
<tr>
<td>2004</td>
<td>515</td>
<td>225</td>
<td>50</td>
</tr>
<tr>
<td>2005</td>
<td>280</td>
<td>169</td>
<td>26</td>
</tr>
<tr>
<td>2006</td>
<td>361</td>
<td>212</td>
<td>37</td>
</tr>
<tr>
<td>2007</td>
<td>296</td>
<td>143</td>
<td>23</td>
</tr>
</tbody>
</table>

**Total N** | 13,505 | 5,580 | 982

**Average N per year** | 436 | 180 | 32
Table 2.2 Fixed Effects Model Predicting Percentage of Presidential Democratic Vote 1980-2004 across the States

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion Democrat $t-2$</td>
<td>.30</td>
<td>.075</td>
</tr>
<tr>
<td>Proportion Liberal $t-2$</td>
<td>.46</td>
<td>.124</td>
</tr>
</tbody>
</table>

Note: Dummy indicators were also included for year, but not shown.
Table 2.3 Fixed Effects Model Predicting Exit Poll Data on State Partisanship and State Ideology across the States

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>Standard Error</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion Democrat t-2</td>
<td>.43</td>
<td>.061</td>
<td>0.00</td>
</tr>
<tr>
<td>Proportion Liberal t-2</td>
<td>.15</td>
<td>.078</td>
<td>0.06</td>
</tr>
</tbody>
</table>

*Note*: Dependent variable for proportion Democrat model is the proportion Democrat obtained from state exit polls. Dependent variable for proportion liberal model is the proportion liberal obtained from state exit polls.
Figure 2.1 Absolute Mean Error Pooled Across Years
Figure 2.2 Standard Deviation Pooled Across Time
Figure 2.3 Summary Statistics across Different Model Specifications using MRP on 3 Year Window Predicting Support for Democratic Party
Figure 2.4 Maps of Proportion Democrat in the US States for 1978 and 2006
Figure 2.5 Maps of Proportion Liberal in the US States for 1978 and 2006
Chapter 3

Measuring Dynamic State Public Opinion on Specific Issues

Chapter 2 introduced a method for measuring dynamic state public opinion and presented state-to-state differences in partisanship and ideology across time. Knowing how the general tendencies of the states change over time is important for understanding electoral politics at the sub-national level. Yet, describing the partisan and ideological landscape of the fifty states is just part of the story about how state public opinion changes over time and how these changes are subsequently related to policies. We also care about state public opinion on specific policy issues.

By having public opinion measures on specific policy issues, scholars can begin to more fully understand how state preferences are related to policies across time (and vice versa). For example, we can ask whether policymakers are equally responsive across issue areas or whether particular issues receive greater attention compared to others. If unequal, we can explore how issue characteristics, such as saliency, influence the degree of responsiveness (Burstein 2003). We can ask whether public opinion responds to policy changes; specifically, is there a sense of public acceptance after certain policies have been enacted? We can also compare the model of dynamic policy responsiveness across types of policy change or issues. In order to test these topics, however, we must have specific public opinion measures that can easily be linked to specific policy changes. Having state policy preferences on specific issues will also enable scholars to study dynamic policy responsiveness on state political issues, which is important to state politics research generally. For instance, we will be able to focus on individual programs (like capital punishment or education), policy subsystems (Brace & Jewett 1995) and policy innovations (Berry & Berry 1990) instead of having to create a composite measure of state policy outputs along a liberal/conservative continuum (Erikson, Wright, & McIver 1993).
At a more fundamental level, we can assess whether representation is specific to individual issues, as traditionally argued by scholars (Page and Shapiro 2002; Geer 1996; Bartels 1991; Manza & Cook 2002) or global (Kingdon 1984; Erikson, Wright, & McIver 1993; Erikson, MacKuen, and Stimson 2002). If representation is specific, people have preferences for policies in different domains and politicians are able to gauge shifts in public opinion on these particular domains. In addition, politicians will be responsive on those domains that are particularly important to the public and less so on less salient issues. This view is most in line with a populist version of democracy where policymakers gauge public opinion on specific issues and enact specific policies that are closely aligned with those preferences (Dahl 1971; Druckman and Jacobs 2006). If representation is global, then politicians respond to a single underlying preference when making policy and largely ignore shifts in opinion for particular domains, exercising autonomy in their decision making on specific policies. Hence, there exist two fundamentally different theories about policy responsiveness, which can be tested by comparing the effects of global indicators and specific policy preferences on policy change.

In this chapter, I measure dynamic state public opinion on several domestic issues that are relevant to states politics by applying the MRP approach introduced in Chapter 2. Using a variety of survey organizations, I measure dynamic state public opinion on the death penalty, abortion, education spending, welfare spending, and anti-smoking legislation. Though not a comprehensive list of important issues, the issues selected are representative of a wide range of issues typically studied at the sub-national level and are linked to policy changes enacted by states in a straightforward way, as I explain below.

First, I present my rational for choosing the particular issues to study. I proceed to describe previous research on state public opinion in each of these areas and present the measures. Chapter 4 includes analyses about the dynamic properties of specific state public opinion across the six issues as well as the global indicators presented in Chapter 2. The
measures presented in this chapter provide the basis for our analyses about dynamic policy responsiveness in the states in Chapters 5 and 6.

**Issue Areas**

Defining what an issue is and deciding on which issues to measure state public opinion are not easy tasks. Part of the problem is that there is no universe of issues from which to sample (Baumgartner and Leech 1998). Since there are no issues from which to randomly sample, I use three criteria to choose issues: jurisdiction, data availability, and previous research. Though not exhaustive, the issues for which I measure state public opinion are those where states have primary jurisdiction, where polls have a high frequency of questions, and where previous studies have been extensive. Hence, the dynamic measures will be directly linked to policy changes in the states, have high reliability, and are useful to the broader scholarly community.

**Jurisdiction**

Jurisdiction refers to the level of government at which issues are legislated. Scholars have long recognized that issue priorities differ across levels of government because of federalism. Building on Tiebout (1959), Peterson (1981) suggests that state government are primarily interested in issues that maintain or enhance the economic position of the state since they are in direct economic competition with other states to attract and retain the most prosperous residents. As a result, states are primarily concerned with developmental policies, such as highway construction, whereas the federal government is better suited for redistributive policies, such as welfare (Peterson 1981).

Issues are often shared between the national government and state governments and the primary jurisdiction of issues changes across time. Welfare policy, for instance, was heavily regulated by the federal government in the 1960s (Davis 1993; Melnick 1994; Schram et al. 2003), gained greater state control under the AFDC program (Peterson and Rom 1990; Weaver
2000), and eventually devolved to the states with the enactment of welfare reform in 1996 (Mettler 2000). Education is primarily a state concern, however, it became it more nationalized with the introduction of The No Child Left Behind Act of 2001 by President Bush, which created national standards by which teachers and students were assessed. Other issues are primarily legislated in the states, but states take cues as outlined by Supreme Court cases. For example, in Roe v. Wade (1973), the Supreme Court ruled that no state could infringe upon a woman’s right to an abortion before the third trimester of pregnancy. At the same time, however, states’ power to regulate abortion has grown particularly since Webster v. Reproductive Health (1989), where the court permitted a Missouri law that regulated abortions prior to the third trimester. Hence, although Roe placed some restrictions on state policies regarding abortion, the states still have a great deal of discretion in regulating abortion policy (Arceneaux 2002).

For my purposes, I measure state public opinion on issues that are traditionally the responsibility of state governments or on those issues in which the federal government has given substantial leeway to state governments. In doing so, I guarantee that there are both cross-sectional and temporal variations in state policies, which can then be linked to variations on state public opinion on these same issues.

**Data Availability**

Besides choosing issues that the states have substantial discretion on, I also decide on issues for which data are available. The data are a driving force for reliably measuring time trends because not all issues are polled equally over time. Instead, issues typically wax and wane on the polling agenda depending on the historical context. For instance, questions about racial segregation were plentiful during the 1950s, 1960s and 1970s, but as the controversy surrounding the “equal, but separate” policy declined (or it was less acceptable to be against these issues), polling specifically on racial segregation also declined. Similarly, questions regarding the Equal Rights Amendment (ERA) persisted throughout the late 1970s and early 1980s, but as the
Amendment failed to be ratified, it also fell off survey radars. Other issues are important for current politics, such as gay marriage, but have not been asked enough in recent years to adequately obtain time series measures. For my purposes, a particular question must be asked frequently over a couple decades in order to observe changes in state public opinion over time. The primary goal was to obtain dynamic public opinion over at least thirty years. In order to obtain long time series data on specific issues, I had to combine responses across several survey organizations (though the exact number of survey organizations depends on the issue as I explain below) that used consistent question wording.

**Issue Areas Previously Researched in the States**

Finally, I choose issues that have a rich history in past research so that I can build on previous findings. There are many issues that have been studied at the sub-national level. Early research on public policy in the states focused exclusively on economic issues, such as specific expenditures on education, highway construction, or general expenditures per capita (Dye 1969; Sharkansky 1967; Hofferbert 1966). These early works concentrated primarily on the relative importance of economic and political factors in explaining cross-sectional differences in expenditures. Following this precedence, other scholars have concentrated on various economic policies including the use of state lotteries (Berry and Berry 1990; Grossback, Nicholson-Crotty, and Peterson 2004; Berry and Baybeck 2005), composite measures of state expenditures (Schneider and Jacoby 2006; Jacoby and Schneider 2009; Case, Rosen, and Hines, Jr. 1993; Camobreco 1998), Indian gaming (Boehmke and Witmer 2004), and the adoption of enterprise zone programs (Turner and Cassell 2007). Finally, research has also been conducted on education spending with a special emphasis on per pupil expenditures (McLendon, Hearn, and Deaton 2006; Lowery, Gray, and Hager 1989; Berkman and Plutzer 2005).

More recently, attention has turned away from economic policies and towards morality policies, such as issues dealing with life and death, sexuality, and drugs and alcohol. Morality
policies have several distinctive characteristics: they are relatively easy for the majority of citizens to understand (Carmines and Stimson 1980; Mooney and Lee 1995; Mooney and Schuld 2008), salient to the public (Mooney 2001; Mooney and Schuld 2008), and are characterized by conflicts over first principles that evoke strong moral reactions from citizens (Mooney and Lee 1995; Mooney 2001; Mooney and Schuld 2008). Given these characteristics, scholars have sought to explain policy differences—often focusing on public opinion—across the states. Previous research has looked at abortion policy (Norrander and Wilcox 1999; Mooney and Lee 1995; Arceneaux 2002; Cohen and Barrilleaux 1993; Berkman and O’Connor 1993; Goggin and Wlezien 1993; Camobreco and Barnello 2008; Roh and Berry 2008; Langer and Brace 2005; Brace et al. 2002), the death penalty (Norrander 2000; Nice 1992; Mooney and Lee 1999; Jacobs and Carmichael 2002; Brace et al. 2002), homosexual rights (Haider-Markel and Kafumann 2006; Lax and Phillips 2008; Haider-Markel, Querze, and Lindaman 2007; Soule and Earle 2001; Haider-Markel and Meier 1996), evolution (Berkman and Plutzer 2009), and physician-assisted suicide (Dinan 2001; Hoefler 1994).

A large bulk of the research at the state level has also been conducted on redistributive policies. The states offer a great opportunity to explore how race influences welfare programs because there is large heterogeneity in the generosity of welfare policies and the racial makeup of residents across the states (Soss, Schram, and Fording 2003). Scholars have explored the correlates of welfare spending (Hill and Leighley 1992; Albritton 1990; Dye 1984; Jennings 1979; Howard 1999; Johnson 2003), Aid to Families with Dependent Children (AFDC) benefits (Orr 1976; Hero 1998; Howard 1999; Plotnick and Winters 1985; Gilens 1995; Hill and Leighley 1992), welfare reform initiatives, such as state AFDC waiver adoptions (Fording 2003) or welfare provisions, such as family caps or time limits (Soss, Schram, Vartanian, and O’Brien 2001; 2003), changes in welfare rolls (Johnson 2003), and composite measures of the leniency of welfare programs generally (De Jong, Graefe, Irving, and St. Pierre 2006). Welfare research is
not entirely restricted to assistance for the poor; research has also been conducted on general social welfare policies such as health care policy (Tolbert, Steuernagel, and Bowman 2003), Medicaid (Hero 2003; Hero and Tolbert 1996; Grogan 1994; Plotnick and Winters 1985), children’s health insurance plans (Volden 2006), and Supplemental Security Income-State (SSI-S) policy (Bailey and Rom 2004).

Hence, economic, moral, and redistributive policies comprise the majority of issues studied at the sub-national level. As a result, I chose issues that come from these categories and, thus, build upon previous research. In addition to measuring dynamic state public opinion on the death penalty, abortion, education spending, and welfare spending, I also explore preferences towards anti-smoking policies. Anti-smoking policies have been studied elsewhere (Shipan and Volden 2006; 2008), although much less is known about the public’s preferences on smoking bans across the states.

To summarize, I used three criteria for deciding on which issues to measure dynamic state public opinion. First, I chose issues that states have large discretion over; by doing so, I increase the probability that states exhibit heterogeneous policy changes across time. Second, I chose issues for which there is a large amount of data availability with consistent question wording. Finally, I selected issues for which there are precedents in the literature. By building on previous research, I contribute to the accumulation of knowledge about public opinion and policies at the state level. Five issues that fit these criteria include: the death penalty, abortion, education spending, welfare spending, and smoking bans. As we will see in the next section, a common theme across all these issues is that we know relatively little about how state public opinion changes across time. Hence, exploring the dynamic properties of state public opinion on these specific issue areas is a worthwhile research project on its own.
The Death Penalty

Capital punishment has historically been the responsibility of the states causing policy and implementation differences across the country. After the Supreme Court cleared the way for executions in 1976 following a brief moratorium, 36 states reestablished the death penalty though at different times. Thirty one states adopted the death penalty by 1977. Since 1977, only 5 other states have adopted the death penalty with zero adopting after 1994. Recently, there has been a push for some of the states that reestablished the death penalty to voluntarily abolish it; New Jersey became the first state in more than 40 years to abolish capital punishment legislatively in December 2007 (Gramlich 2008). Other states have recently voted to abolish the death penalty (e.g., New Mexico in March 2009) or have legislation pending, effectively making capital punishment abolished (e.g., New York, Nebraska).

Although many states have the death penalty, there is a large discrepancy in the extent to which states execute inmates. Southern states top the list of executions with Texas and Virginia leading the way (Baumgartner, De Boef, and Boydstun 2007). Since 1976, Texas and Virginia have executed 408 and 102 inmates, respectively, where eleven other states, like Pennsylvania, have executed 3 inmates or less (Death Penalty Information Center). In California, more than 600 inmates are awaiting execution, where the leading cause of death on death row is natural causes, followed by suicide and then execution (Gramlich 2008). There are also timing differences in how quickly states implemented the death penalty after adoption. Of the 36 states with the death penalty, 4 have yet to execute an inmate and only 10 have done so prior to 1983. Hence, although capital punishment formally is on the books in several states, there is wide variation in the extent to which it is used in practice.

The total number of death sentences has ranged over time and across states as well. Death sentences increased throughout the 1970s and 1980s with a peak of 317 in 1996, only to decline in recent years (Baumgartner, De Boef, and Boydstun 2007). The majority of these
sentences are in the South, although not exclusively. For instance, Texas, Florida, and California have sentenced more than 770, 730, and 650 individuals since 1977, respectively (The Death Penalty Information Center). Oklahoma, Pennsylvania, and Ohio also topped the charts with 257, 316, and 285 individuals sentenced from 1977-1999. Although the death penalty is used almost exclusively for the crime of murder, state statutes contain various capital crimes other than murder such as kidnapping resulting in death (e.g., California, Georgia), capital drug trafficking (e.g., Florida), and repeat offenders of criminal sexual conduct (e.g., South Carolina, Texas, Louisiana).

Generally, the majority of individuals—64% according to a 2008 Gallup poll—support the death penalty for persons convicted of murder, yet there are also important state differences. Using the SNES, Norrander (2000) finds that in the early 1990s 61% of residents in Rhode Island favored the death penalty, 76% favored the death penalty in Indiana, 81% favored the death penalty in Texas, and 91% favored the death penalty in Florida. Comparing these estimates with those measured from an early 1936 Gallup Poll, which had large state sample sizes, Norrander (2000) finds some evidence that preferences for the death penalty changed over time. Support for the death penalty was generally higher in the 1990s compared to 1936, regardless of state (Norrander 2000). And, although state differences were smaller in the 1990s compared to 1936, states experienced heterogeneous changes over time; some states increased support (e.g., Texas), while other states decreased support for the death penalty (e.g., Mississippi). As we will see below, we can expand upon these preliminary analyses using the annual measures of state preferences towards the death penalty estimated via the MRP approach.

There is some evidence that the cross-sectional differences in public opinion play a role in shaping state-to-state differences in capital punishment policy and implementation. Norrander (2000) finds that cross sectional differences in death sentencing rates in the 1990s were influenced by state public opinion on the death penalty (measured from the SNES) as well as
political culture (measured as state ideology). Nice (1992) finds that conservative states are more likely to have death row inmates and higher execution rates, although he did not control for specific public opinion on the death penalty. Others have found demographic characteristics to be correlated with death penalty legislation, for instance, states that are the most economically unequal and with the highest percentage of blacks are more likely to have the death penalty (Jacobs and Carmichael 2002) although it is unclear exactly what the mechanism is for these effects. Few studies have looked at how yearly changes in state preferences towards the death penalty influenced the legislation or implementation of the death penalty. Hence, little is known about how specific public opinion towards the death penalty influences the timing differences in policy outputs across the states, such as when states first executed an inmate or re-established the death penalty.

This is an important shortcoming, particularly in light of the fact that support for the death penalty has changed over time at the national level. Using Gallup, GSS, and Harris questions, Page and Shapiro (1992) find that support for the death penalty “declined gradually from the mid-1950s to the mid-1960s, jumped up in 1966-1967, and then rose gradually through the 1970s and 1980s” (93). Page and Shapiro (1992) attribute these changes to rational responses to current events, such as the urban riots in the 1960s. Baumgartner, DeBoef, and Boydstun (2007) combine responses across 292 survey organizations to create a single indicator of the public’s preferences towards the death penalty from 1953 to 2005. They find that preferences towards the death penalty are quite stable over time; any shifts in public opinion are slight. These minimal shifts include a downward change (indicating less support for the death penalty) until the 1960s and a slow drift towards more support after the Furman decision in 1972. The 1990s saw some slight shifts downward again as DNA evidence and concerns about the innocence of death row inmates increased (Baumgartner, DeBoef, and Boydstun 2007). By having dynamic
measures of state public opinion towards the death penalty, I test whether the national dynamics occurred at similar rates across the states, as shown in Chapter 4.

**Abortion**

While the US Supreme Court has engaged in the controversial topic of a woman’s right to end a pregnancy, the states have had large discretion over abortion policy since at least the 1800s (Vestal 2006). Massachusetts was the first state to outlaw abortion in the mid-1800s with nearly all states passing similar bans throughout the 1900s. From 1962-1973, 17 states amended their laws to allow abortions in particular situations, such as rape or a health risk to the mother (Vestal 2006). And, since the Supreme Court legalized abortion in *Roe v. Wade*, overturning all state abortion bans in 1973, states have actively passed laws attempting to limit the access to and practice of abortion as well as laws to protect the women’s right to an abortion. For instance, since 1973 all states (with the exception of Vermont) have passed one or more abortion laws (Vestal 2006).

State abortion policies vary from those that regulate parental consent and notification, consultation, and waiting periods to those that limit or increase access to public funding and insurance coverage. Thirty-four states have passed some sort of legislation involving parental consent or notification for minors (Guttmacher Institute). These include parental consent laws, which require parents to approve the procedure and parental notification laws, which require doctors to notify parents before performing an abortion on a minor (Vestal 2006). Currently, twenty-two states enforce parental consent laws; twelve other states enforce parental notification laws with Oklahoma and Utah enforcing both. Twenty-eight states require doctors to provide counseling about the risks of abortion, with 26 providing counseling for adoption. Waiting periods—typically of 24 hours—designed to give women time to reconsider their options, are required in 24 states. South Dakota limits funding for abortions (except in cases of life endangerment) while 17 other states, including Hawaii, Maryland, New York, and Washington
use their own funds to pay for all or most abortions for low-income women through Medicaid (Guttmacher Institute). Four states restrict private insurance coverage to cases in which the woman’s life is in jeopardy (Guttmacher Institute).

Although abortion bans are illegal, several states have “trigger laws” that ban abortion, but delay the effective date until the Supreme Court allows states to make abortion illegal (Vestal 2006). Illinois was the first to pass a trigger law in 1975 followed by Louisiana, Kentucky, South Dakota, Mississippi, and North Dakota. Other states, such as Arkansas and Missouri, have weaker laws called “statements of policy” that establish their intentions to ban abortion if federal prohibitions are ever reversed (Vestal 2006). And still other states, such as Nevada, Maryland, Maine, Washington, Connecticut, and California, have passed laws explicitly protecting a woman’s right to an abortion if federal prohibitions are lifted (Vestal 2006).

A minority of Americans favor abortion without restrictions—only 41% support a woman’s right to an abortion for any reason as reported in the 2008 General Social Survey. Yet, a majority opposes restricting abortions under most, if not all, circumstances (Cook et al. 1992; Norrander and Wilcox 1999). Support for legal abortion increases for medical reasons (for instance, for the health of the mother) and depends on other social and economic situations (Page and Shapiro 1992).

Similar to public opinion on the death penalty, aggregate level analyses at the state level suggest that there are important cross-sectional differences on state preferences towards abortion. Using the SNES 1988-1992, Norrander and Wilcox (1999) find that states like Arizona, California, and Colorado showed the strongest support for legalized abortion in a general case while other states like Kentucky, Mississippi, and West Virginia showed the least support (see also Wetstein 1996). Moreover, attitudes towards specific policies, such as government funding for abortion or parental consent, were only moderately correlated with general opinions towards abortion (r=.83 and -.50, respectively; parental consent was coded in the opposite direction from
the general question). Similarly, Cohen and Barrilleaux (1993) use state exit polls in 1990 to measure general abortion attitudes. They find that the average state shows a slight net opinion favoring the pro-choice position (at 19.14% on their composite scale), but that there is great variability with some states being slightly pro life (e.g., Kentucky and South Dakota) and others being strongly pro-choice (e.g., California, Connecticut, Maine, Oregon, and Vermont).

Again, there is evidence that these important cross-sectional differences in public opinion are at least somewhat responsible for the policy differences across the states. States with higher levels of support for abortion are more likely to use public funding for abortions (Norrander and Wilcox 1999), less likely to have passed a constitutional amendment to ban abortion (Cohen and Barrilleaux 1993) and have less restrictive abortion policies (Camobreco and Barnello 2008; Wetstein 1996). Other state characteristics also matter. For instance, states with a large Catholic population have more conservative abortion policies while states with a large number of women legislators have more liberal abortion policies (Norrander and Wilcox 1999; Berkman and O’Connor 1993).

Only one study has looked at the relationship between state abortion policy and public opinion over time. Camobreco and Barnello (2008) compare the effect of state public opinion on the restrictiveness of abortion policies at three time points: 1983, 1993, and 2003. Using the SNES to measure state attitudes towards abortion, they find that the effect of abortion attitudes on policy has strengthened over time, particularly in relation to elite attitudes on abortion. Although Camobreco and Barnello (2008) use the same measure for abortion attitudes in each of the three time points, their research underscores the need for dynamic models of policy responsiveness.

National studies have found abortion attitudes to be remarkably stable over time, although there have been some small, statistically significant shifts. Page and Shapiro (1992) find that during the 1970s and 1980s opinion stayed relatively stable after increasing support for abortion in various circumstances in the late 1960s. Others have found small increases in the
support for abortion policies following *Roe v. Wade* (1973), a slight drop during the 1980s, a
rebound in 1989 prior to the *Webster* decision, and then a slight decline in the 1990s (Jelen and
Wilcox 2003; Wlezien and Goggin 1993). Though these changes are statistically significant, they
are quite small and caused by slow, gradual changes, as opposed to abrupt fluctuations.

**Education Spending**

Although spending has traditionally been the responsibility of local governments, the
states gradually became more active in school funding beginning in the 1950s by directing funds
to districts (Education Commission of the States). By 1971, the states began focusing on equity
in the distribution of funds after the *Serrano v. Priest* (1971) California court decision held that
California’s financing system was unconstitutional and that education was a fundamental state
right (Berkman and Plutzer 2005). Since the decision in *Serrano*, more than forty other states
have had similar equity lawsuits. Nineteen of those states ruled in a way similar to the California
court, effectively overturning (at least partially) the funding systems these states (Berkman and
Plutzer 2005; Education Commission of the States). Responding to these court decisions, state
legislators sought ways to equalize school funding by assuming a greater financial responsibility
without removing the autonomy of local school boards (Wong 1999).

More recently, states have concentrated on the topic of finance adequacy, which “focuses
on defining a minimum level of funding needed for every school to effectively teach its students”,
as opposed to the issue of equity, which “focuses on the disparity in funding between districts”
(Education Commission on the States). This shift in focus had caused several states (e.g., Ohio,
New Hampshire, and Wyoming) to move to a statewide tax structure and others (e.g., Maryland
and Oregon) to move to an adequacy-based formula for funding as opposed to a formula based on
equity (Education Commission of the States). Other states have pushed towards funding the
construction of school facilities in efforts to avoid litigation.
State legislator responses to these rulings have contributed to the states now providing the largest porting of funding for public education. In 2005, for example, states contributed close to 3% more to total public education revenues than did local governments (http://www.ncsl.org/programs/educ/NCSLEducationFinance.htm). This is in stark contrast to figures in 1956 when states contributed 16% less to total public education revenues compared to local governments. Despite the overall upward trend towards increased education expenditures, important cross-state differences persist. New Jersey, DC, New York, Connecticut, and Alaska top the charts on average per-pupil expenditures on K-12 from FY1969-FY2004 while Utah, Mississippi, Idaho, Arizona, and Tennessee comprise the bottom in terms of education expenditures (National Center for Education Statistics, Table 174). Changes in education expenditures also vary across states. From FY1981 to FY2001, changes in per-pupil spending varied from a low in Alaska, which decreased spending by $2,878 (in 2001 dollars), to a high in Connecticut, which increased spending by $4,300 (Griffith 2004). The average change in education expenditures for this time period was an increase of $2,209 across all states (Griffith 2004).

The majority of Americans support increases in education spending (Page and Shapiro 1992; Berkman and Plutzer 2005). When asked whether we’re spending too much, too little, or about the right amount on improving the nation’s education system by the General Social Survey in 2006, 74% of citizens answered that we are spending too little compared with 21.6% who answered too much. As Page and Shapiro (1992) note, “even at the end of recession-ridden 1982…61% said they wanted to expand spending on education while only 7% wanted to cut it back” (133). Moreover, there is evidence that aggregate support for education spending increased since the 1970s when it hovered around 51% (Page and Shapiro 1992; Wlezien 1995).

Public opinion towards education spending also appears to have cross-sectional variation in the states, though much less is known about the within-state variation in public opinion.
because of the data limitations explained in Chapter 2. Berkman and Plutzer (2005) measure state public opinion towards education spending in 1995 using the General Social Survey and advanced pooling and aggregation techniques. They find that residents in California, Maryland, and Arizona topped the list for support of additional education spending while residents in Nebraska, Indiana, and Minnesota were less supportive of additional education spending. As we will see in Chapter 4, there are also important intra-state changes in support for education spending.

Much of the research in explaining the cross-sectional differences in education spending has focused on the political and economic characteristics of states instead of the policy preferences of state residents. For instance, wealth (Hwang and Gray 1991), active unions (Randcliff and Saiz 1998), and the presence of Democratic officials (Wong 2004) are all positively related to education spending in the states. At the school district level, there is evidence that public opinion matters even after controlling for important political and economic variables, such as median income, revenues, or whether school districts are autonomous (Berkman and Plutzer 2005). Specifically, districts with higher levels of support for additional spending on education had higher levels of per pupil spending in fiscal 1995 (Berkman and Plutzer 2005, Table A4-1, A4-2). In Chapter 5, I explore whether state preferences towards education spending have an influence over public policy and whether this relationship is dynamic over time.

Welfare Spending

The passage of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) marked a historic transition of responsibility of welfare from the federal government to the states. By ending the federal entitlement to welfare (AFDC) and setting up the block grant program known as Temporary Assistance for Needy Families (TANF), PRWORA opened up new opportunities for state governments to make welfare policy responsive to local
needs through the setup of new benefit and eligibility requirements, creation of innovative new welfare programs, and the imposition of stiff new requirements on welfare beneficiaries (Lieberman and Shaw 2000).

States have been active in redistributive policies however for years before PRWORA was enacted. For instance, forty-three states were granted federal waivers to set aside federal regulations and guidelines to introduce their own reform proposals prior to PRWORA. However, the act ushered in other ways in which states can vary the generosity of their programs including the benefits accrued per recipient and the access of welfare programs by the poor population (Bailey and Rom 2004).

There are many different programs that classify as public welfare expenditures in the states. Two broad categories of these programs include cash assistance and Medicaid. Cash assistance programs include AFDC, TANF cash assistance, general assistance, and state supplements to the Supplemental Security Income (SSI) (US Department of Health and Human Services 2004). TANF cash assistance provides monthly cash benefits to very low-income families based on eligibility requirements set by states, but unlike AFDC families are not guaranteed benefits (National Center for Children in Poverty). In 2005, income eligibility criteria ranged from a maximum of $19,692/year in Hawaii to a low of $3,228/year in Alabama for a one-parent family of three. Similarly, the maximum monthly benefit for a family of three ranged from a high of $923 in Alaska and $704 in California to a low of $170 in Mississippi and $185 in Tennessee (National Center for Children in Poverty). SSI was created by the federal government in 1972 and provides cash payments to disabled, blind, or elderly persons who are also poor (Bailey and Rom 2004). Yet, states can choose to supplement any or all of the federal beneficiaries or other groups that the states identify. In FY2000, state and local governments spent nearly $20 million in cash assistance programs. Since 1977, the wealthiest states saw gradual increases on per capita spending on cash assistance until the middle and late 1990s as
caseloads dropped (US Department of Health and Human Services 2004). Meanwhile, spending on cash assistance in the poorest states remained relatively stable throughout until the 1990s when it declined slightly (US Department of Health and Human Services 2004).

Medicaid, the state-federal program that provides medical care to low-income persons and families, is by far the largest state welfare program (Bailey and Rom 2004) with states spending roughly $155 billion in FY2000 (US Department of Health and Human Services 2004). In 2005, states ranged in the percentage of general fund spending on Medicaid with a high of 38.9% in Ohio to a low of 3.3% in Alabama (Kaiser Family Foundation). Per enrollee Medicaid spending also varied across states; in FY2006, Arizona spent the least on total enrollees at $2,206 per enrollee while DC spent the most on total enrollees at $8,484 per enrollee (Kaiser Family Foundation). Unlike cash assistance programs, all states have increased in their average per capita spending on Medicaid since 1977 (US Department of Health and Human Services 2004).

Public support for increased welfare spending is generally low. Only 25% of the population thought we are spending too little on welfare when surveyed in 2008 by the General Social Survey. On the other hand, 38% felt we were spending too much money on welfare. There is evidence that attitudes toward welfare spending has changed over time. In the late 1970s, the proportion of individuals saying we were spending too much on welfare rose by 19%, to a total of 63%, while only 14% said that we were spending too little on welfare (Page and Shapiro 1992 125). During the 1980s, the proportion who said we were spending too much on welfare decreased to 41% while 25% said that we were spending too little on welfare (Page and Shapiro 1992). And, in the 1990s the percentage of Americans who thought we spent too much on welfare rose quickly—most likely in response to welfare reform—to 57% in 1993 and 62% in 1994.

At the state level, there appears to be substantial cross-sectional variation in public opinion towards welfare spending (Brace et al. 2002), although the majority of research has
focused on explaining these differences as opposed to describing them. Johnson (2003) finds a moderate correlation ($r=.26$) between white attitudes about blacks and support for additional welfare spending, both measured from pooling and aggregating responses from the General Social Survey. And, there is some evidence that this relationship may be mediated by state ideology; whites in more liberal states tended to be more supportive of welfare spending compared to those in conservative states (Johnson 2003).

The majority of research on state welfare policies has concentrated on economic, political, and demographic variables. For instance, democratic legislators tend to enact more generous programs (Bailey and Rom 2004) as do states with greater bureaucratic capacity (Johnson 2003; Skocpol 1992). The racial composition of states also has a significant influence over state welfare policies (Hero 1998); for instance, states with a higher African American population have stricter eligibility requirements (Fording 2003). There is some evidence that public opinion influences cross-sectional differences in state welfare policies, although the majority of these studies have not measured welfare attitudes specifically. For instance, liberal leaning states have more expansive welfare policies compared to conservative leaning states (Hill, Leighley, and Hinton-Andersson 1995; Johnson 2003). States with low turnout of less affluent citizens are also less likely to be supportive of welfare policies (Hill, Leighley, and Hinton-Andersson 1995; Johnson 2003). Johnson (2003) measures state preferences towards welfare by pooling and aggregating responses to the spending question using the General Social Survey, 1974-1998. He finds that states with higher support for additional spending have been less vigorous in their efforts to reduce the number of welfare beneficiaries. However, specific public opinion towards welfare spending had no effect on the amount of welfare spending per recipient in a state (Johnson 2003). Like the majority of studies on policy responsiveness in the states, Johnson’s (2003) research focused on cross-sectional relationships. As we will see in
Chapter 5, changing public opinion towards welfare spending has a significant impact on how much a state spends on welfare from year to year.

**Anti-Smoking Legislation**

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 anti-smoking legislation can improve public health and provide strong reinforcement of nonsmoking as a social norm (Wisotzky et al. 2004). It is because of the significant risks to public health that states have enacted various anti-smoking policies including restrictions on smoking in public places, laws to protect youth access to cigarettes, and excise taxes on cigarette sales.

As of 2008, 31 states have banned smoking in government workplaces, 26 have prohibited smoking in private workplaces, 25 have banned smoking in restaurants, and 17 have prohibited smoking in bars (STATE Fact Sheet 2009). Some states allow locations to provide designated areas for smokers and non-smokers or separate ventilated areas instead of having a complete smoking ban. 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 while Montana and Oregon recently passed smoking bans that took effect in 2009. Smoke-free laws have been most prolific on the east and west coasts of the US although within the last few years other states have followed suit (State of Tobacco Control 2008).

Tobacco policies that limit the sale of cigarettes to minors have become a major part of anti-smoking legislation since it is estimated that approximately 80% of tobacco users initiated use before age 18 years (Youth Tobacco Surveillance 2000). These policies include regulations of face-to-face tobacco sales at retail outlets such as restrictions on the minimum age of purchase, packaging, clerk intervention, photographic identification, vending machine availability, and free
distribution of samples (Chriqui et al. 2002), as well as more recent laws to restrict the delivery sales of tobacco products by Internet and mail-order vendors (Chriqui et al. 2008). Using numerical scores rating the extensive of state laws on youth access to tobacco from 1993-1999, Chriqui et al. (2002) find that the most restrictive states were California, Connecticut, and Delaware where the least restrictive states were Maryland, Arizona, and Pennsylvania. Moreover, states varied in whether they became more or less restrictive over the 6 year period; Idaho, for instance, became more restrictive, while Florida became slightly less restrictive in their youth access laws (Chriqui et al. 2002). In regards to Internet and mail-order restrictions, between 1992 and 2006, 34 states enacted a relevant law, with 27 states’ laws becoming effective between 2003 and 2006 (Chirique et al. 2008).

Another way that states have controlled smoking behavior is through excise taxes on cigarette sales. California led the way in 1988 when voters passed Proposition 99, which raised the cigarette tax by $.25/pack; the revenue from these taxes were used to support anti-tobacco initiatives (Tauras et al. 2005). In 2008, the national cigarette tax average was $1.19; New York has the largest tax in the nation at $2.75/pack while South Carolina has the lowest ($.07). Massachusetts, New Hampshire, New York, and DC increased their excise taxes in 2008, while other states remained at the same level or failed to pass proposals to increase the excise tax (e.g., Kentucky). As with other anti-smoking legislation, there are large geographic variations. Twelve states, mostly in the Northeast, have a tax at or above $2.00/pack while eleven states, mostly in the South, have a tax of less than $.50 per pack (State of Tobacco Control 2008).

Public opinion towards anti-smoking legislation depends on the particular question asked. According to recent Gallup polls, few Americans (17%) believe that smoking should be made totally illegal in this country, yet a majority believes that some type of restriction should be made on smoking in hotels, workplaces, bars, and restaurants. In a 2007 Gallup poll, people were less willing to support a smoking ban in bars (29%) compared to restaurants (54%), workplaces
(44%), and hotels (34%) (see also Gilpin et al. 2004). There is also evidence that opinion towards smoking legislation has become more supportive since the 1980s. According to Gallup, only 10% of Americans supported a smoking ban in hotels; this figure rose to 34% in 2007. Public opinion is divided on tax increases on cigarettes. In a 2005 Gallup Poll, 33% of adults felt that taxes were too high, 35% said that tax rates were about right, and 25% stated that taxes were too low. There is some evidence, however, to suggest that those who stated that taxes on cigarettes were about right increased over time; only 27% answered about right in a 2002 Gallup poll.

Most research on public support for anti-smoking policies focuses on the individual level correlates of smoking and public opinion instead of aggregate support for anti-smoking policies across the states. The strongest predictor of support for anti-smoking legislation is smoking status; smokers are less likely than non-smokers to support smoking bans in nearly every public place, including restaurants and bars (Smith et al. 2008; Gilpin et al. 2004). Moreover, smoking rates vary significantly across the states. In 2007, the median prevalence of adult smoking was 19.8% across all states. Prevalence was highest in Kentucky (28.3%), West Virginia (27%), and Oklahoma (25.8%) and lowest in Utah (11.7%), California (14.3%) and Connecticut (15.5%). There is also evidence to suggest that smoking prevalence has changed over time in certain states. Prevalence decreased in 28 states from 1998-2007, although no change was observed in Alabama, Arizona, Tennessee, or West Virginia. Since smoking rates vary across the states and over time, it is logical to assume that public support for smoking restrictions should also exhibit cross-sectional and longitudinal variation, although much less is known about trends in public opinion. I examine the cross-sectional and longitudinal variation in public preferences towards smoking bans near the end of this chapter and in Chapter 4, respectively.

Similar to other issues, the majority of research on the correlates of state anti-smoking policies has focused on economic and political variables, as opposed to the role of public preferences. For example, anti-smoking legislation is more likely in states that have strong and
plentiful health organization lobbyists and less likely is states where tobacco lobbyists are active (Givel and Glantz 2001; Glantz and Begay 1994; Monardi and Glantz 1998; Shipan and Volden 2006). States are also more likely to adopt anti-smoking legislation if cities have already adopted similar laws, although this effect is mediated by legislative professionalism (Shipan and Volden 2006). Finally, there is evidence that states are more likely to adopt restrictions in public places if neighboring states have already adopted similar restrictions (Shipan and Volden 2006).

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 ($\mu=52\%$) and Virginia ($\mu=45\%$) 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, like I do in Chapters 5 and 6, I provide stronger tests of the hypotheses examined by Shipan and Volden.

**Measuring Public Opinion on Specific Policies**

I measure state public opinion on specific issues using the MRP approach as introduced in Chapter 2. However, to increase the amount of information per state, I employ the MRP approach using a five time point moving average. For instance, to get a point estimate for 1975, I combine surveys from 1972, 1974, 1975, 1976, and 1977 (1973 was missing for all states). In early years, there were gaps in the data such that not every point prediction is exactly a five year
moving average, however, in later years there was less missing data. There is more detail about the amount of missing data across each issue area in the Appendix.

As we saw in Chapter 2, using a five year pooled window does not introduce large amounts of error into the estimates. And, since we have less information to start with, the five year pooled window actually helps increase the reliability of our measures. As a consequence, however, we are potentially smoothing over large yearly fluctuations in public opinion. This is something to keep in mind particularly for Chapter 4 when I investigate the dynamic properties of state public opinion on the death penalty and other issue areas. The MRP approach to measure dynamic preferences towards specific issues is identical to that in Chapter 2; covariates include education, race, age, and gender and estimates are weighted using Census figures.

I use responses across several survey organizations which have identical question wording to increase the amount of information; however, the number of surveys used depends on the issue. Detailed information about question wording, survey organizations, and the time span for each issue is included in Table A1.\(^\text{12}\) For the death penalty, I measure the proportion who favored the death penalty for a person convicted of murder from 1960-2002.\(^\text{13}\) For abortion, I measure the proportion who favored legalized abortion regardless of the situation or who felt that abortion should always be permitted from 1980-1998. For the two spending issues (education and welfare spending), I measure the proportion who favored an increase in spending out of those who favored a decrease or wanted spending to stay the same. Public opinion on education spending spans from 1975-2000 while public opinion on welfare spending is measured from 1974-2000.

\(^\text{12}\) In order to pool responses across organizations for a given year, I assume that each survey is measuring the same latent opinion; that bias is not introduced due to the survey design or survey implementation, such as question ordering or interviewer characteristics. Even still, I am confident that the pooling of surveys across five years should decrease the influence of outlying estimates in a particular year for a particular survey organization.

\(^\text{13}\) For all issues, “don’t know” or “no opinion” were excluded.
Public preferences towards smoking bans are measured differently in two ways from the other specific opinion measures. First, I use the Current Population Survey Tobacco Use Supplement (CPS-TUS) in addition to Gallup Polls. Since the sample sizes are so large for the CPS-TUS, I decide to use a three year moving average, similar to the analyses in Chapter 2 to measure preferences towards smoking legislation. Second, I include an additional covariate that captures differences in question wording into the multi-level modeling. In particular, I include a dummy variable that measures whether or not responses are from the CPS-TUS. This variable is important to include since responses were significantly different across the two surveys. This difference was no doubt due to question wording; the CPS-TUS asked whether respondents thought that smoking “should not be allowed” in various public places, while the Gallup polls asked respondents about “bans” in various public places. Naturally, respondents are less likely to support bans compared to simple restrictions. Details about question wording are shown in Table A1 in the Appendix. In the end, I measure the proportion of residents who support a ban or thought that smoking should not be allowed at all in restaurants and workplaces from 1991-2006.

Table 3.1 reports the sample size across all states and years as well as the average sample size for each five-year time span. All of the state-level measures are continuous and range from 0 to 1 (in proportions).

Table 3.2 provides descriptive analyses of the public opinion measures. Specifically, it reports the average value (across all states and years) as well as the standard deviation (across all states and years).

Figure 3.1 shows the geographic makeup of state preferences towards the death penalty in 1966 and in 2002. We see that throughout this period, there are large cross-sectional differences in state public opinion; support for the death penalty ranges from .30-.82 in 1966 and .44-.81 in 2002. Generally the western and southern states support the death penalty at higher rates compared to other states, though these differences are not as clear in early years. More
interestingly, the descriptive evidence suggests that some states have changed over time and that these changes are relatively heterogeneous. For instance, Texas was in the second to lowest quartile in 1966, but by 2002 it had one of the highest levels of support for the death penalty. California, on the other, remained quite stable throughout the time period, although it moved relative to other states from the highest quartile in 1966 to the second to lowest quartile in 2002. I return to a more rigorous assessment of the dynamic properties of state public opinion towards the death penalty as well as on other issues in Chapter 4.

Figure 3.2 shows maps of state preferences towards abortion legalization in 1982 compared with 1998.\textsuperscript{14} In 1982, the states that are most support of abortion, regardless of the situation are located in the Northeast and the West whereas the least supportive states are in the South and upper Midwest. These patterns are generally the same in 1998, suggesting that abortion attitudes are stable across the entire time period.

Figure 3.3 shows maps of the proportion of state residents who support additional spending in education in 1975 compared with 2000.\textsuperscript{15} We see that in 1975, the states with the highest proportion of individuals who wanted additional spending on education were located on the coasts (for instance, California and New York) as well as in the South (e.g., Louisiana). The Midwest housed the least supportive residents for additional spending in education. In addition, the range in 1975 of education spending preferences was .38-.64 suggesting large variation in whether a majority of state resident supported additional spending. By 2000, we see that the all of the states have increased in their support for education spending; the range is .65-.80 suggesting that every state has majority support for additional spending on education. In general, the coastal states that were most favorable towards education spending in 1975 remain so in 2000.

\textsuperscript{14} Missing states in 1982 include: Alaska, Delaware, Hawaii, Idaho, Nevada, New Mexico and Vermont.

\textsuperscript{15} The following states are missing for 1975 for education spending: Alaska, Hawaii, Idaho, Maine, New Mexico, North Dakota, and Vermont.
These patterns suggest that while states increased in their support towards education, some states did so at much higher rates compared to others.

Figure 3.4 shows maps of the proportion supporting additional spending on welfare in 1974 compared with 2000.\textsuperscript{16} In general, there has been some convergence in attitudes towards welfare spending as the range in 2000 is much tighter compared to in 1974. Welfare attitudes in general also seemed to decline for the majority of states. And, in neither time period is there a state where the majority of state residents favor additional welfare spending. In 1974, the highest support for welfare spending was in some Southern states (Texas) as well as Midwest states (Illinois) and northeast states (New York). The lowest quartile is generally found in the middle of the United States. By 2000, many states are in similar quartiles, other some have decreased in their support for welfare spending (Illinois) while others have increased (Idaho) support for welfare spending.

Finally, Figures 3.5 and 3.6 show maps of the proportion of residents who favor a smoking ban in restaurants and workplaces in 1991 compared to 2006, respectively. In Figure 3.5, there is evidence that residents, overall, have increased their support for a smoking ban in restaurants. In 1991, the proportion of respondents who favored a smoking ban in restaurants ranged from .26 to .52 while in 2006, the proportion of respondents who favored a smoking ban in restaurants ranged from .45 to .82. The least supportive states in 1991 include many that rely on the tobacco industry for their revenue including North Carolina and South Carolina, but also include states that are traditionally against government intervention such as Kentucky, Tennessee, and many Midwest states including South Dakota, Nebraska, Montana, and Wyoming. The most supportive states are those on the West coast (e.g., California and Washington) and in the Northeast (e.g., Connecticut). By 2006, the geographic pattern has not changed much; the least supportive states still reside in the Deep South and Midwest while the most supportive states are

\textsuperscript{16} The following states are missing for 1974: Alaska, Hawaii, Maine, North Dakota, and Vermont.
on the West coast and in the Northeast. Yet, there is some evidence that states trended
differently; Mississippi, Alabama, and Georgia remained relatively unchanged compared to 1991
while other states (e.g., Nevada and Utah) showed a significant increase in support for smoking
bans.

Figure 3.6 shows similar patterns in regards to preferences towards smoking restrictions
in workplaces. In 1991, the most supportive states are located in the Northeast and West coast
while the least supportive states are in the South and Midwest; the same is true for 2006. Similar
to preferences towards restrictions in restaurants, there is evidence that support for smoking bans
in workplaces increased from 1991 to 2006. Finally, even though residents are more likely to
support restrictions in workplaces compared to restaurants, in general, states that are supportive
of restrictions in workplaces are also likely to be supportive of smoking bans in restaurants.

**How Do the Public Opinion Measures Relate to One Another?**

In this final section, I explore how the public opinion measures on specific issues relate to
one another as well as the global indicators of public opinion developed in Chapter 2. Table 3.3
shows the correlations averaged over time and states between the six specific public opinion
measures, state partisanship, and state ideology. The highest correlation exist between the two
measures towards anti-smoking legislation ($r=.93$), which confirms the patterns seen in Figures
3.5 and 3.6. There are also high correlations between the proportion liberal and support for
abortion ($r=.58$), proportion Democrat and opposition of the death penalty ($r= -.32$), and
proportion Democrat and support for additional spending on welfare ($r=.48$). Interestingly, there
is a slight positive relationship between states that support smoking bans in restaurants and
workplaces and those that support allowing abortions in any circumstances ($r=.37$ and .22,
respectively). Hence, states that reject government intervention into the private decisions of
women are supportive of government intervention when dealing with public health. Finally, there
is a weak relationship between state ideology and state partisanship ($r=.18$), most likely because
of the Democratic support in the conservative Southern states in the early years. Indeed the correlation between proportion liberal and proportion Democrat increases if the analyses is limited to the non-Southern states ($r=.40$). The peculiar relationship between abortion and proportion Democrat in Table 3.2 ($r=-.42$) can also be explained by the presence of Southern states; the correlation increases to .21 when limited to the non-Southern states.

Not only am I interested in how public opinion on a particular issue is related to another issue, but also in how public opinion on particular issues may (or may not) trend together over time. In other words, are changes in state preferences towards the death penalty related to changes in state preferences towards abortion? Table 3.4 shows the correlations between the public opinion measures after they have been differenced.

As can be seen by Table 3.4, many changes in public opinion on one particular issue are unrelated to changes in public opinion on another issue. For instance, changes in support of abortion have little to do with changes in support for additional spending on welfare. Yet, there are some positive correlations that are worth mentioning. Not surprisingly, the largest correlation between trends is with the two anti-smoking opinion measures; changes in support for smoking bans in restaurants is strongly related to changes in support for smoking bans in workplaces ($r=.69$). Changes in anti-smoking opinion is modestly related to changes in state ideology, but in the negative direction ($r=-.24$ for smoking bans in restaurants, $r = -.33$ for smoking bans in workplaces). This suggests that as support for anti-smoking legislation increases, the proportion of liberal citizens decreases. Changes in preferences towards abortion are modestly and positively related to changes in anti-smoking legislation ($r=.27$ for smoking bans in restaurants, $r=.18$ for smoking bans in workplaces), suggesting that as support for abortion increases so too does support for anti-smoking legislation. Additionally, support for additional welfare spending is positively related to changes in support for anti-smoking legislation in restaurants ($r=.30$).
Finally, changes in preferences towards the death penalty are positively related to changes in state ideology ($r=.34$).

**Summary**

The specific public opinion measures developed here supplement the global indicators from Chapter 2. We can now characterize the states on important policy areas of which states have substantial jurisdiction including capital punishment, abortion, education, welfare, and anti-smoking legislation. Yet, we still know little about how state residents change (or not) their preferences over time. Exploration of the dynamic properties of these public opinion measures is the subject of Chapter 4. In particular, I ask is state public opinion stable or dynamic over time? If dynamic, are states trending at similar rates or do states exhibit unique patterns of change? And, are the answers to these questions dependent on the issue?
References for Chapter 3


<table>
<thead>
<tr>
<th>Issue</th>
<th>Total N Across All States and Years</th>
<th>Average N Per 5 Year Time Span</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion Favoring the Death Penalty</td>
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<td>12,177</td>
</tr>
<tr>
<td>Proportion Favoring Legalized Abortion</td>
<td>51,785</td>
<td>10,523</td>
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<tr>
<td>Proportion Increase in Education Spending</td>
<td>84,928</td>
<td>16,502</td>
</tr>
<tr>
<td>Proportion Increase in Welfare Spending</td>
<td>62,958</td>
<td>11,021</td>
</tr>
<tr>
<td>Proportion Favoring Smoking Restrictions in Restaurants *</td>
<td>943,149</td>
<td>184,160</td>
</tr>
<tr>
<td>Proportion Favoring Smoking Restrictions in Workplaces*</td>
<td>938,356</td>
<td>183,217</td>
</tr>
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</table>

Note: *Preferences towards anti-smoking legislation used a 3 year time span
Table 3.2 Descriptive Information for Specific Public Opinion Measures

<table>
<thead>
<tr>
<th>Measure</th>
<th>Mean Across All States and Years</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion Favoring the Death Penalty</td>
<td>.70</td>
<td>.10</td>
</tr>
<tr>
<td>Proportion Favoring Legalized Abortion</td>
<td>.39</td>
<td>.09</td>
</tr>
<tr>
<td>Proportion Increase in Education Spending</td>
<td>.63</td>
<td>.09</td>
</tr>
<tr>
<td>Proportion Increase in Welfare Spending</td>
<td>.20</td>
<td>.06</td>
</tr>
<tr>
<td>Proportion Favoring Smoking Restrictions in Restaurants</td>
<td>.51</td>
<td>.10</td>
</tr>
<tr>
<td>Proportion Favoring Smoking Restrictions in Workplaces</td>
<td>.66</td>
<td>.10</td>
</tr>
</tbody>
</table>
### Table 3.3 Correlation Matrix of State Public Opinion Measures

<table>
<thead>
<tr>
<th></th>
<th>Abortion</th>
<th>Education Spending</th>
<th>Welfare Spending</th>
<th>Smoking Ban: Restaurants</th>
<th>Smoking Ban: Workplaces</th>
<th>Proportion Democrat</th>
<th>Proportion Liberal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abortion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education Spending</td>
<td>.33</td>
<td>.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Welfare Spending</td>
<td>- .20</td>
<td>- .21</td>
<td>.27</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smoking Ban: Restaurants</td>
<td>- .30</td>
<td>.37</td>
<td>.28</td>
<td>- .15</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smoking Ban: Workplaces</td>
<td>- .41</td>
<td>.35</td>
<td>.29</td>
<td>- .16</td>
<td>.94</td>
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<td></td>
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<tr>
<td>Proportion Democrat</td>
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<td>- .17</td>
<td>.09</td>
<td>.48</td>
<td>- .21</td>
<td>- .17</td>
<td></td>
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<tr>
<td>Proportion Liberal</td>
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<td>.12</td>
<td>.13</td>
<td>.24</td>
<td>.24</td>
<td>.18</td>
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Table 3.4 Correlation Matrix of Trends in State Public Opinion Measures

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<th>Δ Death Penalty</th>
<th>Δ Abortion</th>
<th>Δ Education Spending</th>
<th>Δ Welfare Spending</th>
<th>Δ Smoking Ban: Restaurants</th>
<th>Δ Smoking Ban: Workplaces</th>
<th>Δ Proportion Democrat</th>
<th>Δ Proportion Liberal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Abortion</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Δ Education Spending</td>
<td>-.14</td>
<td>.23</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Welfare Spending</td>
<td>-.07</td>
<td>-.03</td>
<td>.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Smoking Ban: Restaurants</td>
<td>-.11</td>
<td>.27</td>
<td>-.03</td>
<td>.30</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Smoking Ban: Workplaces</td>
<td>-.25</td>
<td>.18</td>
<td>-.15</td>
<td>.03</td>
<td>.69</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Proportion Democrat</td>
<td>-.10</td>
<td>.23</td>
<td>.07</td>
<td>-.05</td>
<td>.06</td>
<td>.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Proportion Liberal</td>
<td>.34</td>
<td>-.17</td>
<td>-.07</td>
<td>.10</td>
<td>-.24</td>
<td>-.33</td>
<td>.18</td>
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</tbody>
</table>
Figure 3.1 Maps of Proportion Supporting the Death Penalty in 1966 and 2002
Figure 3.2 Maps of Proportion Favoring Abortion in All Circumstances in 1980 and 1998
Figure 3.3 Maps of Proportion Favoring Increase in Education Spending 1975 and 2000
Figure 3.4 Maps of Proportion Favoring an Increase in Welfare Spending 1974 and 2000
Figure 3.5 Maps of Proportion Favoring a Smoking Ban in Restaurants 1991 and 2006
Figure 3.6 Maps of Proportion Favoring a Smoking Ban in Workplaces 1991 and 2006
Chapter 4

Stability and Change in State Public Opinion

In Chapters 2 and 3, I described the political landscape of the states in terms of global political preferences, such as state partisanship and state ideology, as well as on specific policy preferences, such as opinions towards the death penalty, abortion, education spending, welfare spending, and smoking bans. Comparisons of the geographic distribution of public opinion over time suggested that the dynamic properties of state public opinion depend on the issue. As we saw in Chapter 2, state partisanship seemed to be dynamic and changing over time while state ideology showed stability in the relative positions of the states. Descriptive analyses from Chapter 3 suggest that relative state preferences towards the death penalty, education spending, welfare spending, and anti-smoking legislation change over time, while abortion attitudes are relatively stable. Together, the results from Chapters 2 and 3 underscore the need for dynamic measures of the general tendencies of state residents as well as specific public opinion measures.

Yet, the descriptive analyses in the previous chapters are just a beginning to fully understanding the dynamic properties of state public opinion. In this chapter, I undertake more rigorous tests to see whether state public opinion is stable or dynamic. As I will show, state partisanship changes gradually over time with evidence of heterogeneous trends, yet there is also evidence that it responds to short term factors. On the other hand, state ideology is characterized by stability and when it does change, it does so in small increments. Patterns of change on specific state public opinion depend on the issue. Preferences towards the death penalty and welfare spending, and anti-smoking legislation are dynamic with heterogeneous trends, particularly across regions. Preferences towards education spending are also dynamic, yet with much more homogeneous trends compared to preferences towards the death penalty or welfare spending. Finally, abortion attitudes are quite stable across time in the states. More generally, the results suggest that regional or state specific characteristics are influencing change for state
partisanship, preferences toward the death penalty, attitudes on welfare spending, and attitudes towards ant-smoking legislation. On the other hand, national events are probably more influential for preferences towards education spending. Finally, state ideology and abortion attitudes are fairly immune to current events as it is stable throughout the time period.

State Public Opinion: Stable or Dynamic? Homogeneous or Heterogeneous?

Understanding whether (1) state public opinion is stable or dynamic and (2) whether the patterns of dynamism are homogeneous or heterogeneous across the states have important theoretical and methodological implications. Consider four possible patterns of state public opinion based on how quickly opinion changes and whether these changes are homogeneous or heterogeneous as shown in Figure 4.1. Each graph shows hypothetical trends for four different states. The first scenario illustrates a world in which state public opinion moves over time, though these changes are gradual and fairly homogeneous across states. This scenario may represent a stable attitude that is immune to short term political or economic events. In Scenario 2, state public opinion has both a long term trend (the mean opinion is higher at the end of the series than at the beginning) but also changes abruptly from time to time, waxing and waning quickly, again with fairly homogeneous trends. Unlike the first scenario, public opinion responds to short term political or economic events. The first and second scenarios are similar, however, in that they represent parallel publics (Page and Shapiro 1992) in which changes in public opinion occur in the same direction and at roughly the same rate on a particular issue across the states. In both of these instances, the relative ranking of states would be highly correlated over time even as state public opinion moves.

In Scenario 3, state public opinion moves gradually over time, yet these changes are unique to particular states; states exhibit heterogeneous trends. Again, the third scenario represents public opinion which is fairly immune to short term factors, but long term factors serve
to alter the relative ordering of the states. Finally, in Scenario 4, state public opinion moves abruptly over time in response to transient events, but with heterogeneous trends. Heterogeneous trends imply that state public opinion may be becoming more favorable in some states while in other states it is becoming less favorable. Moreover, the relative rankings of states are weakly correlated as time progresses and as states change relative positions.

What can we deduce about public opinion from these four varying patterns of state public opinion? When public opinion moves gradually across time as in Scenarios 1 and 3, changes could be caused by population changes that are also gradual over time, such as migration, immigration, generational replacement, differential birth and death rates among different demographic segments of the population (Carmines and Stimson 1989; Page and Shapiro 1992; Brace et al. 2004), or gradually changing cultural sensibilities or norms. When public opinion moves abruptly, as in Scenarios 2 and 4, scholars find that public opinion is responding to current events, the economy, or other transient outcomes (Page and Shapiro 1992; Erikson, MacKuen, and Stimson 2002). If state public opinion trends identically across the states such as in Scenarios 1 and 2, national level phenomena are the primary causes of shifting state public opinion. Where state public opinion changes are unique to particular states or regions, such as in Scenarios 3 and 4, state-specific characteristics must be responsible for shifts in public opinion, not national level phenomenon. For instance, in Scenario 3, opinion changes are caused by gradual population changes, but these changes are state-specific. This might reflect, for example, the migration of Boston liberals to New Hampshire. In Scenario 4, public opinion responds to state- or regional-specific events, perhaps political corruption. Scenario 4 is also consistent with a scenario in which states are responding differently to the same national event. Hence, the combination of the rate of change in state public opinion (i.e., gradual or abrupt) and the patterns of change across states (i.e. heterogeneous or homogeneous) may provide insights into about the causes of changing public opinion.
The patterns of state public opinion over time also have important implications for the study of dynamic policy responsiveness at the sub-national level. If state public opinion is relatively stable across time, then our theories of policy responsiveness need not have a dynamic component. State public opinion may correlate with policy outputs at a particular point in time (as shown by Erikson, Wright, and McIver 1993), but if that is so, changes in policy across the states cannot be explained by changes in public opinion. This also means that dynamic theories of policy responsiveness such as the thermostatic model (Johnson et al. 2005; Wlezien 1995) or the historical chain model (Norrander 2001) are inappropriate at the state level.

Methodologically, if state public opinion is stable or if state trends are homogeneous with the relative rankings remaining unchanged, then pooling surveys across time to measure state public opinion is acceptable to investigate policy responsiveness. To study dynamic policy responsiveness with homogeneous trends, scholars need only measure the timing in which state public opinion crosses the majority threshold instead of obtaining long time series data for each state. The data demands for studying state public opinion and policy responsiveness are much greater if state public opinion trends differently across states. Scholars would need to obtain measures of state public opinion across time.

Previous Research

Given the political and theoretical implications of the dynamic behavior of state public opinion, scholars have explored whether and how state preferences have changed over time. Yet, the empirical research is mixed on answering whether state public opinion is stable or dynamic and homogeneous or heterogeneous. One camp of researchers argues that public opinion is stable across time. Erikson, Wright, and McIver (1993) originally measured state ideology by aggregating the mean ideological self-identification of respondents in CBS News/New York Times Polls from 1976-1988. They have recently extended their data to 2003 for a total span of
27 years (2006; 2007). Using the entire extended dataset, they find a high degree of stability for state ideology with an over-time correlation of .96 over four years, .95 over eight years, .91 over twelve years, and a .83 over their entire time period (Erikson, Wright, and McIver 2007 145). When looking specifically at the eight most populous states, they find an average correlation of .97, after adjusting for reliability (145). In addition, because the ratio of imputed sampling error to observed variation is so great, the authors conclude that any relative changes in the ranking of states are due to sampling error instead of true change.

Brace et al. (2002) use aggregated data from the General Social Survey to look at trends in state public opinion on specific issues, such as the death penalty, environmental spending, and abortion from 1974-1998. And, even though they were looking at specific policy preferences, Brace et al. (2002) find a similar degree of stability for the majority issues with over time correlations ranging from .73-.91. The exception was with opinions towards welfare spending which exhibited an overtime correlation of .48. 

The argument that state opinion is mostly stable over time is in contrast to others who believe that state public opinion has changed over time. Instead of using self reports of individual ideology, Berry et al. (1998; 2007) measure state ideology using interest group ratings of members of the roll call voting of state congressional delegations. Using this proxy measure, state ideology is dynamic with states frequently shifting from liberal to conservative preferences. In their recent article, Berry et al. (2007) argue that their measure captures policy mood or operational ideology where citizens react to what government is “doing at the moment” (Stimson

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17 Erikson, Wright, and McIver (2007) calculate overtime correlations by correlating their measurements across various time points and then adjusting for statistical reliability. Specifically, they “infer the over-time stability of state ideology by adjusting the over-time correlations for statistical reliability” (Erikson, Wright, and McIver 2007 145). This adjustment is important since high over time correlations can account for either stability or reliability.

18 Brace et al. (2002) employ the split halves method to assess stability. This method divides the sample into two subsets; the first subset is from 1974-1985 and the second subset is from 1986-1996. The authors then correlated state public opinion across the two subsets and obtained the Spearman-Brown coefficients to assess the degree of stability. Erikson, Wright, and McIver (1993) employ a similar method on their state ideology measures.
1991). Others have found evidence of dynamism when comparing state public opinion on specific policy areas across two or three time points. Norrander’s (2000) comparisons of state preferences in 1936 with preferences in the 1990s suggest that state attitudes towards the death penalty have changed over time; the over time correlation is .43. Moreover, this moderate level of congruency is lower in southern states compared to others, implying heterogeneous trends, although these results may also be reflective of the reduced variance among a small set of states. Johnson et al. (2004) compare public preferences towards the environment from 1985-1987 to 1989-1991. They find quite a bit of change in state preferences towards the environment with an overtime correlation of .56. Of course, correlations can depart from 1.0 because of true change or because of measurement error. Hence, these analyses are preliminary, but suggest that public opinion, particularly on specific issues, may not only be dynamic but heterogeneous as well, consistent with Scenario 4.

Within this debate, there is an additional disagreement about how scholars should adequately capture state public opinion. Some believe that state public opinion is best captured by a global measure of state ideology (Erikson, Wright, and McIver 1993; Berry et al. 1998) while others think that state public opinion is best captured with policy-specific survey questions (Johnson et al. 2004; Norrander 2000; 2001). Resolving the debate about the dynamic properties of state public opinion requires direct, over time measures of policy preferences on specific issues as well as global indicators as developed in Chapters 2 and 3. Simply assuming that state public opinion is either stable or dynamic is not sufficient. As we will see in this chapter, the patterns of dynamism vary across issues, underscoring the need for opinion measures across a wide range of policy areas.
The Dynamic Properties of State Partisanship and State Ideology

To explore whether state partisanship and state ideology is stable or dynamic across time, I first perform basic descriptive time series cross sectional analyses. Recall that the measures developed in Chapters 2 and 3 describe macro public opinion in each of the fifty states across time, although the specific time span varies across issues. For instance, state ideology is measured for each of the fifty states (plus the District of Columbia) from 1978 to 2006. This creates a database with 51 states x 28 years for a total of 1,428 observations. Each issue varies in the total number of years. Regardless, for the remainder of the dissertation, analyses are conducted at the state-year level.

The upper part of Table 4.1 shows the overall mean, variance, and standard deviation for all of the public opinion measures. For this section, I first concentrate on state partisanship and state ideology. Overall, the mean state has about 38% of its residents identified with the Democratic Party across time while the mean state has 21% of its residents indicating that they are liberal. In addition, Table 4.1 shows that there is greater variance to be explained both across time and states for state partisanship compared to state ideology. Looking specifically at how much variance occurs across time, Table 4.1 shows that state ideology has very little variance within states relative to state partisanship. And, while state partisanship has some variance to be explained across time, the majority of the variance occurs across states; 83% of the variance in state partisanship occurs across states while only 19% occurs across time.

In order to illustrate exactly how states are trending in their global indicators, Figures 4.2 and 4.3 track state partisanship and state ideology, respectively, in four select states across the four regions. For all states, changes in state partisanship occur gradually, although there are some short term shifts as well. Figure 4.2 shows that some states, such as Pennsylvania and California, exhibited little net change over the time period while support for the Democratic Party declined in other states, such as Alabama or Arizona. The Southern states are particularly interesting in that
all have declined substantially in support for the Democratic Party. Even more fascinating, the
South shows a pattern of convergence to a regional norm, which suggests heterogeneous trends in
changes in state partisanship. There is also a large degree of divergence in the West; California
has stayed relatively stable throughout the time period while Arizona and Washington have
declined in support for the Democratic Party, producing more variation at the end of the period
than earlier. And while many states exhibited a decline in support of the Democratic Party over
the entire time period, Figure 4.2 suggests that the trends differed across states. Alabama and
Texas saw the largest net decline over the time period by about 20 points whereas other states
saw smaller overall declines. Finally, not all states showed a decline in support for the
Democratic Party; Illinois, New York, Connecticut, and Massachusetts all became more
Democratic after 1990.

Aside from these overall trends, Figure 4.2 also shows some short term dynamics in state
partisanship, although these short term fluctuations vary across states. For instance, in Ohio
support for the Democratic Party increased during the Clinton years and decreased following the
2000 election. These patterns are generally consistent with what has been found at the national
level; Democratic support tends to increase under Democratic presidential regimes (Erikson,
MacKuen, and Stimson 2002). Yet, I find that these short term patterns are not consistent across
all states. California residents exhibited little change across presidential regimes, while Michigan
residents increased in Democratic support during the Reagan years (e.g., a Republican regime).

Figure 4.3 shows that state ideology has much less net change compared to state
partisanship. While some states changed by 20 points for state partisanship, the largest change
for ideology is a mere 5 points. Most states stayed relatively stable throughout the time period
even though there were some short term fluctuations. For instance, Pennsylvania residents stayed
relatively stable in state ideology although there was a slight decline in the proportion liberals
from 1990 to 1995; yet again, this decline is minimal and—at most—only 5 points of a decline.
Similar to state partisanship, we see some evidence of divergence in the West, although again, state ideology is quite stable over the entire time period compared to state partisanship.

While Figures 4.2 and 4.3 tell us descriptively about the dynamic properties of state partisanship and state ideology, they invite more rigorous testing about whether trends are stable or dynamic and homogeneous or heterogeneous. To assess time trends in each state more rigorously, it is important to first purge estimates of common national trends and cross-state differences (Brace et al. 2004). Once we account for unit heterogeneity and common temporal trends, we can begin to assess the longitudinal variation within states. One way to control for both unit heterogeneity and temporal dependence is to use multilevel models (MLM). MLM can be used just as one would do to assess changes over time in individuals; hence, instead of time clustered within individual (which is the case with longitudinal analyses) I model time clustered within states (Shor, Bafumi, Keele, and Park 2007).

Specifically, I estimate an unconditional polynomial model for state partisanship and state ideology. Time (measured as a counter with the first year equaling zero) is the only predictor included in the model. Hence, these models are not exhaustive, yet provide only a descriptive analysis about trends over time. In notation

\[
\text{Eq. 1} \quad \text{Level 1} \quad Y_{ti} = \beta_{0i} + \beta_{1j}(\text{Year}_{tj}) + \beta_{2j}(\text{Year}^2_{tj}) + \beta_{3j}(\text{Year}^3_{tj}) + r_{tj}
\]

\[
\text{Level 2} \quad \beta_{0i} = \gamma_{00} + U_{0j} \\
\beta_{1i} = \gamma_{10} + U_{1j} \\
\beta_{2i} = \gamma_{20} + U_{2j} \\
\beta_{3i} = \gamma_{30}
\]

where \(j\) indexes state and \(t\) indexes time.\(^{19}\)

The intercept (\(\beta_{0i}\)) represents the average level of state public opinion in the first year, which is 1978 for both state partisanship and state ideology. To capture non-linear change, I include a year slope (\(\beta_{1i}\)), a year squared slope (\(\beta_{2i}\)), and a year cubed slope (\(\beta_{3i}\)). These three

\(^{19}\) For state ideology, the only difference is that the error term for year squared (\(U_{2j}\)) is not included.
terms ($\beta_1$, $\beta_2$, and $\beta_3$) work together to describe curved trajectories that are common among all states. While we can keep adding polynomials past cubic, these are rarely seen in practice and hard to interpret. The model parameters for these common elements are shown in Table 4.2 under the fixed effects heading.

The fixed effects in Table 4.2 generally confirm the descriptive analyses about the overall variance to be explained as well as the over time trends in state partisanship and state ideology. All of the year coefficients are significant for state partisanship indicating that it is changing over time, although the exact trend is difficult to ascertain unless the effects of all the polynomials are combined. For state ideology, none of the year coefficients are significant at traditional significance levels. This indicates that state ideology is quite stable over time.

The random effect of the intercept ($U_{0j}$) accounts for unit heterogeneity for state partisanship and state ideology in 1978. In other words, it estimates how much each a state’s proportion of Democrats (or liberals) deviates from the mean level of state partisanship (or state ideology) across all states in 1978. The variance component of the intercept is shown in Table 4.2 under the random effects heading. We can obtain the 95% confidence interval (CI) for the random variation around the intercepts by adding and subtracting 2 standard deviations of the accompanying random variance terms. State partisanship has a mean level of .42 for the proportion of Democrats in 1978 with a 95% CI of .26 to .58 indicating that some states had relatively low levels of Democrats in 1978 while others had a majority of self-identified Democrats among their state residents in 1978. For state ideology, the mean level of the proportion of liberals in 1978 is .21 with a 95% CI of .16 to .25. Consistent with our descriptive analyses, there is larger unit heterogeneity with state partisanship compared to state ideology.

To assess patterns of change across states—that is whether states are changing differently across time—I test whether the year and year squared slopes are varying across states. Specifically, I test whether to include random slopes for the year and year squared coefficients via
model fit and REML deviance differences. Via model comparisons, the addition of the random slope for the year and year squared coefficients resulted in significant improvements to a random intercept model with REML deviance differences (5 df)=570 \( (p<.001) \) for state partisanship. For state ideology, the addition of a random slope for the year coefficient resulted in a significant improvement to a random intercept model with REML deviance differences (3 df)=169. The variance components of the random slopes of year and year squared are shown in Table 4.2 under the random effects heading.

Similar to the intercepts, we can obtain the 95% confidence interval (CI) for the random variation around the fixed effects of year and year squared by adding and subtracting 2 standard deviations of their accompanying random variance terms. Table 4.2 shows that the mean year slope for state partisanship is -.01 with a 95% CI of -.002 to -.018. This indicates that some states stayed relatively stable in their proportion of identified Democrats while others changed slightly more quickly than others over time. The mean year squared coefficient for state partisanship is .0006 with a 95% CI of .0003 to .0008. The mean year slope for state ideology is .0003 with a 95% CI of -.002 to .002. Though there is a random effect of the year slope for state ideology, the difference across states is very small. In addition, the fixed effect is not significant, indicating that state ideology does not move much if at all over time.

As a final investigation about the dynamic properties of state partisanship and state ideology, I rank the states according to their state partisanship or state ideology in each year. I then calculate the correlation of each state’s rank in the first year, 1978 for both state partisanship and state ideology, with their ranks in subsequent years (using Spearman correlations). Finally, I plot the rank correlations across time. The logic here is that if states are changing in

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20 Restricted maximum likelihood (REML) was used in estimating model parameters and to assess the significance of random effects; degrees of freedom were estimated using the Satterthwaite method.

21 The model fit did not show a significant improvement with the addition a random slope for the year squared coefficient.
heterogeneous ways over time then the rank correlations with the first year should decrease over time. That is, the rank of a state in the first time period should change and be less correlated with other yearly ranks over time. A high correlation over time suggests that state public opinion is either stable or that states are changing in homogeneous ways. Hence, because we cannot discern which scenario (Scenario 1, 2, or 3) high correlations suggest, these results are simply supplemental to the above analyses. The plotted rank correlations over time for both state partisanship and state ideology are shown in Figure 4.4.22

Figure 4.4 shows that the correlations for state partisanship and state ideology decrease over time, suggesting that states have different ranks at the end of the time period compared with earlier. Yet, the rank correlation for state partisanship in 2006 remains relatively high ($r = .58$) while the rank correlation is a mere .33 in 2006 for state ideology. We know, however, from the above analyses that states stayed relatively stable in their state ideology over time.23 State ideology stayed relatively stable throughout the time period, though when state ideology changed it did so in small increments that caused slight shifts in the rankings of states.

In this section, I explored the dynamic properties of state partisanship and state ideology using estimates obtained from the MRP approach developed in Chapter 2. First I asked: are state global preferences stable or dynamic over time? The answer depends on whether we are talking about state partisanship or state ideology. State partisanship shows gradual movement overall, although there is also evidence from raw values that state partisanship may be responding to short term events. In contrast, state ideology is characterized by stability, something that is echoed in previous research using other methods (Erikson, Wright, and McIver 1993, 2006, 2007). Second,

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22 Similar results are obtained when using Pearson correlations.
23 Because rank correlations may also be influenced by the reliability of our estimates, I redo the analyses using only the 40 largest states. Using the 40 largest states, we see that the correlation for state partisanship is lower ($r = .49$) in the last time period compared with when we used the entire dataset. For state ideology, the correlation is higher ($r = .44$) in the last time period compared with the entire dataset. Given that state ideology started at a lower correlation compared to state partisanship, these results are fairly consistent with the above analyses.
if state preferences are changing, are states sharing a common trend or do states exhibit heterogeneous time trends? For state partisanship, states exhibit different trends; some states decreased in the proportion of Democrats while other states showed in increase. These heterogeneous trends result in changes in the ranking of states over time.

**The Dynamic Properties of Specific Public Opinion**

Knowing the dynamic properties of state partisanship and state ideology does little to inform us about the dynamic attributes of specific public opinion measures. While there is some correlation between global indicators and specific public opinion measures, as we saw in Chapter 3, this correlation is far from perfect. Hence, in order to fully understand whether state public opinion is stable or dynamic and homogeneous or heterogeneous and whether these patterns are conditioned by issue, we must also look at the dynamic properties of specific public opinion measures, which is the subject of this section.

I start with a basic descriptive time series cross sectional analyses. The lower panel of Table 4.1 shows the overall means, variances, and standard deviations in state public opinion for the death penalty, abortion, education spending, welfare spending, and anti-smoking legislation. The majority of the public supports the death penalty, increases in education spending, and restrictions on smoking in workplaces as evident by the overall means of .70, .63, and .66 respectively. Fewer state residents support abortion (µ=.39) and additional spending on welfare (µ=.20). Public support for smoking restrictions in restaurants is evenly split (µ=.51). Generally, welfare spending has the least variance to be explained, while the death penalty and preferences towards smoking bans in workplaces has the most variation across states and time. Additionally, Table 4.1 shows that the majority of variance for the death penalty, education spending, smoking bans towards restaurants, and smoking bans towards workplaces is across time (85%, 80%, 58%, and 63% respectively), while the majority of the variance in abortion attitudes is across states
Finally, the variance is equally split for attitudes towards welfare spending across states (48%) and time (53%). The descriptive analyses in Table 4.1 suggest that preferences towards the death penalty, education spending, smoking restrictions in restaurants, smoking restrictions in workplaces and to a lesser degree, welfare spending, are dynamic whereas state abortion attitudes are fairly stable across time.

To observe the over time trends more closely, Figures 4.5-4.10 track changes in specific public opinion measures in four select states in each of the four regions. Figure 4.5 shows that preferences towards the death penalty gradually increased from the 1970s until the late 1990s, where it then declined; yet, there are important regional differences to this general trend. The largest changes in opinion towards the death penalty occurred in the Southern states, which saw an increase from .40 to .80 from the 1970s until the 1990s. Other regions, such as in the West, experienced an increase of less than .10 over the same time period. States in the Northeast (e.g., Connecticut, Massachusetts) experienced a much more pronounced decline in support for the death penalty in the later years compared to Southern states (e.g., Texas, Arizona). Coastal states are clearly “leaders” in changes in public opinion while the Southern and Midwest states tend to be laggards. Overall, the starkest differences in the trends appear to be across regions as opposed to within regions.

Changes in state residents’ attitudes toward abortion are shown in Figure 4.6. Generally, preferences towards the legality of abortion stayed relatively stable throughout the time period. Any changes that states experienced were generally gradual changes over many years. For instance, Pennsylvania, Alabama, and California, remained relatively stable throughout the time period with changes occurring (if at all) of less than .10. While other states, such as Illinois or Colorado, experienced gradual increases towards favoring legalized abortions over the entire time period, these changes are minimal. States in the Midwest all experienced a relative increase in
support for abortion, while other regions, such as the South, experienced little net change over the time period.

Figure 4.7 trends state public opinion towards additional education spending. Figure 4.7 shows large net changes towards education spending with the majority of states increasing by .20 to .30 until the late 1990s where public opinion remained fairly stable. Overall, few states decreased in their support towards education spending throughout the time period; that is, there is a certain degree of similarity as all states increased support for additional education spending throughout the time period until the late 1990s. Indeed, education spending appears to have more homogeneous trends compared to other public opinion measures, yet some states exhibit unique trends. For instance, the increase towards additional spending is much steeper for Illinois and Minnesota compared to Ohio and Michigan.

Figure 4.8 shows how state residents changed their preferences towards welfare spending. Unlike other issues, welfare spending exhibits a cyclical pattern of change where public support tends to wax and wane over time. For instance, Pennsylvania and New York experienced an increase towards additional welfare spending throughout the 1980s and then a subsequent decrease in the early 1990s only to be followed by an increase in the late 1990s. This same pattern is evident in other states, yet we also see some evidence of heterogeneity, particularly across regions. The Midwest had large heterogeneity in the 1970s and 1980s followed by a period of convergence. Southern states also experienced a period of convergence after the 1990s. Looking at individual states, Alabama and Illinois experienced much more pronounced movement in state public opinion towards welfare spending compared to other states, such as California or Minnesota, suggesting heterogeneous trends across states.

Finally, Figures 4.9 and 4.10 show how state residents changed their preferences towards smoking restrictions in restaurants and workplaces, respectively, from 1991 to 2006. Similar to education spending, state residents have increased support for smoking restrictions in both
restaurants and workplaces, regardless of state or region. In addition, support for restrictions in workplaces has increased at a faster rate compared to support for restrictions in restaurants. However, there are also some important differences across regions and states. For both restaurants and workplaces, the West and Northeast are more supportive of restrictions compared to the South and Midwest, which confirms patterns shown in Chapter 3. There is some evidence of heterogeneous trends, particularly across regions. For instance, states in the West and Northeast trended at much faster rates for both types of restrictions compared to other regions. The Midwest, in particular, showed much more of a gradual movement in support for restrictions in restaurants compared to other regions. In addition, there is some evidence of divergence in the Northeast as states started to trend separately in their preferences towards restrictions in restaurants and workplaces. Looking at individual states, the most striking pattern in Figure 4.9 is the trend in California, which is an anomaly, compared to other states. California increased its support for smoking restrictions in restaurants at a faster rate and earlier compared to other states suggesting that it lead the way in public opinion. Alabama also shows a decline in support for smoking restrictions in both public places in the 2000s, which makes it quite different from other states in the region and across the country.

Once again, I use MLM to empirically assess whether state public opinion is changing over time and whether these changes are unique to particular states after controlling for unit heterogeneity and common temporal trends. Specifically, I estimate an unconditional polynomial model with a fixed cubic effect of time for each state-level measure. As before, the intercept represents the average level of state public opinion in the first year (where year is set to zero for the first year in the series). For the death penalty the first year is 1960, for abortion it is 1980, for education and welfare spending the first years are 1975 and 1974, respectively and for anti-smoking preferences the first years are 1991. To capture non-linear change, I include a year slope, a year squared slope, and a year cubed slope. These three terms work together to describe
curved trajectories. There is one exception to this overall model, however. With welfare spending, the addition of year to the fourth power greatly improved model fit. Hence, a year slope to the fourth power is added to the model for welfare spending.

I test whether the year slopes are varying across states to assess heterogeneous patterns of change. Via model comparisons, the additions of the random slopes for the year and year squared coefficients resulted in significant improvements to random intercept models with REML deviance differences (5 df)=956 ($p<.001$) for the death penalty, (5 df)=380 ($p<.001$) for abortion, (5 df)=340 ($p<.001$) for education spending, (5 df)=396 ($p<.001$) for smoking restrictions in restaurants, and (5 df)=288 ($p<.001$) for smoking restrictions in workplaces. For welfare spending, the random slope for the year squared or year cubed coefficient did not result in a significant improvement of the model. However, for welfare spending the addition of a random slope for the year coefficient resulted in a significant improvement to a random intercept only model with REML deviance differences of (2 df)=248 ($p<.001$).

Results for the fixed and random components of the models are shown in Table 4.3. We can obtain the 95% confidence interval (CI) for the random variation around the intercepts by adding and subtracting 2 standard deviations of the accompanying random variance terms to explore state heterogeneity in the first time period. As shown in Table 4.3, the mean level of the proportion favoring the death penalty in 1960 is .52 with a 95% CI of .34 to .71 indicating that some states had relatively low levels of support for the death penalty in 1960 while others had a majority who favor the death penalty for persons convicted of murder. The mean level of the proportion favoring abortion in 1980 is .37 with a 95% CI of .22 to .52. This suggests that there are a few states in which the majority of residents favor legalized abortion in 1980. The mean level of the proportion favoring additional spending in education in 1975 is .51 with a 95% CI of .37 to .64. The mean level of the proportion favoring additional spending in welfare in 1974 is .24 with a 95% CI of .13 to .35. This suggests that no state has a majority of residents
who favor additional spending on welfare. Finally, the mean level of the proportion favoring smoking restrictions in restaurants in 1991 is .41 with a 95% CI of .33 to .49 while the mean level of the proportion supporting restrictions in workplaces in 1991 is .55 with a 95% CI of .44 to .65. There are no states with a majority who supports smoking restrictions in restaurants in 1991, while opinion is much more divisive across states in regards to smoking restrictions in workplaces in 1991. Generally, these analyses underscore the large unit heterogeneity in state preferences towards specific policy issues. Moreover, it confirms the descriptive analyses in Table 4.1; preferences towards the death penalty, education spending, and anti-smoking legislation have larger unit heterogeneity compared to preferences towards abortion or welfare spending.

We can also obtain the 95% confidence interval (CI) for the random variation around the fixed effects of year and year squared by adding and subtracting 2 standard deviations of their accompanying random variance terms. For the death penalty, the mean year slope is .02 with a 95% CI of .001 to .04 indicating that some states changed more quickly than others over time. The mean year squared coefficient for the death penalty is .0002 with a 95% CI of -.0004 to .0004. The mean year slope for abortion attitudes is -.01 with a 95% CI of -.04 to .02 indicating that some states saw little or no change in abortion attitudes over time while others experienced a slightly larger decline than the average. The mean year squared coefficient for abortion attitudes is .003 with a 95% CI of -.002 to .002. The mean year slope coefficient for education preferences is .01 with 95% CI of -.01 to .02 indicating that some states changed faster in their education preferences over time while others stayed relatively stable in education preferences. The mean year squared slope for education preferences is .0009 with a 95% CI of -.0006 to .0005. The mean year slope for welfare spending preferences is -.06 with a 95% CI of -.064 to -.057 indicating that while all states declined in their welfare spending preferences some did so more steeply than others. Finally, the mean year slope for restrictions in restaurants is .02 with a
95% CI of .030 to .002 while the mean year slope for restrictions in workplaces is .005 with a 95% CI of .021 to .011. While the analyses suggest that state public opinion across all of these issues experienced heterogeneous trends, we know from Figures 4.4-4.10 that the differences are larger for some issues (e.g., the death penalty) compared to others (e.g. education spending).

Finally, Figure 4.11 tracks the Spearman rank correlations over time for all states. As before, I rank the states according to their levels on each public opinion measure for each year. I then look at the correlations of the rank orders in the first year with the subsequent years. Again, the logic is that if states are trending heterogeneously on state public opinion, then the relative rankings of states should be less correlated as time progresses. As shown in Figure 4.11, for the death penalty, rank correlations with the 1960 state ranks have declined substantially over time, suggesting that states are exhibiting heterogeneous trends. For abortion, correlations with 1980 state ranks remain relatively stable throughout the entire time period. This pattern is consistent with the above analyses suggesting that state abortion attitudes are relatively stable across time. Figure 4.9 shows that education spending shows a general decline in state ranks particularly in the 1980s followed by a gradual increase until 2000. This suggests that although states are changing their support for additional funding for education, the majority of states are moving in fairly homogeneous ways. Interestingly, the rank correlations for welfare spending point to a cyclical pattern of change across time. State ranks are highly correlated with the 1972 state ranks in the early and later years, but decline in the middle of the time trend. Coupled with the analyses above, this suggests that public opinion towards welfare spending is changing over time in heterogeneous ways, yet because the change is cyclical, state ranks at later years are similar to early years. Finally, the rank correlations for preferences towards anti-smoking legislation in restaurants and workplaces have declined throughout the entire time period. This suggests that movement in anti-smoking preferences exhibits some heterogeneity across states.
In this section, I performed more rigorous analyses about the dynamic properties of state public opinion on specific issues. I find that the patterns of change depend on the issue and are vastly different from global indicators presented at the beginning of the chapter. Preferences towards the death penalty changed gradually over time with evidence of heterogeneous changes. On the other hand, abortion attitudes were relatively stable throughout the time period. Preferences towards education spending also experienced large changes over time, although this change was felt similarly across states. Preferences towards welfare spending changed in cyclical ways across time with evidence of heterogeneous trends. Finally, preferences towards anti-smoking legislation experienced large changes and there is some evidence of heterogeneous changes.

Summary

The goal of this chapter was to explore the dynamic properties of state public opinion. I asked: is state public opinion stable or dynamic? And, if state public opinion is dynamic, do states share a common trend or are they trending uniquely over time? Table 4.4 provides a summary analysis of the stability and trends of the various public opinion measures examined in this chapter. State partisanship, preferences towards the death penalty, preferences towards welfare spending, and anti-smoking preferences are dynamic across time with strong regional heterogeneity. On the other hand, state ideology and attitudes towards abortion show stability across time with slight changes occurring infrequently.

Methodologically, this suggests that scholars are missing important dynamics when pooling information across time to measure state partisanship, the death penalty, education spending, welfare spending, and anti-smoking preferences. Moreover, it is not enough to only include yearly information about time trends for state partisanship, the death penalty, welfare spending, and anti-smoking legislation to capture linear change, particularly since states and
regions exhibit heterogeneous patterns of change in these areas. On the other hand, there is evidence that pooling information across time to measure state ideology and abortion are acceptable ways to capture cross-sectional heterogeneity in state public opinion.

Theoretically, the analyses suggest that important changes in state policy may be accounted for by differential trends in state public opinion, particularly for policy relating to the death penalty, welfare spending, and anti-smoking legislation. Education policy, however, may be less responsive to specific state trends once national trends are accounted for, since states tend to move in parallel ways. Changes in state abortion policies cannot be accounted for simply by attitudes towards abortion since they are fairly stable across time (at least in relation to the general abortion question used here). Instead, abortion policies reflect cross-sectional differences in abortion attitudes as opposed to changes in attitudes in specific states. In the next chapter, I test some of these hypotheses directly by linking the dynamic public opinion measures to specific policy changes in the states.
References for Chapter 4


Table 4.1 Descriptive Information for State Public Opinion across States and Years

<table>
<thead>
<tr>
<th>Global Indicators of Public Opinion</th>
<th>Mean</th>
<th>Variance</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>State Partisanship</td>
<td>Overall</td>
<td>.38</td>
<td>.0060</td>
</tr>
<tr>
<td></td>
<td>Across States</td>
<td>.0050</td>
<td>.07</td>
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<tr>
<td></td>
<td>Across Time</td>
<td>.0011</td>
<td>.03</td>
</tr>
<tr>
<td>State Ideology</td>
<td>Overall</td>
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<td>.0011</td>
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<td></td>
<td>Across States</td>
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<tr>
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<td>Across Time</td>
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<td>.02</td>
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</tbody>
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<table>
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<th>Specific Indicators of Public Opinion</th>
<th>Mean</th>
<th>Variance</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Death Penalty</td>
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<td></td>
<td>Across States</td>
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<td>.04</td>
</tr>
<tr>
<td></td>
<td>Across Time</td>
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<td>.09</td>
</tr>
<tr>
<td>Abortion</td>
<td>Overall</td>
<td>.39</td>
<td>.0078</td>
</tr>
<tr>
<td></td>
<td>Across States</td>
<td>.0056</td>
<td>.07</td>
</tr>
<tr>
<td></td>
<td>Across Time</td>
<td>.0020</td>
<td>.04</td>
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<tr>
<td>Education Spending</td>
<td>Overall</td>
<td>.63</td>
<td>.0079</td>
</tr>
<tr>
<td></td>
<td>Across States</td>
<td>.0017</td>
<td>.04</td>
</tr>
<tr>
<td></td>
<td>Across Time</td>
<td>.0063</td>
<td>.08</td>
</tr>
<tr>
<td>Welfare Spending</td>
<td>Overall</td>
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<td>.0033</td>
</tr>
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<td>Across States</td>
<td>.0016</td>
<td>.04</td>
</tr>
<tr>
<td></td>
<td>Across Time</td>
<td>.0017</td>
<td>.04</td>
</tr>
<tr>
<td>Smoking Bans: Restaurants</td>
<td>Overall</td>
<td>.51</td>
<td>.0096</td>
</tr>
<tr>
<td></td>
<td>Across States</td>
<td>.0041</td>
<td>.06</td>
</tr>
<tr>
<td></td>
<td>Across Time</td>
<td>.0056</td>
<td>.07</td>
</tr>
<tr>
<td>Smoking Bans: Workplaces</td>
<td>Overall</td>
<td>.66</td>
<td>.0102</td>
</tr>
<tr>
<td></td>
<td>Across States</td>
<td>.0039</td>
<td>.06</td>
</tr>
<tr>
<td></td>
<td>Across Time</td>
<td>.0064</td>
<td>.08</td>
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Table 4.2 Hierarchical Linear Model of the Effect of Time on State Partisanship and State Ideology

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Random Effects</th>
<th>Fit Statistics</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Intercept</td>
<td>Year Variance</td>
</tr>
<tr>
<td>Proportion Democrat</td>
<td>.42 *** (.01)</td>
<td>-.01 *** (.001)</td>
</tr>
<tr>
<td>Proportion Liberal</td>
<td>.21 *** (.004)</td>
<td>.0003 (.001)</td>
</tr>
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</table>

Note: * p<.05, ** p<.01, *** p<.001 with a two-tailed test. Standard errors in parentheses. The model also estimates the covariance between all of the random effects; these are not presented in the table to preserve space, but are available from the author by request.
Table 4.3 Hierarchical Linear Model of the Effect of Time on Specific Public Opinion

<table>
<thead>
<tr>
<th></th>
<th>Fixed Effects</th>
<th>Random Effects</th>
<th>Fit Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intercept</td>
<td>Year Slope</td>
<td>Year² Slope</td>
</tr>
<tr>
<td>Proportion Favoring</td>
<td>.52 ***</td>
<td>.02 ***</td>
<td>.00001</td>
</tr>
<tr>
<td>the Death Penalty</td>
<td>(.01)</td>
<td>(.001)</td>
<td>(.00006)</td>
</tr>
<tr>
<td>Proportion Favoring</td>
<td>.37 ***</td>
<td>-.01 ***</td>
<td>.003 ***</td>
</tr>
<tr>
<td>Legalized Abortion</td>
<td>(.01)</td>
<td>(.003)</td>
<td>(.0003)</td>
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<td>Proportion Favoring</td>
<td>.51 ***</td>
<td>.01 ***</td>
<td>.0011 ***</td>
</tr>
<tr>
<td>Increase in Education</td>
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<td>(.002)</td>
<td>(.00013)</td>
</tr>
<tr>
<td>Spending</td>
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<td></td>
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</tr>
<tr>
<td>Proportion Favoring</td>
<td>.24 ***</td>
<td>-.06 ***</td>
<td>.013 ***</td>
</tr>
<tr>
<td>Increase in Welfare</td>
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<td>(.002)</td>
<td>(.0003)</td>
</tr>
<tr>
<td>Spending</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Proportion Supporting</td>
<td>.41 ***</td>
<td>.02 ***</td>
<td>-.001 ***</td>
</tr>
<tr>
<td>Smoking Restrictions</td>
<td>(.01)</td>
<td>(.002)</td>
<td>(.0003)</td>
</tr>
<tr>
<td>in Restaurants</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion Supporting</td>
<td>.55 ***</td>
<td>.006 *</td>
<td>.003 ***</td>
</tr>
<tr>
<td>Smoking Restrictions</td>
<td>(.01)</td>
<td>(.002)</td>
<td>(.0003)</td>
</tr>
<tr>
<td>in Workplaces</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: * p<.05, **p<.01, ***p<.001 with a two-tailed test. Standard errors in parentheses. The model also estimates the covariance between all of the random effects; these are not presented in the table to preserve space, but are available from the author by request.
Table 4.4 Summary Table of Opinion Trends Across States

<table>
<thead>
<tr>
<th>Global Indicators of Public Opinion</th>
<th>General Trend</th>
<th>Homogeneity across States</th>
</tr>
</thead>
<tbody>
<tr>
<td>State Partisanship</td>
<td>Dynamic</td>
<td>Heterogeneous</td>
</tr>
<tr>
<td>State Ideology</td>
<td>Stable</td>
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</table>

<table>
<thead>
<tr>
<th>Specific Indicators of Public Opinion</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Death Penalty</td>
<td>Dynamic</td>
<td>Heterogeneous</td>
</tr>
<tr>
<td>Abortion</td>
<td>Stable</td>
<td></td>
</tr>
<tr>
<td>Education Spending</td>
<td>Dynamic</td>
<td>Homogeneous</td>
</tr>
<tr>
<td>Welfare Spending</td>
<td>Dynamic</td>
<td>Heterogeneous</td>
</tr>
<tr>
<td>Smoking Bans: Restaurants</td>
<td>Dynamic</td>
<td>Heterogeneous</td>
</tr>
<tr>
<td>Smoking Bans: Workplaces</td>
<td>Dynamic</td>
<td>Heterogeneous</td>
</tr>
</tbody>
</table>
Figure 4.1 Four Hypothetical Scenarios of State Public Opinion Change

**Scenario 1: Gradual Change and Homogeneous Trends**

**Scenario 2: Abrupt Change and Homogeneous Trends**

**Scenario 3: Gradual Change and Heterogeneous Trends**

**Scenario 4: Abrupt Change and Heterogeneous Trends**
Figure 4.2 Proportion Democrats 1978-2006

Northeast

South

West

Midwest
Figure 4.3 Proportion Liberals 1978-2006

Northeast

South

West

Midwest

Legend:

PA, NY, MA, CT

AL, FL, TX, VA

CA, AZ, WA, CO

IL, MN, OH, MI
Figure 4.4 Spearman Rank Correlations over Time on Global Indicators
Figure 4.5 Proportion Favoring Death Penalty 1960-2002
Figure 4.6 Proportion Favoring Abortion 1980-1998
Figure 4.7 Proportion Favoring Additional Education Spending 1974-2002

Northeast

South

West

Midwest
Figure 4.8 Proportion Favoring Additional Welfare Spending 1973-2002

Northeast

South

West

Midwest
Figure 4.9 Proportion Favoring Smoking Restrictions in Restaurants 1991-2006

Northeast

South

West

Midwest
Figure 4.10 Proportion Favoring Smoking Restrictions in Workplaces 1991-2006
Figure 4.11 Spearman Rank Correlations for Specific Public Opinion over Time

Death Penalty

Abortion

Education Spending

Welfare Spending

Smoking Restrictions: Restaurants

Smoking Restrictions: Workplaces
Chapter 5

Dynamic Policy Responsiveness in the States

How policymakers 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; Burstein 2003).

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 (e.g., Erikson, Wright, and McIver 1993). More recent studies have compared models across two or three points in time (Johnson et al. 2005; Camobreco & Barnello 2008; Norrander 2000). These studies are important first steps toward investigating the dynamic relationship between public opinion and policy, but all lack dynamic—e.g. yearly—measures of state public opinion, no doubt because of the difficulties in reliably measuring state public opinion over time as discussed in Chapter 2. Without truly dynamic measures of state public opinion, scholars have been unable to test whether dynamic models of responsiveness characterize policymaking at the state level to the same extent as at the national level. For instance, we do not know whether and to what magnitude public opinion exhibits short or long term effects on policy and vice versa over time in the US states. This is an important
shortcoming since state governments determine issues (e.g., education and poverty) and regulate services (e.g., health care) that directly impact people’s lives.

Using the measures developed in Chapters 2 and 3, I test theories of dynamic responsiveness in the American states using two types of policy changes: incremental policy changes in this chapter and policy innovations in Chapter 6. Incremental policy changes are those that occur continuously over time, such as expenditures, while policy innovations are episodic as states adopt new policies at one point in time. More detail about policy innovations is provided in Chapter 6. For the current chapter, I start by outlining various theories of dynamic responsiveness, most of which are drawn from studies conducted at the national level. I then use three issue areas: education, welfare, and anti-smoking legislation to test these theories. I find that the thermostatic model of policy responsiveness best characterizes the dynamic relationship between state public opinion and policy for education and welfare expenditures. The dynamic relationship between policy and opinion for anti-smoking legislation is consistent with traditional theories of responsiveness, but goes against what is predicted by the thermostatic model. I end with a discussion about the implications of these results.

Models of Dynamic Policy Responsiveness

The dynamic relationship between public opinion and policy has been of interest to scholars of American politics since at least the 1960s (e.g. Miller and Stokes 1963), yet it is only since the early 1990s that scholars have had the methodological capacity to empirically examine how policy preferences are translated into policy over time. Since then, scholars have concentrated on three interrelated research questions. First, do changes in public opinion influence changes in policy? Second, does public opinion respond in rational ways to policy changes over time? And, finally, is the direction of causality from opinion to policy one directional or does opinion and policy exist in equilibrium constantly reacting to each other?
In a democracy, most would answer the first question with an emphatic “yes” since the principle of popular sovereignty implies some degree of dynamic policy responsiveness. The expectation is that if large numbers of ordinary citizens shift their opinions, policies should shift in the direction that people want. And, the main mechanism that links mass preferences to policies is elections. Legislators, who are primarily interested in re-election, actively gauge public opinion and enact policies that fall in line with changing preferences or otherwise risk being ousted from office. The most comprehensive evidence that national policy changes respond to changes in mass opinion comes from Erikson, MacKuen, and Stimson’s (2002) seminal book *The Macropolity*. Using their national policy mood measure and aggregate measures of policy liberalism in the House, the Senate, the Presidency and the Supreme Court, Erikson, MacKuen, and Stimson (2002) find that changes in policy mood positively influences policy liberalism in the future. As policy mood becomes liberal so does policy activity and output within the House, the Senate, the Presidency and the Supreme Court. The authors conclude that “there exists about a one-to-one translation of preferences into policy” (Erikson, MacKuen, and Stimson 2002 316). Dynamic policy responsiveness has also been demonstrated using case studies on particular issue domains such as welfare (Weaver 2000), Medicare (Jacobs 1993), foreign policy (Hartley and Russett 1992), and expenditures (Wlezien 1995; Wlezien 2004) to name a few (see also Geer 1996; Bartels 1991).

The question of whether public opinion responds to policy changes also has a long history in public opinion research. Some assume that the public is unable to respond to policy changes since the majority of citizens have either non-attitudes (Converse 1964) or little political knowledge and information (Delli Carpini & Keeter 1996; Zaller 1992) from which to form true policy preferences. Yet, at the aggregate level, the evidence suggests that the public responds in rational ways to political events and policy changes. There were hints that public opinion and policy moved in tandem across time in Page and Shapiro’s (1992) study of public support
towards economic, social, and foreign affairs issues. Page and Shapiro (1992) concluded that the mass public reacts in “rational” and expected ways to current affairs and policy outputs, at least at the national level. Wlezien and Goggin (1993) find similar results when looking at abortion policy and opinion during the 1980s; national preferences became more supportive of abortion, albeit only slightly, in response to court cases and Supreme Court nominations that challenged precedent set by Roe v. Wade. More recent work confirms this early work finding that public opinion responds to actual political activity over time (Erikson, MacKuen and Stimson 2002; Wlezien 1995).

While past research suggests that there exists a dynamic relationship between opinion and policy, debates continue concerning the direction of causality. Does causality run from opinion to policy, from policy to opinion, or does opinion and policy exist in equilibrium constantly reacting to each other? The answer to this question has profound implications for how we think about and gauge our democracy. Consider first a one directional model called the *simple responsiveness model* whereby changes in public opinion positively influences policy changes and not vice versa (Norrander 2000). This model is the conventional one in which the elections serve as the main mechanism linking the public to policy outputs. The simple responsiveness model is most consistent with Erikson, Wright, and McIver (1993) who find a high correlation between state ideology and state policy liberalism; “thus, state opinion is virtually the only cause of the net ideological tendency of policy in the state” (Erikson, Wright, and McIver 1993 81).

The simple responsiveness model is in stark contrast to another one directional model in which elites actively shape mass preferences instead of the other way around. The “*competitive elitism model*” suggests that elites have policy proposals in mind and use political rhetoric to increase the public’s reception and support of these proposals (Jacobs and Shapiro 2000). Moreover, institutional advantages make some elites, particularly popular presidents, more successful at priming issues and changing the public’s perceptions of these issues (Cohen 1997;

Many believe that both one-directional models call into question the success of our democracy. A main assumption of the simple responsiveness model is that public opinion is mostly exogenous from policy changes. Public opinion may change in response to political events or other stimuli, but it moves independently and before policy changes. Theoretically, this suggests that politicians who understand complex problems better than the common person (e.g., on economic trends or foreign policy) do not shape new policy before the public demands it or as a result of anticipating public opinion. As a result, many have questioned this assumption on methodological (Page 1994; 2002; Burstein 2003) as well as theoretical grounds (Norrander 2000; Page and Shapiro 1983). Others argue that a successful democracy requires the public to respond to policy changes; “after all, if the public did not notice and respond to changes in policy, then politicians would have little interest to represent what the public wants” (Wlezien 1995 981-982; see also Wlezien and Soroka 2009).

The competitive elitism model goes against what scholars, pundits, and theorists traditionally associate with a democracy which is by definition intended to make politicians responsive to constituents. Democracy is often evaluated by how much influence the public has; as Erikson, Wright, and McIver (1993) write “we often gauge the quality of a democratic government by the responsiveness of public policymakers to the preferences of the mass public” (1). If public opinion is completely driven by political elites, we would call into question the quality of our democracy. The competitive elitism model also provides an ironic conundrum: why would elites even bother to influence public opinion if it has little impact on policy outcomes (Manza and Cook 2002)?
It is because of these issues that scholars have started to theorize that public opinion and policy exist in equilibrium over time, constantly reacting to each other. A growing body of work reveals that public opinion and policy often exist in a dynamic relationship characterized as a thermostat (Wlezien 1995, 2004; Soroka and Wlezien 2004, 2005; Gussmano, Schlesigner, and Thomas 2002; Johnson et al. 2005; Eichenberg and Stoll 2003; Erikson, MacKuen and Stimson 2002). The *thermostatic model of policy responsiveness* posits that policy changes follow changes in public opinion; however, public opinion also reacts to policy changes across time. However, unlike the competitive elitism model, public opinion reacts *negatively* to policy changes over time. When policy output increases, the public’s preference for more policy decreases; when policy decreases, the public’s preference for more policy increases. The result is a reactive system of governance where public opinion and policy constantly adjust and readjust to each other over time.

The thermostatic model of representation is consistent with the traditional view of policy responsiveness (Downs 1957) whereby elected officials enact policies based on changing opinions for fear of being ousted at the next election cycle. In addition, citizens react in a collective, rational way to the actions of government officials. Because public opinion is viewed as endogenous, the public as an aggregate is characterized as being reasonably well informed about what policymakers are doing.

Theoretically, the thermostatic model of policy responsiveness implies a specific type of dynamic relationship between public opinion and policy, which I test in this chapter. Specifically, this dynamic model has two moving parts since it is a two directional model. The first part suggests that the public has a measureable influence over policy changes. And, secondly, policy changes have an impact on public opinion. Below I describe these two parts in more detail and consider the short and long term mechanisms that account for the influence of policy on public opinion and vice versa.
The Influence of Public Opinion on Policy

In a responsive democracy public opinion should have a positive influence on policy changes. As public opinion changes, policy changes in the same direction should follow. Elections serve as the main connection between mass preferences and elites (Key 1966; Miller and Stokes 1963; Mayhew 1974; Fiorina 1981). Elections are central to two mechanisms that explain the responsiveness of policy changes to mass public preferences: electoral turnover and political expediency (Erikson, MacKuen, and Stimson 2002). Electoral turnover accounts for the fact that the public elects elites who are in line with their policy preferences who then enact similar policies; for instance, a liberal public elects Democrats into office who then enact liberal policies. At the same time, however, elected officials catch wind of changing public opinion and adjust their behavior accordingly because they are motivated by re-election; this is political expediency. Both of these mechanisms—electoral turnover and political expediency—have been found to explain the relationship between public opinion and policy at the national level (Erikson, MacKuen, and Stimson 2002).

If electoral turnover and political expediency account for the positive effect of public opinion on policy changes, we would expect public opinion to exhibit both short and long term impacts on policy change. In the short term, changing levels of public opinion induce elected officials to enact policies in accordance with the mass preferences. But, the influence of public opinion on policy does not stop there; changing public opinion also influences the ideological balance of officials who are elected to office in the future. Therefore, over the long haul, shifts in public opinion in one direction should also have lasting impacts on policy change as officials who are in line with current levels of public opinion replace other elites.

The Influence of Policy on Public Opinion

While the impact of public opinion on policy is expected to be positive, the influence of policy on public opinion should be negative, according to the thermostatic model, as the public
adjusts its preferences in response to the actions of policymakers. As policy runs in a particular direction, the more the public should demand policies in the opposite direction. The mechanisms by which public opinion responds to policy change rest on the acquisition and availability of political information. First, public opinion may respond to policy almost immediately as political information is transmitted by majority and opposition groups. In this scenario, public opinion responds to political rhetoric and discourse as transmitted by the media and political elites (Jacobs and Shapiro 2000; Zaller 1992; Stimson 1991). Indeed, there is evidence that newspaper and television exposure influences opinions at the individual (Bartels 1993; Mutz and Martin 2001) and aggregate levels (MacKuen, Erikson, and Stimson 1992). And, while the public may not know the specifics about the policy changes, they will be informed enough to understand the direction and scope of the change, particularly if the policy changes are salient (Page and Shapiro 1992; Erikson, Wright, and McIver 2002; Burstein 2003). This is exactly what Erikson, MacKuen, and Stimson (2002) find; the response of the mass public to changing policy was virtually immediate in response to legislative activity.

But, public opinion may also respond to policy changes gradually over time as citizens experience the effects of those changes directly. This second, long term mechanism requires that policy changes occur in the preferred direction, otherwise, the “policy itself may not relieve the thermostatic pressure for policy change” (Johnson, Brace, and Arceneaux 2005 91). In an important paper, Johnson et al. (2005) find that the public responds to policy changes towards the environment in precisely this way. Residents living in states where environmental conditions improved after policy intervention showed the expected negative relationship to policy changes (Johnson et al. 2005). On the other hand, residents living in states where environmental conditions stayed the same still demanded environmentally friendly policies even after policy changes occurred (Johnson et al. 2005).
To summarize, the thermostatic model of policy responsiveness suggests that mass preferences and policy changes react to one another over time. The expectation is that changes in public opinion will be followed by congruent changes in policy. Furthermore, it is hypothesized that changes in public opinion will have both short and long term effects on policy changes as politicians respond to changing public opinion directly through political expediency and indirectly via electoral turnover. Conversely, changes in policy are expected to induce incongruent changes in public opinion. The influence of policy on public opinion also has short and long term components. Mass preferences respond to policy changes in the short term as the public is informed about the policy process. In the long term, public opinion responds to policy as citizens directly experience policy outcomes.

**Testing the Thermostatic Model in the States using Expenditure Data**

For the remainder of the chapter, I test the hypotheses outlined above concerning the thermostatic model of responsiveness in the states. By testing for the thermostatic model, which is a two directional model of causation, I am also testing for the simple responsiveness model and competitive elitism model. Hence, at the end of the chapter, I am able to assess (1) whether dynamic policy responsiveness exists at the state level, (2) what form this model takes (e.g., simple responsiveness, competitive elitism, or thermostatic), and (3) whether the model of dynamic responsiveness varies across issue domains.

I start the analyses by looking specifically at expenditure data in the areas of education and welfare. To date, the thermostatic model has primarily been tested using expenditure data (Wlezien 1995) or other composite measures of policy activity (Erikson, MacKuen, and Stimson 2002) hence, it is appropriate to start the state level analyses using similar data. As we will see, public opinion and policy on education and welfare spending follow the expected patterns of the thermostatic model quite well. In a later section, I will test whether the thermostatic model continues to perform as well in another issue area: anti-smoking restrictions.
Measuring Policy Changes in Education and Welfare

As explained in Chapter 3, states now provide the largest portion of funding for public education. To capture variation in policy outcomes towards education spending, I measure per pupil spending in fall enrollment in public elementary and secondary schools adjusted by yearly measures of state consumer price index (Berry, Fording, and Hanson 2000) from FY1969 to FY2004. These adjustments correct for differences in the price of products and inflation for each state over time. Measuring education spending via per pupil expenditures or some variant of it is common practice throughout the literature (Berkman and Plutzer 2005; Saeki 2005; Lascher et al. 1996; Radcliff and Saiz 1998; Wong 2004) and captures both longitudinal and cross-sectional variation in education policy across the states.

To capture policy changes on welfare across the states, I measure the AFDC/TANF benefits for a family of four with no income adjusted by yearly measures of state consumer price index. Capturing state differences towards welfare using AFDC benefits based on family size is well established in the literature (Berry, Fording, and Hanson 2003; Hill and Leighley 1992; Gilens 1995; Howard 1999; Plotnick and Winters 1985).

Measuring Dynamic Public Opinion on Education and Welfare

I use the public opinion measures developed in Chapter 3 to capture state preferences towards education and welfare spending over time. Specifically, I measure the percentage who favored an increase in education spending out of those who favored a decrease or wanted spending to stay the same using the General Social Survey, National Election Survey, Gallup polls, CBS/NYT polls, and Roper polls. Similar to education, I measure the percentage who favored an increase in welfare spending out of those who favored a decrease or wanted spending to stay the same using the General Social Survey, National Election Survey, Gallup polls, CBS/NYT polls, and Roper polls.
As can be seen from the question wording in Table A1 in Appendix A, few questions specifically mention the national government and none capture individual preferences towards spending at the state level. I follow the lead of other scholars (e.g., Berkman and Plutzer 2005; Brace et al. 2002) and assume that these questions capture a broader ideology about government spending. For instance, questions about education spending represent citizens’ “tastes” for education more generally, regardless of the level of government. This is exactly what Berkman and Plutzer (2005) argue when using the General Social Survey to capture state level preferences towards education spending. In addition, their opinion measures influenced within-state outcomes, which provide additional evidence that these questions are capturing a broader opinion concerning governmental activity that varies across states in important ways. Furthermore, the lack of state polls that asks about state level spending consistently across time warrants use of national level surveys, even if the questions asked were not specifically about state government.

The aggregate public opinion data cover the 50 states as well as DC from 1975-2000 for education opinion and from 1974-2000 for welfare attitudes, although the exact time series trends varies across states. For instance, the data for Alaska starts in 1988 because of missing data on the public opinion measure whereas California has valid data throughout the time period. All states are missing on both public opinion measures in 1995, 1997, and 1999 because questions were not asked about education or welfare spending in these time periods. These gaps limit our ability to make inferences about dynamic relationships between public opinion and policy, which require continuous time series. There are a number of different options to impute data for the missing values including mean interpolation (for instance, to get a value for time $t$ simply take the mean of the values at $t-1$ and $t+1$), pooled time series cross sectional multiple imputation, and individual level multiple imputation estimated prior to MRP.

As explained in Appendix B, I estimated state public opinion for the three missing years (1995, 1997, and 1999) using each of these techniques. I find little difference in the estimates.
using each of these techniques (see Tables B1 and B2 and Figures B1-B3 in Appendix B). The models reported in this chapter use the estimates for 1995, 1997, and 1999 obtained from performing multiple imputation at the pooled time series cross sectional state level. More detail on how multiple imputation was performed at the state level can be found in Appendix B. In addition, the models presented in this paper are nearly identical regardless of which technique is used to recover missing data for 1995, 1997, and 1999 (see Tables B3-B6 in Appendix B). The exception, however, is the influence of welfare policies on public support for additional welfare spending, which I discuss below.

**Results: The Influence of Public Opinion on Expenditures**

I first investigate the short and long term influences of public opinion on education and welfare policy. I control for a number of other state level factors that may influence policy changes in education and welfare expenditures. For both issue areas, I control for various economic and demographic indicators that capture the capacity of states to provide for their residents (Hanson 1984; Plotnick and Winters 1985; Bailey & Rom 2004). State income is measured as the per capita income adjusted by state consumer price index. This data was obtained from the Bureau of Economic Analysis (Table SA04). I expect states with more wealth to spend more on education and welfare policies. Racial diversity, as many scholars have shown, has a pervasive influence over state policies, particularly for welfare (Hero and Tolbert 1995; Johnson 2001; Hero 2003), but also for education spending (Gray and Jacob 1996; Hero 2003). To capture racial diversity, I measure the percentage of the adult state population that is African American. I expect for states with larger numbers of African Americans to spend less on education and welfare.

Political variables also matter for policy changes with the typical expectation that states under Democratic control, with more competitive partisan politics, and with liberal legislators tend to spend more on education and welfare. Democratic strength is measured as a sum of
percentages of state house and senate that are Democrats plus 100 if the governor is a Democrat (Bailey and Rom 2004). Party competition is measured using an index based on district level outcomes of state legislative elections with higher values indicating greater competition (Holbrook and Van Dunk 1993). Government ideology is measured using updated scores from Berry et al. (1998) where higher values reflect more liberal elite preferences. Finally, I control for the ideological and partisan preferences of state residents. While the expectation is for more liberal and democratic leaning states to spend more on education and welfare (Erikson, Wright, and McIver 1993; Hill, Leighley, and Hinton-Andersson 1995), it is unclear whether global indicators will still predict policy changes once specific attitudes are taken into account. The percentage of residents who support the Democratic Party or who are liberal is measured using the MRP approach as explained in Chapter 2.

Because public opinion and policy are hypothesized to occur in equilibrium, I model the dynamic relationship via an Error Correction Model (ECM) shown in Equation 1.

\[
\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_0 \Delta X_t + \beta_1 X_{t-1} + \epsilon_t
\]

An ECM allows for the estimation of both short and long term effects of independent variables and tells us how quickly or slowly the system returns to equilibrium or the overall mean after being disrupted. The dependent variable captures the changes in policy over time and is measured by differencing per pupil spending for education and AFDC benefits for welfare. A lagged dependent variable (LDV) is included to account for time dependence, but also to directly capture the speed with which the system returns to equilibrium, as explained below. All independent variables are time varying with the exception of partisan competition, which only captures cross-sectional differences in policy changes. For all time varying covariates, I include both short and long term effects; that is, for each variable, I include both the differenced independent variable ($\Delta X_t$) and the lagged independent variable ($X_{t-1}$).
Table 5.1 shows the results from estimating an ECM for education and welfare policy in the US states across time. The coefficient on the lagged dependent variable ($\alpha_1$) gives the error correction rate with a value closer to zero indicating a slow return to equilibrium; this value is always negative. The coefficient on the lagged dependent variable for per pupil spending is -.02 compared with -.08 for AFDC benefits suggesting that per pupil spending is slower to return to its mean value when disrupted compared to welfare benefits.

Consistent with the thermostatic model of policy responsiveness, both public opinion measures have significant effects on policy changes, although the size and timing varies across policy. First, I focus on the results for education policy in the first column of Table 5.1. The coefficient on the differenced public opinion variable ($\beta_0$) gives us the short term effect of public opinion on the per pupil spending or welfare benefits. To get the estimated effect of a unit change in $X$, we simply multiply this effect with the coefficient ($\beta_0$). For example, the model predicts that an increase by 7 points (which is 2 standard deviations above the mean change) in support of additional education spending results in an increase in per pupil spending by roughly $50 and this impact is felt immediately (7*7). In more substantive terms, the model predicts that just a 3 point increase in support for education spending results in an additional $500 spent per classroom in the following time period (assuming 25 students per class). These results are not trivial. In contrast, the long term effect of public opinion on education spending is not significant using conventional significance levels.

Interestingly, the model in Table 5.1 shows that state ideology has a strong influence over education expenditures in both the short and long term. From Table 5.1, the short term effect of a 3 point change in state liberalism corresponds to an increase in per pupil spending by about $46.

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24 I also estimated a fixed effects and random effects ECM as well as an ECM with panel corrected standard errors (Beck and Katz 1995). The substantive results were nearly identical across the various models. These are available from the author by request.
The long term effect of public opinion on policy changes can be calculated using the coefficient of the lagged public opinion variable ($\beta_1$) by (De Boef and Keele 2008)

$$\text{Eq. 2} \quad \text{Long Run Effect} = \frac{\beta_1}{-\alpha_1} \times X$$

Using Equation 2, an increase by 3 points also equates to an increase in per pupil spending by about $900, which is distributed gradually over time. Hence, state liberalism has a direct, immediate, positive effect on per pupil spending and another, much bigger positive impact, distributed gradually over time. And, this effect rivals any changes in public opinion towards education spending specifically. We know, however, from Chapter 4 that state ideology is quite stable over time; hence, in substantive terms, the influence that changing state ideology has on education spending is quite small.

Turning to the results on welfare expenditures in Table 5.1, welfare attitudes exhibit both short and long term effects on AFDC benefits. State attitudes towards welfare spending have significant and positive short and long term effects on AFDC benefits. An increase by 3 points in support of additional welfare spending results in an increase in AFDC benefits for a family of four by roughly $4 immediately. Using Equation 2, the long run effect of a 3 point increase in attitudes towards welfare spending is $41. Again, this long run effect on welfare spending is not felt immediately; instead it is distributed gradually over time. Hence, public opinion towards welfare spending has a direct, positive, and immediate impact on the amount of AFDC benefits for a family of four and another, much bigger, positive impact, distributed over time.

How quickly does it take for the long run effect of welfare opinion to dissipate through the system? For instance, does a change in welfare opinion influence AFDC benefits in the first few years or does it take several decades to be realized? Figure 5.1 answers these questions by plotting the cumulative proportion of the long run effect of welfare opinion on benefits over time. The y-axis shows the proportion of the effect while the x-axis shows number of time periods into
the future that the effects occur. As shown in Figure 5.1, the effect that welfare opinion has on AFDC benefits takes time to be realized; by 10 years out only 60% of the effect of a 3 point increase has been felt by the system. In substantive terms, of the $41 maximum increase in AFDC benefits caused by an increase in support for welfare spending, only about $25 has been realized after 10 years. Hence, it takes over a decade for the effect of welfare opinion to fully influence policy changes in welfare.

In contrast to education spending where the ideology of state residents had a strong impact on per pupil spending, state liberalism is not significant for welfare policy. On the other hand, political competition and the proportion of African Americans have significant effects on AFDC benefits where they were not significant for per pupil spending. The more political competition in a state, the higher are AFDC benefits, which is consistent with early work on the effect of political competition on social benefits (e.g., Key 1949). In addition, the proportion of African Americans has a significant negative impact on AFDC benefits in the long term, which is consistent with previous research (e.g., Hero and Tolbert 1996).

To summarize, both education and welfare expenditures respond to changing levels of state attitudes. Consistent with the thermostatic model of policy responsiveness, per pupil spending increases in the short term as public support for education spending increases and AFDC benefits increase in the short and long term as public support for welfare spending increases. Next, I test whether policy changes on spending influence public support for education and welfare spending.

**Results: The Influence of Expenditures on Public Opinion**

As explained above, the thermostatic model of policy responsiveness asserts that public opinion and policy exist in equilibrium, constantly acting and reacting to each other. Not only should public opinion influence policy over time, but policy should also have a measureable influence over changes in public opinion. I theorized that policy may have both short and long
term impacts on public opinion via the acquisition of political information and experiences to actual policy changes. In this section, I test whether policy changes on per pupil spending and AFDC benefits exert significant influences over changes in public attitudes towards education and welfare spending. To ease interpretation of the coefficients, per pupil spending is now coded in $100s and AFDC benefits is now coded in $10s.

I control for a number of other factors that may influence changes in state public opinion over time. For both education and welfare, I control for certain state demographic characteristics. States with large numbers of African American residents are expected to endorse additional spending towards welfare (Johnson 2003). And, because blacks tend to be more liberal compared to other ethnicities, I expect states with large percentages of African Americans to also endorse additional spending on education. States that are highly educated are expected to endorse additional spending towards education (Berkman and Plutzer 2005); hence, the percentage of state residents with a college degree or higher is included in both models. Income is also typically associated with increased support for social spending; this is measured via the per capita income variable used in the previous analyses. State ideology and partisanship are included with the usual expectation that more liberal and democratic states will be more likely to endorse additional spending towards social programs (Erikson, Wright, and McIver 1993). These are the same measures as described in the preceding analyses. Finally, I include a national measure of public opinion towards education and welfare spending by simply taking the average across the states in each year. This accounts for any large, universal shifts in public opinion that may be occurring across the states in response to national phenomena (Page and Shapiro 1992).

I estimate the effect of policy on public opinion via an ECM as shown in Equation 1 to account for the short and long term effects of policy on public opinion. All independent variables are time varying, hence I include both lagged and differenced versions of the independent variables in the models. Results are shown in Table 5.2. As before, the coefficient on the lagged
dependent variable \((\alpha_1)\) gives the error correction rate with a value closer to zero indicating a slow return to equilibrium. The coefficients on the lagged dependent variable for state attitudes towards education spending and welfare spending are \(-.30\) suggesting that state public opinion is quicker to return to equilibrium when disrupted compared to policy.

The coefficient on the differenced policy variable \((\beta_0)\) gives us the short term effect of policy changes on public opinion towards education or welfare spending. Interestingly, for both education and welfare, there are no immediate short term influences of policy on public opinion since the coefficients are not significant. The null findings may be a result of low salience; perhaps there is no immediate political discourse on per pupil spending or AFDC benefits for state residents to respond. How the public opinion reacts to changes in policy across issues of varying salience is beyond the scope of this chapter, but is an interesting topic for future work.

On the other hand, policy changes have the expected negative influence over changes in public opinion for both education and welfare over the long term. For instance, the long run effect of a $600 increase (roughly 2 standard deviations above the mean dollar change) in per pupil spending is \(-1\). As per pupil spending increases, the proportion of residents endorsing additional spending on education will decrease by about 1 point. Yet, this long run effect on education spending is not felt immediately; instead it is distributed gradually over time. The long run effect of a $60 (roughly 2 standard deviations above the mean dollar change) increase in AFDC benefits for a family of four with no income is \(-.3\), which is distributed gradually over time. While these effects are small, they do suggest that sustained changes in policy have meaningful impacts on public opinion over the long run.

As before, I graph the long run effects of these policy changes on public opinion to assess how quickly these changes occur. Figure 5.2 plots the cumulative proportion of the long run effect of policy on opinion for both education and welfare. As can be seen from Figure 5.2, the long run effects of policy are realized much quicker compared to the effect of welfare opinion on
policy. For both education and welfare, close to 80% of the long run effects of policy on public opinion have occurred.

A note of caution must about the influence of AFDC benefits on welfare spending. As shown in Appendix B (see Table B6), inferences differ depending on the specific public opinion measure. Using mean interpolation, AFDC benefits appear to have insignificant short and long term effects on changes in attitudes towards welfare spending. Similarly, the model using MI at the individual level suggests that AFDC benefits have insignificant short and long term effects on changes in attitudes towards welfare spending. In models using the raw estimates on state public opinion towards welfare spending suggest similar inferences as reported in Table 5.2; there is a significant long term effect of AFDC benefits, but an insignificant short term effect of AFDC benefits on welfare attitudes.

For both education and welfare attitudes, national shifts in public opinion exert much larger, positive effects over changes in state public opinion in both the short and long term, as can be seen in Table 5.2. The percentage of state residents with a college degree or higher is also significantly related to changes in public opinion in the short term for education and welfare attitudes. An increase in the percentage of state residents who identify with the Democratic Party increases public support for education and welfare spending in the short term as does the percentage of state residents who are African American.25

**Testing the Thermostatic Model in the States using Anti-Smoking Legislation**

The analyses to this point suggest that the thermostatic model explains the dynamic relationship between public opinion and policy on education and welfare expenditures quite well. For the effect of opinion on policy, I find that both education and welfare opinion have significant

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25 In results available upon request, I also included lagged and differenced versions of consumer price index (CPI) to see if public opinion on expenditures is influenced by inflation. For support on education spending, CPI made no difference and was not significant at traditional levels. For support on welfare spending, CPI has a negative, short term influence ($\beta = -.28^{**}$). More important, substantive conclusions were unchanged with the addition of the CPI variables.
short term effects on expenditures. Welfare opinion has an additional long run effect on AFDC benefits. For the effect of policy on opinion, I find significant, long run effects of policy on both education and welfare opinion, however, no short run effects of policy on opinion were found. These results are consistent with previous research on the thermostatic model, which find that opinion influences policy and vice versa over time. Yet, the majority past research on the thermostatic model falls short in fully explaining the dynamic relationship between opinion and policy in two respects. First, most research has been conducted on incremental policy changes such as expenditure data (Wlezien 1995) or global measures of policy activity (Erikson, MacKuen, and Stimson 2002). Should we expect a similar dynamic relationship between opinion and policy using episodic policy changes, such as the adoption of smoking restrictions?

In fact, we may expect a different dynamic relationship between public opinion and episodic policy changes. Instead of a thermostatic relationship where small changes in public opinion influence small policy changes, we may expect large shifts in majority public opinion would be required to influence the adoption of a new policy. Unlike incremental policy changes, there would not be a continuous “give and take” relationship between public opinion and episodic changes.

We may also expect for public opinion to respond differently to episodic changes compared to incremental changes. Instead of responding in a thermostatic manner, we may expect public opinion to respond to episodic changes negatively in the short run and positively in the long run. For example, suppose a state adopts a new policy allowing grocery stores to distribute alcohol. At first, there may be some backlash among state citizens, particularly those who believe that alcohol should be regulated to the fullest extent. But, over the long term, it is reasonable to suspect that citizens will become more supportive of the policy as it becomes commonplace with culture. In addition, I suspect that citizens who come of age under the new policy will be more supportive of that policy compared with earlier born cohorts. As successive
cohorts are replaced, public opinion changes gradually to become supportive of the policy. What I am suggesting is that through cohort replacement, public opinion may gradually fall in line with policies that are enacted.

Secondly, the majority of research on the thermostatic model uses survey questions that are relative. For the analyses above, respondents were asked whether they thought the government was spending “too much”, “too little”, or “about the right amount” on education and welfare. And, while the analyses above suggest that public opinion responded to policy changes, it is unclear whether public opinion actually shifted its position or whether citizens simply responded in a different manner to the survey instrument. For example, suppose that the ideal amount of spending that a citizen wants on education is $500, but the government is spending only $400. In response to the survey question, the respondent would answer that the government is spending too little on education. Suppose in the next year, the government is now spending $600 on education. The citizen may still want the government to spend $500 on education even though the respondent would now answer that the government is spending too much. In this scenario, the citizen’s ideal point is unchanged even though the survey response did change; public opinion is still exogenous from policy changes even though survey responses have changed. Contrast this scenario with one in which a citizen who has changed the ideal point from $500 to $600 because of policy changes. Hence, because the survey instrument used to gauge public opinion is relative, we are unable to assess whether public opinion has truly changed its ideal point in response to policy or whether only survey responses have changed.

I overcome both of these shortcomings by testing the thermostatic model of responsiveness using anti-smoking legislation. Unlike education and welfare spending, which is incremental, anti-smoking legislation is more episodic in nature; states enact certain restrictions at certain points in time instead of continuously every year. For instance, in 1990, New Hampshire enacted a piece of anti-smoking legislation that prohibited smoking in hospitals and grocery
stores and restricted smoking to designated areas in several public places including hotels, restaurants, and worksites. Smoking restrictions in restaurants remained unchanged until 2007 when New Hampshire passed legislation that banned smoking in restaurants. Hence, unlike expenditure changes, many years may pass before states enact additional policies in the area of anti-smoking legislation. Additionally, the public opinion measure used to gauge state preferences towards anti-smoking legislation is not relative. As stated in Chapter 3, respondents were asked about whether they supported a smoking ban or restrictions in restaurants and hotels. The question of whether state residents will be more or less supportive of smoking restrictions once enacted, hence, is directly assessed since the survey instrument is more absolute.

**Measuring Policy Changes in Anti-smoking Legislation**

To capture state policy changes in anti-smoking legislation, I measure the number and type of restrictions in various public places. Specifically, I measure whether a state has banned smoking, designated separate areas, designated separate ventilation areas, or has no restrictions on smoking in hotels/motels, restaurants, and government workplaces from 1990-2006. The majority of the anti-smoking legislation data come from the Centers of Disease Control and Prevention’s State Tobacco Activities Tracking and Evaluation (STATE) System. Where there were gaps in the data (e.g., prior to 1995), I used the National Cancer Institute’s State Cancer Legislation Database Program to determine if and when states enacted certain restrictions. The goal is to have a measure where higher numbers indicate higher restrictiveness on smoking in public places, hence, a smoking ban is coded as a 2, designated areas/ventilation is coded as a 1, and no restrictions is coded as a 0. The final measure is simply an additive scale across these three public places from 1990-2006 with the mean of a 2.1 and a standard deviation of 1.55. This means that from 1990-2006 the average state had a smoking ban in one of the three public places or restrictions in two of the three public places.
Measuring Public Opinion on Anti-smoking Legislation

To capture state preferences towards anti-smoking legislation, I use the public opinion measures developed in Chapter 3. Specifically, I measure the percentage who favored a smoking ban in restaurants using the CPS-TUS and Gallup polls. I decide to use the public preferences on restaurants instead of workplaces, however, it should not matter because the public opinion measures on smoking restrictions in restaurants and workplaces are highly correlated (see Chapter 3 for more detail).

The aggregate public opinion data cover the 50 states as well as DC from 1991-2006 for anti-smoking opinion. Similar to the spending preferences measure above, all states are missing on the anti-smoking public opinion measure in 1997 and 2004 because questions were not asked about anti-smoking legislation in these years. The time gaps limit our ability to make inferences about dynamic relationships between public opinion and policy, which require continuous time series. As before, there are a number of different options to impute data for the missing values including mean interpolation (for instance, to get a value for time $t$ simply take the mean of the values at $t-1$ and $t+1$), pooled time series cross sectional multiple imputation, and individual level multiple imputation estimated prior to MRP.

As explained in Appendix B, I estimated state public opinion for the two missing years (1994 and 2004) using each of these techniques. I find little difference in the estimates using each of these techniques (see Tables B7 and B8 and Figure B4 in Appendix B). The models reported in this chapter use the estimates for 1994 and 2004 obtained from performing multiple imputation at the pooled time series cross sectional state level. More detail on how multiple imputation was performed at the state level can be found in Appendix B. In addition, the models presented in this Chapter are nearly identical regardless of which technique is used to recover missing data for 1994 and 2004 (see Tables B9 and B10 in Appendix B).
Results: The Influence of Opinion on Anti-Smoking Legislation

As before, I test the dynamic relationship between anti-smoking preference and legislation by estimating two ECMs, as described in Equation 1. For this first analysis, anti-smoking legislation is the dependent variable while anti-smoking preferences towards restaurants is the main independent variable. I control for other variables that may influence the enactment of anti-smoking legislation in restaurants, government workplaces, and hotels. Past research has found that organized interests play a large role in the adoption of anti-smoking legislation. States with a high number of health organization lobbyists have more anti-smoking legislation while those with a high number of tobacco industry lobbyists have less anti-smoking legislation (Shipan and Volden 2006). Similar to past research (e.g., Shipan and Volden 2006), I capture the influence of state organized interests via four variables. The first pair of variables is a ratio of the number of health (or tobacco) lobbyists in the state to the total number of registered lobbyists (Goldstein and Bearman 1996; Shipan and Volden 2006). These variables capture the presence of health and tobacco lobbyists compared to other organized interest groups. The second pair of variables captures perceived power. Specifically, I measure whether health (or tobacco) interests were listed as one of the ten most effective lobbies within a state (coded as 2), one of the top 20 groups (coded as 1) or not mentioned (coded as 0). This variable comes from a survey of public officials and political observers in each state as conducted by Thomas and Hrebenar (1999). All four of these interest group variables are non-varying with respect to time and come directly from Shipan and Volden’s (2006) work.

I also include a time-varying measure of the percentage of adult smokers, collected from the CDC’s STATE system. In this past, this variable has been used to capture state preferences towards anti-smoking legislation (e.g., Shipan and Volden 2006). Indeed, this is not an unreasonable assumption since the percentage of adult smokers and the percentage of state residents who support smoking bans are highly correlated ($r = -.69$). For these analyses,
however, I include the percentage of adult smokers to test whether public opinion as measured in Chapter 3 captures something different from a variable that measures the percentage of adult smokers in each state once other variables are controlled. In effect, then, I am testing whether using the percentage of state smokers is sufficient to capture important state differences in anti-smoking preferences or whether the measure developed in Chapter 3 are better.

Finally, political variables also matter for policy changes with the typical expectation that states under Democratic control and with liberal legislators will be more likely to adopt anti-smoking legislation. Democratic strength is measured as a sum of percentages of state house and senate that are Democrats plus 100 if the governor is a Democrat (Bailey and Rom 2004). Party competition is measured using an index based on district level outcomes of state legislative elections with higher values indicating greater competition (Holbrook and Van Dunk 1993). Government ideology is measured using updated scores from Berry et al. (1998) where higher values reflect more liberal elite preferences. Finally, I control for the ideological and partisan preferences of state residents. The percentage of residents who support the Democratic Party or who are liberal is measured using the MRP approach as explained in Chapter 2.

Table 5.3 shows the results from estimating a ECM using the differenced anti-smoking legislation variable as the dependent variable. All time-varying independent variables are included with a lag and differenced transformation to capture both short and long term effects. Also included is a lagged dependent variable to account for time dependence in policy changes. As before, the coefficient on the lagged dependent variable ($\alpha_1$) gives the error correction rate with a value closer to zero indicating a slow return to equilibrium; this value is always negative. The coefficient on the lagged dependent variable for anti-smoking legislation is -.09 suggesting that anti-smoking legislation is quite slow to return to its mean value when disrupted.

Consistent with the thermostatic model of policy responsiveness, public opinion towards anti-smoking legislation has a significant effect on policy changes in both the short and long term.
Recall that the coefficient on the differenced public opinion variable ($\beta_0$) gives us the short term effect of public opinion on anti-smoking legislation while the lagged public opinion variable gives us the long term effect. As shown in Table 5.3, an increase by 7 points (which is 2 standard deviations above the mean change) in support of smoking restrictions in restaurants results in an increase in anti-smoking legislation by roughly .28 and this impact is felt immediately. In other words, as public support for smoking restrictions increases, the number of smoking restrictions in three public places (restaurants, government workplaces, and hotels) increases by .28. But, the effect of public opinion on anti-smoking legislation does not stop there.

Using Equation 2, the long run effect of a 7 point increase in attitudes towards smoking restrictions in restaurants is .80. Again, this long run effect on anti-smoking legislation is not felt immediately; instead it is distributed gradually over time. Hence, public opinion towards smoking restrictions in restaurants has a direct, positive, and immediate impact on the amount of anti-smoking policies and another, much bigger, positive impact, distributed over time.

How quickly does it take for the long run effect of anti-smoking opinion to dissipate through the system? Figure 5.3 answers this question by plotting the cumulative proportion of the long run effect of anti-smoking opinion on legislation over time. As shown in Figure 5.3, the effect that anti-smoking opinion has on legislation takes time to be realized; by 10 years out only 60% of the effect of a 7 point increase has been felt by the system. In substantive terms, of the .80 maximum increase in smoking restrictions only about .48 has been realized after 10 years. Hence, it takes over a decade for the effect of anti-smoking opinion to fully influence policy changes.

Surprisingly, very few of the other independent variables matter for anti-smoking legislation across time. Interest groups, as measured here, do not explain any cross-sectional differences in anti-smoking legislation. Government ideology as well as partisanship does not have a significant influence on anti-smoking legislation across the states. As expected, the
percentage of adult smokers has a negative impact on the number of anti-smoking policies however, this effect is only felt in the long term; the percentage of adult smokers has little immediate impact on the number of anti-smoking policies adopted by state governments. Overall, these results suggest that the percentage of adult smokers is not a very good proxy for state public opinion on anti-smoking legislation and that, once public opinion is measured correctly the percentage of adult smokers has little effect on policy changes.

Results: The Influence of Anti-Smoking Legislation on Opinion

As explained above, the thermostatic model of policy responsiveness asserts that public opinion and policy exist in equilibrium, constantly acting and reacting to each other. Not only should public opinion influence policy over time, but policy should also have a measurable influence over changes in public opinion. And public opinion should respond in a negative way to policy changes; as policy overshoots the public’s ideal, the public should respond by supporting policy in the opposite direction. In this section, I test whether policy changes on anti-smoking legislation exert significant influences as expected by the thermostatic model on changes in public attitudes towards smoking restrictions in restaurants.

I control for a number of other factors that may influence changes in state public opinion over time. First, I control for certain state demographic characteristics. The most important determinant of public support for smoking restrictions at the individual level is smoker status with the expectation that smokers are less supportive of anti-smoking legislation compared to non-smokers. Hence, I include a measure of the percentage of adult smokers in each state. But other demographic characteristics may also matter. States that are highly educated are expected to endorse anti-smoking legislation; the percentage of state residents with a college degree or higher is included the model. State ideology and partisanship are included with the usual expectation that more liberal and democratic states will be more likely to endorse anti-smoking legislation. These are the same measures as described in the preceding analyses.
Historical state culture towards the production of tobacco may also influence state opinion towards smoking restrictions. The expectation is that a state with a long history of tobacco production may be less likely to support smoking restrictions compared to other states, even after accounting for other important determinants. Hence, I include a dummy variable equal to 1 in all states where tobacco is produced and 0 otherwise. Finally, I include a national measure of public opinion towards anti-smoking legislation by simply taking the average across the states in each year. This accounts for any large, universal shifts in public opinion that may be occurring across the states in response to national phenomena (Page and Shapiro 1992).

I estimate the effect of policy on public opinion via an ECM as shown in Equation 1 to account for the short and long term effects of policy on public opinion. All independent variables are time varying, with the exception of the tobacco producer dummy variable. For all time-varying variables, I include both lagged and differenced versions in the model. Results are shown in Table 5.4. As before, the coefficient on the lagged dependent variable \( \alpha_1 \) gives the error correction rate with a value closer to zero indicating a slow return to equilibrium. The coefficient on the lagged dependent variable for state attitudes towards anti-smoking legislation is -0.08 suggesting that state public opinion is slow to return to equilibrium when disrupted.

Interestingly, changes in anti-smoking legislation have both short and term influences on public support for smoking restrictions in restaurants, but in the opposite direction as expected by the thermostatic model of responsiveness. Using the coefficient on the differenced variable, a 1.5 increase in anti-smoking legislation (which is roughly 2 standard deviations above the mean change) increases public support for additional smoking restrictions in restaurants in the next year by about .7. The influence that anti-smoking legislation has on public opinion does not stop there. That same increase in anti-smoking legislation increases public support for smoking restrictions in restaurants by an additional 2.5% over the long run. Additionally, anti-smoking legislation has a significant influence on public opinion towards smoking bans even after
controlling for important demographic variables (e.g., the percentage of adult smokers) and state culture (e.g., tobacco producing state), as well as national sentiment towards smoking restrictions.

As before, I graph the long run effects of these policy changes on public opinion to assess how quickly these changes occur. Figure 5.4 plots the cumulative proportion of the long run effect of policy on opinion for anti-smoking legislation. As can be seen from Figure 5.4, the long run effects of policy take time to influence public opinion. By 10 years out, only 60% of the long run effects of policy on public opinion have occurred.

The results suggest several implications for the study of democratic responsiveness and public opinion. First, the thermostatic model of policy responsiveness does not seem to accurately predict how policy changes will influence public opinion in regards to anti-smoking legislation. The thermostatic model suggests that public opinion will respond to policy changes in a negative way; as policy increases in a certain direction, the public will demand policies in the opposite direction. However, with anti-smoking legislation, the evidence suggests that public opinion changes in the same direction as policy changes. As anti-smoking legislation is enacted, public opinion adjusts to the laws and becomes even more supportive of anti-smoking legislation.

The question then, is why does public opinion respond differently to policy changes for anti-smoking legislation compared to education and welfare expenditures? It may be that public opinion responds differently to policy changes that are more episodic in nature, such as anti-smoking legislation, compared to policy changes that are incremental. Or it may be that public health issues are simply different from other issues. Because the goal of the policy outcome (i.e., to improve public health of state residents) is generally agreed upon among citizens, there may be more of an acceptance of policies compared to when the goal of the policy outcome causes large political divisions. There is no way to know from the current project why public opinion responds differently across these three issue areas; hence, future research would be well suited to answer this question by looking across a large number of issue domains.
Regardless, the results also suggest that policy indeed causes changes in public opinion and not just how individuals respond to survey questions. Because the public opinion measures used to gauge public opinion towards smoking bans is absolute, the findings suggest that the public’s ideal point towards anti-smoking legislation actually did change in response to policy. The results suggest that not only does public opinion change in a more supportive manner to anti-smoking legislation, but it does so both in the short and long term.

**Conclusion**

In this chapter, I tested whether the thermostatic model of policy responsiveness accurately depicts the dynamic relationship between policy and public opinion for three issue areas: education, welfare, and anti-smoking legislation. For all three issue areas, policy changes respond in the expected direction to changes in public opinion. However, the way in which public opinion responds to policy changes varies across issue areas. For both education and welfare, public opinion responds to expenditures in the long run and in a negative way. For anti-smoking legislation, public opinion responds to additional restrictions in both the short and long run in a positive way. The results suggest that the public responds differently to incremental policy changes, such as expenditures, compared to more episodic changes on social issues, such as anti-smoking legislation.

Yet, questions remain about how policy changes respond to public opinion and vice versa. For instance, how does public opinion influence the risk of states adopting new policies, such as the adoption of smoking bans in restaurants? Are contextual variables, such as the policy decisions of neighboring states, more important compared to the public preferences of state residents? Are incremental changes in public opinion enough for states to adopt new policies or does there need to be a large shift in majority opinion? In the next chapter, I begin to answer these questions by conceptualizing policy changes as innovations and modeling the dynamic relationship between opinion and policy using event history analysis. I test whether and how
public opinion towards smoking restrictions in restaurants influences the *timing* of the adoption of smoking bans across the states.
References for Chapter 5


Table 5.1 Error Correction Models Predicting Changes in Per Pupil Spending and AFDC Benefits

<table>
<thead>
<tr>
<th>Per Pupil Spending on Elementary and Secondary Education (N=950)</th>
<th>AFDC Benefits for Family of 4 (N=898)</th>
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<tr>
<td>Per Pupil Spending (t-1)</td>
<td>AFDC Benefits (t-1)</td>
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<tr>
<td>- .02 **</td>
<td>-.08 ***</td>
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<tr>
<td>( .01)</td>
<td>( .02)</td>
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<tr>
<td>Percentage Favoring Increase in Education Spending (t-1)</td>
<td>Percentage Favoring Increase in</td>
</tr>
<tr>
<td>-2.84 (1.73)</td>
<td>Welfare Spending (t-1)</td>
</tr>
<tr>
<td>∆ Percentage Favoring Increase in Education Spending</td>
<td>∆ Percentage Favoring Increase in</td>
</tr>
<tr>
<td>7.43 *** (2.47)</td>
<td>Welfare Spending</td>
</tr>
<tr>
<td>Per Capita Income (t-1)</td>
<td>Per Capita Income (t-1)</td>
</tr>
<tr>
<td>.00 ( .00)</td>
<td>.00 **</td>
</tr>
<tr>
<td>( .00)</td>
<td>( .00)</td>
</tr>
<tr>
<td>∆ Per Capita Income</td>
<td>∆ Per Capita Income</td>
</tr>
<tr>
<td>.11 *** ( .02)</td>
<td>.00 **</td>
</tr>
<tr>
<td>( .02)</td>
<td>( .02)</td>
</tr>
<tr>
<td>Democratic Strength (t-1)</td>
<td>Democratic Strength</td>
</tr>
<tr>
<td>-.85 *** ( .26)</td>
<td>.12 ( .11)</td>
</tr>
<tr>
<td>∆ Democratic Strength</td>
<td>∆ Democratic Strength</td>
</tr>
<tr>
<td>.13 ( .73)</td>
<td>.11 **</td>
</tr>
<tr>
<td>( .73)</td>
<td>( .05)</td>
</tr>
<tr>
<td>Government ideology (t-1)</td>
<td>Government ideology</td>
</tr>
<tr>
<td>1.09 *** ( .40)</td>
<td>.11 ( .07)</td>
</tr>
<tr>
<td>( .40)</td>
<td>( .07)</td>
</tr>
<tr>
<td>∆ Government ideology</td>
<td>∆ Government ideology</td>
</tr>
<tr>
<td>1.16 ( .77)</td>
<td>.25 ( .13)</td>
</tr>
<tr>
<td>( .77)</td>
<td>( .13)</td>
</tr>
<tr>
<td>Percentage Liberal (t-1)</td>
<td>Percentage Liberal</td>
</tr>
<tr>
<td>5.78 ** (2.69)</td>
<td>.51 ( .48)</td>
</tr>
<tr>
<td>(2.69)</td>
<td>( .48)</td>
</tr>
<tr>
<td>∆ Percentage Liberal</td>
<td>∆ Percentage Liberal</td>
</tr>
<tr>
<td>15.42 *** (5.05)</td>
<td>.99 ( .95)</td>
</tr>
<tr>
<td>(5.05)</td>
<td>( .95)</td>
</tr>
<tr>
<td>Percentage Democrat (t-1)</td>
<td>Percentage Democrat</td>
</tr>
<tr>
<td>1.94 (1.40)</td>
<td>-.32 ( .24)</td>
</tr>
<tr>
<td>(1.40)</td>
<td>( .24)</td>
</tr>
<tr>
<td>∆ Percentage Democrat</td>
<td>∆ Percentage Democrat</td>
</tr>
<tr>
<td>-1.37 (4.14)</td>
<td>-1.19 ( .69)</td>
</tr>
<tr>
<td>(4.14)</td>
<td>( .69)</td>
</tr>
<tr>
<td>Percentage African American (t-1)</td>
<td>Percentage African American</td>
</tr>
<tr>
<td>1.73 ( .77)</td>
<td>-1.32 *** ( .36)</td>
</tr>
<tr>
<td>( .77)</td>
<td>( .36)</td>
</tr>
<tr>
<td>∆ Percentage African American</td>
<td>∆ Percentage African American</td>
</tr>
<tr>
<td>-129.93 (98.90)</td>
<td>26.44 (15.56)</td>
</tr>
<tr>
<td>(98.90)</td>
<td>(15.56)</td>
</tr>
<tr>
<td>Political Competition</td>
<td>Political Competition</td>
</tr>
<tr>
<td>-.07 ( .93)</td>
<td>.31 **</td>
</tr>
<tr>
<td>( .93)</td>
<td>( .14)</td>
</tr>
<tr>
<td>Constant</td>
<td>Constant</td>
</tr>
<tr>
<td>94.83 (111.61)</td>
<td>-27.80 (16.72)</td>
</tr>
</tbody>
</table>

Note: Newey-West Standard Errors in parentheses. Significance levels: **.05, ***.01 with a two-tailed test
Table 5.2 Error Correction Models Predicting Changes in State Public Opinion on Education and Welfare Spending

<table>
<thead>
<tr>
<th>Education Spending Opinion (t-1)</th>
<th>Welfare Spending Opinion (t-1)</th>
<th>Per Pupil Spending in $100s (t-1)</th>
<th>AFDC Benefits in $10s (t-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>- .30 ***</td>
<td>- .30 ***</td>
<td>- .04 ***</td>
<td>- .14 ***</td>
</tr>
<tr>
<td>(.03)</td>
<td>(.04)</td>
<td>(.008)</td>
<td>(.037)</td>
</tr>
<tr>
<td>Δ Per Pupil Spending in $100s</td>
<td>Δ AFDC Benefits in $10s</td>
<td>Per Pupil Spending in $100s</td>
<td>AFDC Benefits in $10s</td>
</tr>
<tr>
<td>- .008</td>
<td>.15</td>
<td>(.008)</td>
<td>(.037)</td>
</tr>
<tr>
<td>(.035)</td>
<td>(.15)</td>
<td>(.035)</td>
<td>(.15)</td>
</tr>
<tr>
<td>Per Capita Income (t-1)</td>
<td>Per Capita Income (t-1)</td>
<td>National Opinion on Education</td>
<td>National Opinion on Welfare</td>
</tr>
<tr>
<td>.00</td>
<td>.00</td>
<td>Spending (t-1)</td>
<td>Spending (t-1)</td>
</tr>
<tr>
<td>(.00)</td>
<td>(.00)</td>
<td>(.30) ***</td>
<td>(.41) ***</td>
</tr>
<tr>
<td>(.00)</td>
<td>(.00)</td>
<td>(.04)</td>
<td>(.05)</td>
</tr>
<tr>
<td>Δ Per Capita Income</td>
<td>Δ National Opinion on Education</td>
<td>Δ National Opinion on Education</td>
<td>Δ National Opinion on Welfare</td>
</tr>
<tr>
<td>.00</td>
<td>.89 ***</td>
<td>Spending</td>
<td>Spending</td>
</tr>
<tr>
<td>(.00)</td>
<td>(.09)</td>
<td>(.89) ***</td>
<td>(.09)</td>
</tr>
<tr>
<td>Percentage College Educated (t-1)</td>
<td>Percentage College Educated (t-1)</td>
<td>Percentage College Educated</td>
<td>Percentage College Educated</td>
</tr>
<tr>
<td>.12 ***</td>
<td>.06 ***</td>
<td>.71</td>
<td>-.49</td>
</tr>
<tr>
<td>(.04)</td>
<td>(.03)</td>
<td>(.65)</td>
<td>(.51)</td>
</tr>
<tr>
<td>Δ Percentage College Educated</td>
<td>Δ Percentage College Educated</td>
<td>Percentage Liberal (t-1)</td>
<td>Percentage Liberal (t-1)</td>
</tr>
<tr>
<td>.03</td>
<td>-.49</td>
<td>.03</td>
<td>-.49</td>
</tr>
<tr>
<td>(.02)</td>
<td>(.02)</td>
<td>(.02)</td>
<td>(.02)</td>
</tr>
<tr>
<td>Δ Percentage Liberal</td>
<td>Δ Percentage Liberal</td>
<td>Percentage Democrat (t-1)</td>
<td>Percentage Democrat (t-1)</td>
</tr>
<tr>
<td>-.05</td>
<td>-.04</td>
<td>.03 ***</td>
<td>.03 ***</td>
</tr>
<tr>
<td>(.05)</td>
<td>(.04)</td>
<td>(.01)</td>
<td>(.01)</td>
</tr>
<tr>
<td>Percentage Democrat (t-1)</td>
<td>Percentage Democrat (t-1)</td>
<td>Δ Percentage Democrat</td>
<td>Δ Percentage Democrat</td>
</tr>
<tr>
<td>.03 ***</td>
<td>.03 ***</td>
<td>-.01</td>
<td>-.01</td>
</tr>
<tr>
<td>(.01)</td>
<td>(.01)</td>
<td>(.04)</td>
<td>(.04)</td>
</tr>
<tr>
<td>Δ Percentage African American</td>
<td>Δ Percentage African American</td>
<td>Δ Percentage African American</td>
<td>Δ Percentage African American</td>
</tr>
<tr>
<td>.05 ***</td>
<td>.06 ***</td>
<td>1.01 **</td>
<td>-.16</td>
</tr>
<tr>
<td>(.01)</td>
<td>(.02)</td>
<td>(.45)</td>
<td>(1.03)</td>
</tr>
<tr>
<td>Δ Percentage African American</td>
<td>Δ Percentage African American</td>
<td>Constant</td>
<td>Constant</td>
</tr>
<tr>
<td>1.01 **</td>
<td>-.16</td>
<td>-.86 (1.54)</td>
<td>2.71 ***</td>
</tr>
</tbody>
</table>

Note: Newey-West Standard Errors in parentheses. Significance levels: **.05, ***.01 with a two-tailed test
Table 5.3 Error Correction Model Predicting Changes in Anti-smoking Legislation on State Opinion on Smoking Bans in Restaurants (N=727)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anti-smoking Legislation (t-1)</td>
<td>-.09 ***</td>
<td>(.02)</td>
</tr>
<tr>
<td>Percentage Favor Smoking Bans in Restaurants (t-)</td>
<td>.01 **</td>
<td>(.005)</td>
</tr>
<tr>
<td>Δ Percentage Favor Smoking Bans in Restaurants</td>
<td>.04 **</td>
<td>(.018)</td>
</tr>
<tr>
<td>Ratio Tobacco Lobbyists</td>
<td>1.83</td>
<td>(3.16)</td>
</tr>
<tr>
<td>Ratio Health Lobbyists</td>
<td>-.01</td>
<td>(.38)</td>
</tr>
<tr>
<td>Power Tobacco Lobbyists</td>
<td>.00</td>
<td>(.05)</td>
</tr>
<tr>
<td>Power Health Lobbyists</td>
<td>.01</td>
<td>(.03)</td>
</tr>
<tr>
<td>Percentage Adult Smokers (t-1)</td>
<td>-.02 *</td>
<td>(.01)</td>
</tr>
<tr>
<td>Δ Percentage Adult Smokers</td>
<td>-.01</td>
<td>(.01)</td>
</tr>
<tr>
<td>Democratic Strength (t-1)</td>
<td>-.0004</td>
<td>(.001)</td>
</tr>
<tr>
<td>Δ Democratic Strength</td>
<td>.0003</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>Government ideology (t-1)</td>
<td>.001</td>
<td>(.001)</td>
</tr>
<tr>
<td>Δ Government ideology</td>
<td>-.002</td>
<td>(.002)</td>
</tr>
<tr>
<td>Percentage Liberal (t-1)</td>
<td>.0003</td>
<td>(.01)</td>
</tr>
<tr>
<td>Δ Percentage Liberal</td>
<td>-.03 *</td>
<td>(.02)</td>
</tr>
<tr>
<td>Percentage Democrat (t-1)</td>
<td>-.002</td>
<td>(.004)</td>
</tr>
<tr>
<td>Δ Percentage Democrat</td>
<td>.01</td>
<td>(.01)</td>
</tr>
<tr>
<td>Constant</td>
<td>.19</td>
<td>(.46)</td>
</tr>
</tbody>
</table>

Note: Newey-West Standard Errors in parentheses. Significance levels: *.10, **.05, ***.01 with a two-tailed test
Table 5.4 Error Correction Model Predicting Changes in Anti-smoking Legislation on State Opinion on Smoking Bans in Restaurants (N=746)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-statistic</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage Favor Smoking Bans in Restaurants (t-1)</td>
<td>-0.08***</td>
<td>0.02</td>
<td>4.97</td>
<td>.000</td>
</tr>
<tr>
<td>Anti-smoking Legislation (t-1)</td>
<td>0.17***</td>
<td>0.063</td>
<td>2.90</td>
<td>.004</td>
</tr>
<tr>
<td>Δ Anti-smoking Legislation</td>
<td>0.47***</td>
<td>0.162</td>
<td>2.89</td>
<td>.004</td>
</tr>
<tr>
<td>Tobacco Producer</td>
<td>-0.45***</td>
<td>0.15</td>
<td>-3.00</td>
<td>.003</td>
</tr>
<tr>
<td>Percentage Adult Smokers (t-1)</td>
<td>-0.11***</td>
<td>0.04</td>
<td>-2.70</td>
<td>.007</td>
</tr>
<tr>
<td>Δ Percentage Adult Smokers</td>
<td>-0.10**</td>
<td>0.04</td>
<td>-2.55</td>
<td>.011</td>
</tr>
<tr>
<td>Percentage College Educated (t-1)</td>
<td>-0.01</td>
<td>0.03</td>
<td>-0.44</td>
<td>.658</td>
</tr>
<tr>
<td>Δ Percentage College Educated</td>
<td>0.01</td>
<td>0.28</td>
<td>0.36</td>
<td>.714</td>
</tr>
<tr>
<td>National Opinion on Smoking Bans in Restaurants (t-1)</td>
<td>0.05**</td>
<td>0.02</td>
<td>2.48</td>
<td>.014</td>
</tr>
<tr>
<td>Δ National Opinion on Smoking Bans in Restaurants</td>
<td>0.96***</td>
<td>0.07</td>
<td>13.92</td>
<td>.000</td>
</tr>
<tr>
<td>Percentage Liberal (t-1)</td>
<td>0.07***</td>
<td>0.02</td>
<td>3.47</td>
<td>.001</td>
</tr>
<tr>
<td>Δ Percentage Liberal</td>
<td>0.06</td>
<td>0.06</td>
<td>1.03</td>
<td>.303</td>
</tr>
<tr>
<td>Percentage Democrat (t-1)</td>
<td>-0.02**</td>
<td>0.01</td>
<td>-2.48</td>
<td>.014</td>
</tr>
<tr>
<td>Δ Percentage Democrat</td>
<td>-0.01</td>
<td>0.04</td>
<td>-0.23</td>
<td>.821</td>
</tr>
<tr>
<td>Constant</td>
<td>3.42**</td>
<td>1.42</td>
<td>2.43</td>
<td>.015</td>
</tr>
</tbody>
</table>

Note: Newey-West Standard Errors in parentheses. Significance levels: * .10, ** .05, *** .01 with a two-tailed test
Figure 5.1 Cumulative Proportion of the Long Run Effect of Welfare Opinion on AFDC Benefits
Figure 5.2 Cumulative Proportion of the Long Run Effects of Policy on Opinion
Figure 5.3 Cumulative Proportion of the Long Run Effects of Anti-smoking Opinion on Anti-smoking Legislation
Figure 5.4 Cumulative Proportion of the Long Run Effects of Anti-smoking Legislation on Anti-smoking Opinion
Chapter 6

The Impact of Public Opinion on the Innovation & Diffusion Of Smoking Bans

In Chapter 5, I explored the role of public opinion on continuous policy measures using three case studies: education, welfare, and anti-smoking legislation. I found that the thermostatic model of policy responsiveness accurately describes the dynamic relationship between public opinion and policy for education and welfare expenditures. As public support for additional spending on education and welfare increased, so did actual spending on education and welfare. Moreover, as expenditures increased, public demand for additional spending decreased in the long term. The dynamic relationship between public opinion and policy in regards to anti-smoking legislation followed a different pattern. Similar to education and welfare expenditures, as public support for smoking bans increased so did anti-smoking legislation. Unlike education and welfare opinion, however, public support for additional smoking restrictions increased after policy became more restrictive. Hence, there was a sense of public acceptance of smoking restrictions after policies were enacted.

The results from Chapter 5 suggest that there is something unique about anti-smoking legislation that makes the dynamic relationship between public opinion and policy follow a different pattern from what is expected from current theories on dynamic responsiveness. In this chapter, I take an in-depth look at anti-smoking legislation from the perspective of policy innovation and diffusion. This perspective allows me to model the policy changes as episodic and explore the role that public opinion has on these policy changes by using event history analysis. Via this approach, states adopt a new policy (in this case, smoking bans in restaurants), but at different times. By using event history analysis, I can explore the role that public opinion plays in the timing variations in state adoption of smoking bans. This is different from the
analyses in the previous chapter in which I explored the role of public opinion on a continuous measure of anti-smoking legislation that can (potentially) change every year.

The current chapter proceeds as follows. First, I introduce the reader to the policy innovation and diffusion perspective. This perspective has a rich history, yet, it often underplays the role that public opinion plays in the adoption and diffusion of new policies by the states. Next, I describe why undertaking an analysis on public health, and specifically smoking bans, is appropriate to test theories of policy innovation and diffusion. This section is followed by an empirical analysis on the role that public support for smoking bans plays in the timing variations and diffusion of the adoption of smoking bans across the states.

Public Opinion, Policy Innovation, and Policy Diffusion

According to Walker (1969), an innovation is a “program or policy which is new to the states adopting it, no matter how old the program may be or how many other states may have adopted it” (881). Once a state innovates, the probability that another state will innovate is great; the process by which an innovation spreads across states is called diffusion (Gray 1973). Scholars have studied both the probability of innovation and the diffusion of innovations across states. In particular, researchers have sought to explain why some states are innovators and have explored the correlates of state innovation and diffusion.

Policy Innovation

The probability of a state adopting a new policy, or an innovation, is a function of motivation, resources, and obstacles in a state’s political and economic environment (Berry & Berry 1990; Mohr 1969). If a state has the motivation and resources available to overcome obstacles it is more likely to innovate (Mohr 1969; Berry & Berry 1990). Motivations, however, also interact with the strength of obstacles and the amount of resources available (Mohr 1969). If obstacles are high and resources low, motivation does not matter. If obstacles are low and
resources high, motivation matters a great deal in determining whether a state will innovate. Similarly, the influence of both obstacles and resources is stronger in states where motivation to innovate is high.

Motivation factors are those that encourage public officials to adopt a policy; states must want to innovate. There are several factors that may persuade officials to adopt a new policy. One motivating factor is the extent or severity of the issue to be addressed. The severity of the issue can be conceptualized in a number of ways. Severity may refer to the number of people affected by the issue or the size of the target population (Rocheft & Cobb 1994). For instance, Meier (1994) finds that both the stringency of drug laws and their implementation increased as the number of drug users increased. Severity may also refer to issue attention caused by the media; in this case, officials are more likely to adopt a policy as the media increases attention to particular issue. Finally, severity may refer to triggering events or those events that bring about immediate public attention (Jones 1994). For example, the 2008 Minnesota bridge collapse may induce state politicians to adopt stringent inspection policies. Another type of motivation arises from the political environment: the election cycle. Political officials are more likely to adopt new policies during an election year and less likely in the year immediately following an election (Berry & Berry 1990). This motivation arises out of the desire for re-election.

Resources and obstacles are those factors that might inhibit or contribute to the adoption of innovative policies. These typically refer to the political and economic characteristics of the state such as fiscal wealth, strength of state interest groups, policy entrepreneurs, professional associations, and party control. The presence of neighbor’s policy is also considered a resource. Walker (1969) finds that innovations start in states that are large, wealthy, and urbanized with the assumption that these states have the financial resources to adopt new policies. In line with Walker (1969), Berry and Berry (1990) find that states that are fiscally healthy are more likely to adopt state lotteries. If unfavorable to the new policy, interest groups can be seen as an obstacle
that officials must overcome. If favorable towards the new policy, interest groups can be an enormous information resource for state officials. In their study of anti-smoking innovation, Shipan and Volden (2006) find that states with influential health organizations are more likely to adopt anti-smoking laws, while states with a large number of tobacco lobbyists are less likely to adopt anti-smoking laws. Policy entrepreneurs and professional associations help officials overcome information obstacles because they decrease uncertainty about a new policy (Mintrom 2000; Balla 2001). For instance, Balla (2001) finds that states whose insurance commissioners were actively involved in the Accident and Health Insurance Committee were more likely than other states to adopt the Model Act, a comprehensive set of regulations developed by the National Association of Insurance Commissioners (NAIC). Officials also use information from neighboring states with similar policies to learn about the problems and successes of new policies. The positive influence of a neighbor’s policy has been found across a range of policy issues including Indian gaming (Boehmke & Witmer 2004), the lottery (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).

What role does public opinion play in policy innovation? Public opinion can be viewed as both a motivating factor and an obstacle that needs to be overcome. Public opinion is a motivating factor because state officials are interested in re-election (Mayhew 1974). Consequently, changes in public opinion should encourage officials to adopt a new policy that coincides with constituencies (e.g., Page and Shapiro 1992).

At the same time, however, public opinion may also be viewed as an obstacle that state officials must overcome. This is exactly how Berry and Berry (1990) characterize the
relationship between the probability of adopting a state lottery and the percentage of religious
fundamentalists in a state. Berry and Berry (1990) find that state officials are less likely to adopt
lotteries in states with a high percentage of religious fundamentalists presumably because of the
political costs associated with such approval. The argument here is that state officials have to be
wary of constituencies that have divergent policy preferences and that may jeopardize their desire
to stay in office. If unable to overcome the obstacle of public opinion, officials either maintain
the status quo (by not innovating) or use other tactics to encourage public support of the newly
adopted policy (Jacobs & Shapiro 2000).

The Influence of Public Opinion on Policy Innovation

As shown in the previous chapter and consistent with past research (e.g., Erikson, Wright,
and McIver 1993), there is a positive correlation between public preferences and state policy
outputs generally as well as between public opinion and policy outputs on specific state issues.
These results suggest that public opinion should also be positively related to policy innovation.
As state public opinion changes, politicians catch wind of the new political preferences and
innovations follow. In this model, public opinion encourages policy innovation through political
expediency; state officials are interested in re-election and, thus, have incentives to gauge and
respond to changing state public opinion. Public opinion may also precede policy innovation
through electoral turnover. An issue may become salient during an election causing residents to
vote for new officials who are in line with their political preferences who then adopt new policies
once elected.

While it may seem obvious that public opinion should positively influence policy
innovation, past research has not been able to empirically support this conclusion. Most research
has focused on the political and economic determinants of policy innovation, largely ignoring the
expressed preferences of state residents. Studies that control for public opinion often use a static
measure of ideology (e.g., Berry & Berry 1990) or a proxy for public opinion, such as the
percentage of fundamentalists (e.g., Berry & Berry 1990) or the percentage of adult smokers (Shipan and Volden 2006). In fact, I know of no study on policy innovation that explicitly includes a time-varying measure of public opinion that is specific to the policy innovation, no doubt because of the methodological challenges to measuring state opinion over time as explained in Chapter 2. As a result, scholars do not know whether or how public opinion influences policy innovations. And, if public opinion exerts an impact on policy innovation, many of the past 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.

**Policy Diffusion**

The process by which policy innovations spread across states is called diffusion. Diffusion occurs both across time and space. Consequently, scholars look to explain temporal variations as well as geographical patterns of diffusions. Diffusion models grew out of the social learning model of decision-making (Gray 1973). The social learning model contends that state politicians frequently use heuristics and cues from other states where programs were successful when making decisions. Political officials, in their search for answers to complex problems,
engage in a form of “satisficing” (Simon 1955). Instead of devising their own policies, officials look to other states where a policy has been successfully adopted to solve the problem at hand. Officials use other states as “analogies” because innovation involves electoral risk. Given that politicians are risk averse, it makes sense for them to wait and see how a policy works out before adopting it in their own state. Indeed, there is evidence that states are more likely to emulate policies that have been successful in other states (Volden 2006).

A clear pattern of temporal diffusion follows from the social learning model (Gray 1973). First, one or two states adopt a new policy, while other states wait to see how successful the new program is before adopting a similar policy. After a period of time, a few other states adopt the policy, which gives non-adopting states more opportunities to learn about the consequences and benefits of the new policy. As time passes, more and more states adopt the policy as they see it becoming successful in other states. The few remaining non-adopting states feel pressure to adopt the policy as the policy “gain[s] a stamp of legitimacy” and is viewed as “something all states ought to have” (Walker 1969 890 cited in Mooney & Lee 1999). Finally, “after the bulk of states adopt the policy in a relatively short time, the last few laggards adopt less frequently, as the reluctance of these most resistant states gives way slowly” (Mooney & Lee 1999 767). This pattern yields an S-shaped cumulative frequency distribution of adoptions across time within the states (Rogers 1995). The S-shaped distribution has been seen in a variety of state policies including education, welfare, and civil rights (Gray 1973).

Although the temporal diffusion pattern of most innovations can be described by the S-shape, the exact shape may differ. For example, the slope can be steep indicating rapid diffusion or it can be flat indicating slow diffusion (Mahajan & Peterson 1985). Diffusion patterns can also represent other shapes besides the normal distribution because the decision-making process behind state policymaking may differ across issue areas. For instance, Gray (1973) finds that AFDC diffusions follow a “damped oscillatory pattern” and that states are much quicker to adopt
laws on issues with federal involvement. Welch and Thompson (1980) find that policies with federal incentives diffuse substantially faster than policies that are “the preserve of the states” (715). Mooney and Lee (1995) argue that diffusion patterns for morality issues, which are fought over moral values instead of economic concerns, will be truncated. The truncated pattern of diffusion occurs because risk-averse officials avoid morality issues for fear that they will alienate certain groups with strong opinions. This causes many legislators to maintain the status quo (to not innovate). Even aside from the effects of risk-averse politicians, the very nature of state political culture may prevent certain states from ever adopting a certain policy. Mooney and Lee (1995) provide some support for their argument with abortion reform innovations from 1966-1972. Gray (1973) and Glick and Hays (1991) suggest similar truncated patterns of diffusion with civil rights legislation and living wills, respectively.

The temporal diffusion model makes several assumptions regarding the interactions of states. First, it assumes that states interact with each other on a national basis. There is a national communication network among state officials and this network allows legislators to freely emulate policies already adopted by other states (Berry & Berry 2007). On the contrary, we may expect state actors to be more likely to interact with actors from similar states that are geographically proximate. Another assumption is that each state has an equal probability of adopting a new policy; “the only variable influencing the probability that a potential adopter will adopt during any time period is the cumulative number of adopters prior to that period” (Berry and Berry 2007 228). Instead, we know that states vary in significant ways from each other, which may make the probabilities of adoption unequal. For instance, Alabama differs significantly in demographic, political, and social characteristics from Massachusetts. This difference should be accounted for when looking at temporal diffusion.

These assumptions have led scholars estimating temporal models to usually ignore geographic diffusion. We may expect, however, for policy diffusion to have distinct geographic
patterns. Geographic patterns of diffusion can occur for two reasons: social learning and competition. According to the social learning model, states are influenced by the policy choices of other states because officials learn from the experiences of other states; and officials tend to look towards similar states (in terms of demography, economy, and ideology) when learning about new policies. Neighboring states and those that are in the same region tend to share ideology and demographics (Erikson, Wright, and McIver 1993) and, thus, are more influential than distant states. Geographic policy diffusion can also result from economic competition (Tiebout 1956; Berry & Berry 1990; Volden 2002). States make policy choices in order to gain an economic advantage over proximate states. This economic advantage helps states attract the “best residents” (Tiebout 1956). Because of the mobility constraints of residents, however, states are more likely to compete with nearby states than those far away on economic policies. For example, states who are fearful of attracting lower income residents from neighboring states may adjust their welfare policies when neighboring states adopt new policies (Berry, Fording, and Hansen 2003).

Regional diffusion models assume that states are most influenced by those with which they share a border. A state is more likely to adopt a policy when the proportion of neighboring states who have already adopted the policy is high (Berry & Berry 1990). The challenge, however, has been to identify the mechanism of diffusion—social learning or economic competition—across neighboring states. For instance, Berry and Berry (1990) attribute the positive influence of neighboring states on lottery adoptions to both social learning and economic competition. Recent advances in GIS have shown that the appropriate model of diffusion partly depends on the issue. For instance, Berry and Baybeck (2005) find that economic competition accounts for the diffusion of lottery adoptions while social learning is more appropriate for explaining the diffusion of welfare benefits.
The Influence of Public Opinion on Policy Diffusion

Though less studied, public opinion should have an influence over the temporal and geographical patterns of diffusion. Unlike policy innovation, however, the variation of public opinion across the states matters more than individual changes in public opinion for a particular state. In this case, public opinion may be similar across states or there can be wide variations in the mean value of public opinion across the states. Public opinion variation matters because states look towards other states that are ideologically (Volden 2006) and demographically similar when learning about new policies (Walker 1969; Grossback, Nicholson-Crotty & Peterson 2004). In addition, because state officials are interested in re-election, they are likely to adopt new policies that are congruent with their own state’s public opinion (Erikson, MacKuen, and Stimson 2002). In a scenario where state public opinion is similar across states, officials have more opportunities to learn about newly adopted policies that will be consistent with their state’s level of opinion. We can also think of states being more susceptible or more vulnerable to influence from other states (Soule & Earl 2001) when public opinion is similar across states. Again, this occurs because public opinion motivates officials to adopt new policies that have already been adopted in other states with similar policy preferences. Consequently, we may expect for policy diffusion to occur faster when public opinion is similar across the states than when it is widely varied. In terms of geography, we may expect policies to diffuse to states with similar levels of public opinion. This is an important qualification to previous regional diffusion models, which have assumed that demography or elite ideology motivated similar states to innovate (Volden 2006; Grossback et al. 2004). Instead, it may be that state public opinion is the driving motivation for diffusion across neighbors and regions.

There is some evidence that public opinion influences temporal and geographical patterns of diffusion. Mooney & Lee (1999) look at how the distribution of values among citizens influences the pattern of diffusion for death penalty legislation. They argue that when a majority
of citizens favor a morality policy, such as the death penalty, diffusion will occur quickly with little or no introductory learning period. This occurs because decision makers compete to validate majority values. When advocates of minority-supported morality policy successfully characterize a policy as being one of incremental change, low salience, and high complexity, temporal diffusion will occur via the typical S-curve pattern. Though they did not include a specific measure of state public opinion, Mooney & Lee (1999) find support for their hypotheses by comparing the diffusion patterns of the death penalty in an era of majority support (post-
*Furman* death penalty reestablishment) with a period of minority support (from 1838-1963 with laws for discretionary murder). In the post-*Furman* era, diffusion occurred rapidly following a pattern different from the normal distribution. On the other hand, the temporal diffusion of discretionary sentencing legislation (such as allowing juries and trial judges to impose a sentence of imprisonment instead of death or instituting humane methods of execution) occurred through the typical S-curve distribution.

In his dyad-year event history analysis, Volden (2006) finds that states are more likely to adopt children’s health insurance laws when a state that is similar in government ideology has already adopted a similar policy (see also Grossback et al. 2004). Though government ideology, measured by Berry et al.’s (1998) interest group ratings of members of Congress, is distinct from public opinion, these results suggest that public opinion similarity is also important, particularly since government ideology and state ideology are strongly correlated (Erikson, Wright, and McIver 1993; Berry et al. 1998). And, including both elite ideology and public opinion in empirical models would help identify whether state officials are responding to state governments that are ideologically similar (as argued by Volden 2006 and Grossback et al. 2004) or to states that are similar in public opinion levels.

To summarize, public opinion should influence both the probability that a state adopts a new policy (or an innovation) as well as the process by which innovations spread across the states
(or diffusion). I expect for public opinion to positively influence the adoption of new policies across the states. In other words, as public support in a particular state for a particular policy increases, the probability that that same state innovates on that policy also increases. I expect for diffusion across the states to occur at a faster pace if there is homogeneity in public opinion across the states. Finally, I expect for states to be more likely to adopt a new policy if neighboring states increase their support for that same new policy.

**Testing the Effect of Opinion on Innovation & Diffusion using Anti-Smoking Legislation**

While the above hypotheses are general, and likely to hold in numerous policy areas, I focus on the role that public opinion plays in the innovation and diffusion of anti-smoking legislation from 1990-2008. Specifically, I use the public opinion measures developed in Chapter 3 on public support for smoking bans in restaurants and explore how these measures are related to the probability that states enact smoking bans in restaurants. Over this time period, 27 states enacted comprehensive smoking bans in restaurants. California and Utah lead the way by enacting smoking bans in restaurants in 1994, while other states like South Dakota and Massachusetts enacted smoking bans in restaurants in 2008.

Studies of policy innovation and diffusion using public health issues and anti-smoking legislation in particular are well suited to explore the correlates of policy innovation and diffusion across the states. First, several studies in both the political science and public health fields have conducted analyses on the innovation and diffusion of anti-smoking legislations; this allows me to build on existing literature when thinking about other important factors that influence the adoption of smoking bans across the states. Second, there is large variation in the timing of adoption across the states. Of the 27 states who have enacted smoking bans in restaurants from 1990-2008, 2 enacted bans in 1994, 1 in 2002, 2 in 2003, 6 in 2005, 5 in 2006, 6 in 2007, and 5 in 2008. Hence, unlike other policy areas in which states enact policies over a relatively short time frame, such as the reinstatement of the death penalty post-*Furman*, there is large longitudinal
variation in the enactment of smoking bans in restaurants. Finally, it is important to know what influences states to enact smoking bans in restaurants, since the policy implications of smoke-free laws are so great. 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. Understanding why some states are quicker to enact comprehensive smoke-free laws, such as smoking bans in restaurants, thus has important implications for the health of our society.

Previous studies on the policy adoption of anti-smoking laws have identified important causal influences, which I incorporate in the form of control variables (more detail below). The most comprehensive analysis on the innovation and diffusion of anti-smoking legislation has been conducted by Shipan and Volden (2006). Looking at three types of anti-smoking policies (government building restrictions, restaurant restrictions, and out of package sales restrictions) from 1975-2000, Shipan and Volden (2006) find that states are more likely to adopt anti-smoking restrictions in all three policy domains if neighboring states pass such policies, if health organizations play a prominent role in the state, and if government officials are liberal. Conversely, one of the most important factors that decreased the probability that a state will enact smoking restrictions was whether or not the state was a tobacco-producing state. These findings are congruent with analyses from the public health literature that finds that legislative voting on anti-smoking legislation is influenced by political ideology (Cohen et al. 2000) and the amount of involvement by the health community (Jacobson, Wasserman, and Raube 1993).

Little is known about the role that public opinion plays in the adoption of anti-smoking legislation. 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. Over time, however, there is little evidence that the percentage of smokers correlate with public preferences on anti-smoking legislation; the
correlation between the changes in the percentage of adult smokers and changes in public preferences towards smoking bans in restaurants is a mere -.08. Hence, inferring public preferences via the percentage of adult smokers may have lead to incorrect inferences in the past regarding the influence of public opinion on anti-smoking legislation. Shipan and Volden (2006) also include various measures of political ideology; however, none of these proxies significantly influenced the adoption of anti-smoking legislation. By including direct measures of public opinion on smoking legislation, I not only explore the role that public opinion plays on policy innovation and diffusion generally, but also look at how public opinion influences the adoption of a particularly important population health policy.

**Data Analysis**

I start the data analysis by estimating a typical model of policy innovation and diffusion without controlling for public opinion. I then estimate a sequence of models to explore the role that public opinion plays in the adoption and diffusion of smoking bans in restaurants. By doing this, comparisons can be made against an appropriate baseline once other covariates, particularly public opinion, are added to the model. In the first model, I explore the role that internal and external factors play in the probability that a state adopts a smoking ban in restaurants without controlling for levels of public support for a smoking ban in restaurants. The dependent variable is whether a state adopts a smoking ban in restaurants. Consequently, this variable is coded as having a value of 0 for the years in which the state has not yet adopted a smoking ban in restaurants and a 1 in the year of adoption. In subsequent years, the state is dropped from the dataset since it is no longer “at risk” of innovating; this is the conventional coding scheme for event history analysis (Berry & Berry 1990). This yields one observation per state per year, for a total of 50 x 18 = 900 observations. Excluding observations not in the risk-set for adoption (those states after the policy has already been adopted), leaves 742 observations suitable for analysis. Since the dependent variable is dichotomous, I employ logistic regression. To account for
potential problems of non-independence of observations and of heteroskedasticity, I rely on the cluster procedure whereby observations are clustered by state-year. Hence, Huber/White robust standard errors are reported in the analyses below.

Similar to analyses in Chapter 5, the majority of the anti-smoking legislation data come from the Centers of Disease Control and Prevention’s State Tobacco Activities Tracking and Evaluation (STATE) System. Where there are gaps in the data (e.g., prior to 1995), I used the National Cancer Institute’s State Cancer Legislation Database Program to determine if and when states enacted comprehensive smoking bans in restaurants.26

The most important factor found in previous research that influences the probability that a state innovates is whether neighbors have already innovated (e.g., Berry & Berry 1990; Shipan and Volden 2006). Consequently, I include a measure of the proportion of neighbors with a smoking ban in restaurants, based on the same database used for the dependent variable. The expectation is that states are influenced by the actions of their neighbors in a positive way; a state will be more likely to adopt a smoking ban if neighbors have already adopted a similar ban. This variable is coded as 0 for Hawaii and Alaska since these states do not have neighbors.

State policymakers are also likely to be influenced by various internal factors. As previous research has shown, organized interests can play a large role in whether a state passes certain policies. States with a high number of health organization lobbyists have more anti-smoking legislation while those with a high number of tobacco industry lobbyists have less anti-smoking legislation (Shipan and Volden 2006). Similar to past research (e.g., Shipan and Volden 2006), I capture the influence of state organized interests via four variables.27 The first pair of variables is a ratio of the number of health (or tobacco) lobbyists in the state to the total number

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26 There is still heterogeneity in what exactly constitutes a “comprehensive” smoking ban in restaurants. Some states have exemptions to the smoking ban, while others do not. And, the exemptions are not uniform across states. For these analyses, I ignored the exemptions and simply coded a state as enacting a smoking ban in restaurants if any such bans existed.

27 I am grateful to Shipan and Volden for allowing me to use their dataset from which the interest group variables come from.
of registered lobbyists (Goldstein and Bearman 1996; Shipan and Volden 2006). These variables capture the presence of health and tobacco lobbyists compared to other organized interest groups. The second pair of variables captures perceived power. Specifically, I measure whether health (or tobacco) interests were listed as one of the ten most effective lobbies within a state (coded as 2), one of the top 20 groups (coded as 1) or not mentioned (coded as 0). This variable comes from a survey of public officials and political observers in each state as conducted by Thomas and Hrebenar (1999). All four of these variables come directly from Shipan and Volden’s (2006) analysis of anti-smoking legislation.

I also include a measure of the percentage of adult smokers in each state, collected from the CDC’s STATE system. In the past, this variable has been used to capture state preferences towards anti-smoking legislation (e.g., Shipan and Volden 2006). For these analyses, it is used to test whether public opinion captures something different from a variable that measures the percentage of adult smokers in each state. In effect, then, I am testing whether using the percentage of state smokers is sufficient to capture important state differences in anti-smoking preferences or whether the measure developed in Chapter 3 is better. The contemporaneous measure of the percentage of adult smokers is correlated with the proportion of neighboring states that have already adopted smoking bans in restaurants ($r = -.41$). In order to reduce multicollinearity, I measure the percentage of smokers as a differenced covariate; indeed the correlation between the differenced percentage of smokers and the proportion of neighboring states that have already adopted smoking bans in restaurants is small ($r = -.10$). Including the differenced percentage of smokers variable also allows me to test whether changes in the usage of cigarettes influences the probability that a state will innovate.

Political variables also matter for policy innovations with the typical expectation that states under Democratic control and with liberal legislators will be more likely to adopt anti-smoking legislation. Democratic strength is measured as a sum of percentages of state house and
senate that are Democrats plus 100 if the governor is a Democrat (Bailey and Rom 2004).\textsuperscript{28} Government ideology is measured using updated scores from Berry et al. (1998) where higher values reflect more liberal elite preferences. I control for the ideological and partisan preferences of state residents.\textsuperscript{29} The percentage of residents who support the Democratic Party or who are liberal is measured using the MRP approach as explained in Chapter 2.\textsuperscript{30} Finally, I include a dummy variable to indicate whether a state is a tobacco producer. This is an important variable to include since Shipan and Volden (2006) find that tobacco producing states are significantly less likely to pass anti-smoking legislation.

\textbf{Results: Baseline Model of Enacting Smoking Bans in Restaurants}

Results from estimating a logistic regression are shown in Table 6.1. As shown in Model 1, which is the baseline model located in the first column of Table 6.1, one of the most important influences over whether a state enacts a smoking ban in restaurants is whether neighboring states have already adopted a similar policy. This is consistent with past research on policy innovation (Berry & Berry 1990) and the probability of states adopting anti-smoking legislation (Shipan and Volden 2006). In substantive terms, the model predicts that the probability of enacting a smoking ban in restaurants increases by 5% as the proportion of neighbors with smoking bans goes from 0 to 1, keeping all other variables constant at their mean values.

Also important is Democratic party strength, government ideology, and the ideological preferences of state residents. According to Model 1, a state is more likely to enact a smoking ban if the state legislature is controlled by the Democrats and if the state residents are liberal.

\textsuperscript{28} The democratic strength variable is not available for 2008. Consequently, I use the estimates from 2007 to account for differing levels of democratic strength across the states in 2008.

\textsuperscript{29} Berry et al.’s measure of government ideology is not available after 2006. Consequently, I use the estimates from 2006 for 2007 and 2008 to account for the differing levels of government ideology across the states in these two years.

\textsuperscript{30} The ideology and party identification variables are not available after 2006. Consequently, I use the estimates from 2006 for 2007 and 2008 to account for the differing levels of ideology and partisanship across the states in these two years.
Both of these results are consistent with past research and expectations. Specifically, the model predicts that the probability of enacting a smoking ban in restaurants increases by 28% as states go from little democratic control to the maximum level of democratic control, keeping all other variables at their mean levels. States that house the most liberal citizens have a probability of enacting a smoking ban that is 9% higher than states that house the least liberal citizens. Note that inconsistent with previous research on anti-smoking legislation, the percentage of adult smokers is not significantly related to whether a state enacts a smoking ban in restaurants.

The model also predicts that the more liberal state legislators are, the less likely they are to enact smoking bans in restaurants, which goes against the expectation that liberal politicians are more likely to enact smoking legislation compared to conservative officials. States with the most liberal legislators have a probability of enacting a smoking ban in restaurants that is 6% less than states with the least liberal legislators, keeping all other variables at their mean values. These results are most likely due to collinearity issues between Democratic control and government ideology. Indeed, the Democratic control variable and the elite liberalism are correlated ($r = .16$). When the model is re-estimated without the Democratic control variable (available upon request), elite liberalism is positively related to the adoption of smoking bans in restaurants ($\beta = .14^{**}$).

**Results: The Influence of Public Opinion on Policy Innovation**

I compare the results in Model 1 with a second model in which I include a measure of state preferences towards smoking bans in restaurants. The public opinion variable is measured almost identically to previous chapters; I measure the percentage who favored a smoking ban in restaurants using the Current Population Survey Tobacco Use Supplement and Gallup polls from 1990-2006. There is one difference, however, from previous analyses. Since the dependent variable ranges from 1990-2008, I impute measures of state public opinion towards smoking bans for 2007 and 2008 so that the time period can be extended. Imputation was conducted at the
state-year level using Amelia; details can be found in Appendix B. Similar to the percentage of adult smokers variable, the public opinion measure on smoking bans in restaurants is highly correlated with the proportion of neighboring states that have already adopted a smoking ban \((r=0.59)\). Consequently, I transform the public opinion measure to reflect changes in public support for smoking bans in restaurants by differencing it; via this transformation, the correlation with the proportion of neighbors decreases \((r=0.14)\).

As can be shown in Model 2 of Table 6.1, public opinion plays a key role in the probability that a state innovates. More specifically, the model predicts that a state that experienced the most positive change in preferences towards smoking bans has a probability of enacting smoking bans in restaurants that is 20% higher than a state that experienced a decline in support for smoking restrictions. Consistent with expectations, public opinion has a positive influence over whether a state innovates. This is an important finding since previous research has generally concluded that public opinion plays no or a very little role in the probability that a state innovates (e.g., Berry and Berry 1990).

Interestingly, once public opinion towards smoking bans in restaurants is controlled, the influence of neighboring state policies becomes insignificant. This is especially noteworthy since previous research has found that neighboring states have a large influence over whether a state innovates. Moreover, these results tell us something about the mechanism through which diffusion occurs across states that are geographically proximate. The results in Model 2 suggest that states look towards neighboring states when making decisions about innovating because it provides information about the level of public support within their own borders. Because neighboring states are similar in culture and ideology (e.g., Erikson, Wright, and McIver 1993), state legislators view the adoption of policies in neighboring states as a resource through which to

\[\text{Recall from Chapter 5 that public opinion measures were also imputed for 1997 and 2004. Details can be found in Appendix B.}\]
learn about the public support in their own state for similar policies. This makes sense, especially since the public may be harder to gauge on specific issues, such as smoking bans in restaurants. While others have suggested that the positive influence of neighboring states on innovations is due to economic competition (Berry and Baybeck 2005) or social learning about the success of policies (Volden 2006; Berry and Baybeck 2005), the results in Model 2 suggest that the positive influence of neighboring states is due to social learning about the public preferences of state residents.

**Results: The Influence of Opinion Homogeneity on Diffusion**

In the third model, I test whether diffusion is more likely to occur if there is homogeneity in public opinion across the nation. Above, I hypothesized that diffusion occurs at a faster pace if there is large homogeneity in public opinion across the states. To account for the amount of homogeneity in public support for smoking bans in restaurants across the nation, I include a variable that measures the standard deviation difference between the state with the highest level of support for smoking bans in restaurants (e.g., the maximum level of support) and the state with the lowest level of support for smoking bans in restaurants (e.g., the minimum level of support) per year. If diffusion is more likely in times of homogeneity, then this variable should have a negative coefficient. In other words, as heterogeneity increases, diffusion should be less likely.

Results in Table 6.1 in Model 3 show that the homogeneity of public opinion on smoking bans across the nation has no significant influence over the probability that a state innovates. Similar to results in Model 1, the proportion of neighboring states that have already adopted a smoking ban in restaurants is positively related to the probability that a state will innovate. Also significant is democratic strength, the percentage of liberal residents, and the ideology of state legislators.
Results: The Influence of Neighboring Opinion on Diffusion

In the fourth model, I test whether public preferences towards smoking bans in neighboring states accounts for the diffusion of smoking bans across neighbors. Recall that I hypothesized that neighboring states may be more likely to innovate, not due to geographic proximity, but because they look towards other states with similar levels of public opinion before innovating. To test this directly, I measure the average level of support for smoking bans in restaurants in neighboring states. The contemporaneous measure of the average level of public support for smoking bans in restaurants among neighboring states is correlated with the proportion of neighboring states that have already adopted smoking bans in restaurants ($r = .61$).

In order to reduce multicollinearity, I measure the average level of public support for smoking bans in restaurants among neighboring states as a differenced covariate; indeed the correlation between the differenced average level of support among neighboring states and the proportion of neighboring states that have already adopted smoking bans in restaurants is small ($r = .28$).

Including the differenced level of public support among neighboring states also allows me to test whether changes in the public preferences of neighboring states influence the probability of a state to innovate. More important, if the influence of the proportion of neighboring states that have enacted smoking bans decreases or becomes insignificant once I control for the public opinion of neighboring states, then this indicates that diffusion is occurring across states with similar levels of public support for smoking bans in restaurants.

Results in Model 4 in Table 6.1 suggest that some of the positive effect of neighboring states on the probability of innovating is due to the level of public support on anti-smoking legislation in neighboring states. As shown in Model 4, the proportion of neighboring states is no longer significantly related to the probability of enacting a smoking ban in restaurants once the average support for smoking restrictions of neighboring states is controlled. And, the direction of the coefficient for the neighboring opinion variable is in the expected direction; as public support
for smoking bans increases in neighboring states the probability of innovating increases.
However, these results are not entirely conclusive since neither the proportion of neighboring
states nor the average support of neighbors is statistically significant using conventional
significance levels.

**Results: A Combined Model of Policy Innovation and Diffusion on Smoking Bans**

Finally, in Model 5, I include all the variables previously mentioned. By including all of
the variables, I am able to explore which measure of public opinion is most important in
influencing the adoption and diffusion of smoking bans in restaurants across the states.
Moreover, I compare the relative influence of each variable by computing predicted probabilities.
Results are shown in Table 6.1.

As shown in Model 5 in Table 6.1, public preferences within a state’s borders continue to
influence the probability that a state innovates even after controlling for the proportion of
neighboring states with similar policies, the homogeneity of public support across the nation, and
the public preferences of neighboring states. More specifically, the model predicts that the
probability of a state with the highest change in support for smoking bans in restaurants is 16
percentage points higher than a state that experienced a decline in public support for anti-smoking
legislation, keeping all other variables constant at their means.

Consistent with results in Model 1, democratic strength, the ideology of state legislators,
and the percentage of state residents who are liberal also matter for innovation. Specifically, the
model predicts that the probability of enacting a smoking ban in restaurants increases by 26
percentage points as states go from little democratic control to the maximum level of democratic
control, keeping all other variables at their mean levels. States that house the most liberal citizens
have a probability of enacting a smoking ban that is 9% higher than states that house the least
liberal citizens. And, again, although inconsistent with previous research, the model predicts that
states with the most liberal legislators have a probability of enacting a smoking ban in restaurants
that is 5 percentage points less than states with the least liberal legislators, keeping all other variables at their mean values. Via comparisons, public preferences towards smoking bans in restaurants supersedes the effects of other important variables, such as the political ideology of residents or state legislators and accounts for the large effect that neighboring states have on the probability of innovation.

Conclusions

The goal of this chapter was to dig deeper into the role that public opinion plays in the innovation and diffusion of policies across the states using anti-smoking legislation as a case study. Past research on policy innovation and diffusion has largely ignored the role that public opinion plays in this process, often because of the methodological challenges in measuring state opinion over time, which has lead to inconclusive results in the past. I sought to overcome this gap in the literature by exploring how public preferences towards smoking bans in restaurants, developed in Chapter 3, influence the probability that a state enacts a smoking ban in restaurants.

Through a variety of models, I find that state preferences play a key role in the probability that a state innovates. As public opinion becomes more supportive of smoking bans in restaurants, a state is more likely to enact a smoking ban in restaurants. This finding is consistent with traditional notions of democracy and is not unexpected. What is novel about these findings, however, is that public opinion plays an important role in the adoption of policies even after controlling for policy enactments of neighboring states. The majority of past research has found that neighboring states have a large effect over the adoption of innovations (e.g., Berry and Berry 1990). And, scholars have hypothesized that the mechanism through which neighboring states influence innovation is economic competition or social learning (e.g., Berry and Baybeck 2005).

The results presented in this chapter suggest a different mechanism through which neighboring states influence innovation. In particular, the results suggest that states look towards
neighbors when making decisions about innovating because it provides information about the level of public support within their own borders. State legislators view the adoption of policies in neighboring states as a resource through which to learn about the public support in their own state for similar policies. If neighboring states that are similar in culture, demographics, and ideology have enacted certain policies, then public support is ripe for similar policies in a legislator’s own state.

More research is needed, however, to confirm these conclusions. Are the results presented here unique to anti-smoking legislation or do they characterize the role that public opinion plays in the adoption of innovations more generally? Perhaps state legislators use neighboring states as a resource to learn about public opinion in their own borders only on issues that are less visible in the media, such as support for smoking bans in restaurants. Are there factors that mediate the impact that public opinion has on innovation? For instance, are legislators that are more professional more likely to respond to changing public preferences compared to other legislators? And, are state legislators actually using neighboring policies to inform them about opinion within their own borders? Elite surveys of state legislators that ask about the ways in which officials gauge public opinion could be helpful in answering this last question. Regardless, the results presented in this chapter suggest that the impact that neighboring states and public opinion play in the innovation and diffusion of policies across states is more complex than originally thought.
References for Chapter 6


Table 6.1 Logistic Regression Analysis of the Probability of A State Enacted a Smoking Ban in Restaurants (N=742)

<table>
<thead>
<tr>
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<th>Model 1: Baseline</th>
<th>Model 2: Public Opinion on Smoking Bans in Restaurants</th>
<th>Model 3: Homogeneity in Public Opinion</th>
<th>Model 4: Public Opinion of Neighboring States</th>
<th>Model 5: Final Model with All Covariates</th>
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<td></td>
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<td>Homogeneity of Public Opinion for Smoking Bans</td>
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<td>-0.02</td>
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<td>(.06)</td>
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<tr>
<td>∆ Average Level of Support for Smoking Bans in Neighboring States</td>
<td>.16</td>
<td>0.16</td>
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<td>.06</td>
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<tr>
<td>Ratio Tobacco Lobbyists</td>
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<td>16.34</td>
<td>17.67</td>
<td>16.81</td>
<td>19.10</td>
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<td></td>
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<td>(26.55)</td>
<td>(28.50)</td>
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<td>Ratio Health Lobbyists</td>
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<td>∆ Percentage Adult Smokers</td>
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<td>.21 ***</td>
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<td>.21 ***</td>
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<td>(.06)</td>
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<td>(.05)</td>
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<td>(.05)</td>
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<tr>
<td>Tobacco Producing State</td>
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<td>(1.87)</td>
<td>(2.76)</td>
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Note: Robust Standard Errors in parentheses. Significance levels: **.05, ***.01 with a two-tailed test
Chapter 7

Dynamic Policy Responsiveness in the States: What We Have Learned and Where to Go from Here

The goal of this dissertation was to explore the role that public opinion played in policy decisions over time at the sub-national level, which is called *dynamic policy responsiveness*. Along the way, I developed a measurement strategy for estimating state opinion over time, assessed the patterns of change in state opinion across various issues, explored the role that opinion played in incremental as well as episodic policy changes in the states, and looked at how state opinion reacted to policy changes over time. In this final chapter, I summarize the major findings of the dissertation and give thoughts about future research. While this project has taken a solid first step in investigating dynamic policy responsiveness in the states, there is much more to be done as I talk about below.

Measuring State Opinion over Time via the MRP Approach

A major contribution of the dissertation is the development of a measurement strategy to estimate the longitudinal variation in mass state opinion across time. As explained in Chapter 2, scholars have long struggled with how to reliably and accurately estimate the political preferences of state residents because of the lack of state polls over time. Because scholars cannot rely upon state polls for information, they must use national surveys from which to estimate state opinion. Yet, using national surveys presents two methodological challenges to measuring state opinion because of the national survey design.

First, there are reliability issues, particularly for the less populated states, since in any one national survey there may be a small amount of citizens interviewed from a particular state. Second, there is no guarantee that state estimates will be representative when taken from national surveys. It is because of these two methodological challenges that scholars have often pooled national surveys from a large time frame—and, by doing so, eliminating any longitudinal
variation to measure aggregate state opinion. And without an appropriate measurement strategy to estimate dynamic state opinion, scholars are limited in exploring the role of public opinion on policy changes (and vice versa) in the states.

As shown in Chapter 2, I use a type of small area estimation technique to overcome the two aforementioned problems inherent in using national surveys to measure state opinion. More specifically, I use multilevel modeling, imputation, and post-stratification (MRP) applied to a small pooled time frame to estimate state opinion over time. In Chapter 2, I use the MRP approach to measure two global indicators of state opinion: partisanship and ideology from CBS/NYT polls. I then showed via various validation analyses that this method generates reliable and valid measures of state public opinion across the fifty states and the District of Columbia. I apply this method to estimate state opinion on specific issues, such as the death penalty, abortion, education spending, welfare spending, and anti-smoking legislation using various national surveys in Chapter 3.

From Chapters 2 and 3, a unique database is created with dynamic state opinion on two global indicators of public opinion and five specific indicators of public opinion, although the actual time span varies for each issue. These data may prove useful to other scholars interested in exploring (1) whether state public opinion moves over time, (2) what influences heterogeneous movement across the states, and (3) how public opinion influences the political process over time at the state level on these various issues.

The broader impact of Chapters 2 and 3 is the methodological contribution to the estimation of state opinion over time. The MRP approach 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 and, thus, influence state politics. Having estimates of dynamic state opinion across a wide range of issues can help scholars identify whether the patterns found in this dissertation are unique to the issue areas
studied here or whether there are more general theories that apply to the sub-national level. Moreover, from measuring dynamic state opinion on other issues and attitudes, scholars can also begin to understand how changes in public opinion diffuse across the states. Take changes in consumer sentiment or presidential approval, both of which exhibit large dynamics over time, for example. Do a few states “lead the way” in changes towards the economy or the president? Do all states follow the opinion trends in these leader states or are some states more immune to national or regional changes in opinion? And, what influence does the diffusion of state opinion have for the public preferences of the rest of the nation? Answering questions like these will provide insight into how large national shifts in public sentiment occur.

**Dynamic Patterns of State Public Opinion across Issues**

Once scholars have dynamic estimates of state opinion, we can begin to explore the dynamic properties of state opinion. Specifically, we can explore whether state opinion is stable or dynamic and, if dynamic, whether states generally exhibit homogeneous or heterogeneous trends over time. We can also assess whether these dynamic patterns vary across issue areas.

As explained in Chapter 4, there are four possible scenarios to expect when talking about the dynamic properties of state opinion. First, state opinion may change only gradually over time in roughly the same rates across the states. Second, state opinion may change abruptly over time with states exhibiting similar patterns of change. Third, state opinion may change only gradually over time with the states exhibiting different rates of change. Finally, state opinion may change abruptly with states exhibiting different patterns of change. What can we deduce about public opinion from these four varying patterns of state public opinion?

When public opinion moves gradually across time, changes could be caused by population changes that are also gradual over time, such as migration, immigration, generational replacement, differential birth and death rates among different demographic segments of the population (Carmines and Stimson 1989; Page and Shapiro 1992; Brace et al. 2004), or gradually
changes in social and/or political norms. When public opinion moves abruptly, scholars find that public opinion is responding to current events, the economy, or other transient outcomes (Page and Shapiro 1992; Erikson, MacKuen, and Stimson 2002). If state public opinion trends identically across the states, national level phenomena are the primary causes of shifting state public opinion. Where state public opinion changes are unique to particular states or regions, state-specific characteristics must be responsible for shifts in public opinion, not national level phenomenon. Hence, the combination of the rate of change in state public opinion (i.e., gradual or abrupt) and the patterns of change across states (i.e. heterogeneous or homogeneous) may provide insights about the causes of changing public opinion.

Through various analyses in Chapter 4, I find that the dynamic properties of state opinion depend on the specific issue. State partisanship changes gradually over time with evidence of heterogeneous trends, yet there is also evidence that it responds to short term factors. On the other hand, state ideology is characterized by stability and when it does change, it does so in small increments. Preferences towards the death penalty, welfare spending, and anti-smoking legislation are dynamic with heterogeneous trends, particularly across regions. Preferences towards education spending are also dynamic, yet with much more homogeneous trends compared to preferences towards the death penalty or welfare spending. Finally, abortion attitudes are quite stable across time in the states. More generally, the results suggest that regional or state specific characteristics are influencing change for state partisanship, preferences toward the death penalty, attitudes on welfare spending, and support for anti-smoking legislation. On the other hand, national events are probably more influential for preferences towards education spending. Finally, state ideology and abortion attitudes are fairly immune to current events as it is stable throughout the time period.

At a more basic level, the results in Chapter 4 underscore the need for measures on both global indicators of public opinion as well as specific indicators of opinion. While there is a
debate over whether state opinion is dynamic or stable (e.g., Berry et al. 1998; 2007; Erikson, Wright, and McIver 1993; 2007; Brace et al. 2002), the majority of this debate focuses on global indicators of public opinion, such as state ideology. Resolving the debate about the dynamic properties of state public opinion requires direct, over time measures of policy preferences on specific issues as well as global indicators. Simply assuming that state public opinion is either stable or dynamic is not sufficient. And, we must understand that “public opinion” encompasses more than just ideology.

There is an additional disagreement among state politics scholars about how we should adequately capture state public opinion. Some believe that state public opinion is best captured by a global measure of state ideology (Erikson, Wright, and McIver 1993; Berry et al. 1998) while others think that state public opinion is best captured with policy-specific survey questions (Johnson et al. 2004; Norrander 2000; 2001). By including measures on both global indicators of public opinion as well as specific indicators into our models, scholars can begin to discern what really matters for policy changes across the states. However, in order to do this, we must have (1) dynamic measures of public opinion across a variety of issues and domains and (2) understand the dynamic properties of these measures of public opinion. The analyses in Chapter 4 are important first steps to achieving those two goals.

The results in Chapter 4 are merely suggestive of the causes of state opinion changes. One thing we can conclude from the analyses in Chapter 4, however, is that there is large variation in the dynamic patterns of state opinion across issue areas and that there are probably multiple mechanisms at work. Identifying the exact mechanisms by which state opinion changes and exploring whether similar mechanisms are responsible for more than one issue area are two avenues for future research on the behavior of state opinion over time.
The Dynamic Relationship between Opinion and Policy in the States

In Chapter 5, I ask whether and to what extent dynamic policy responsiveness exists in the states. I explore the extent to which changes in public opinion exhibit congruent changes in state policy in education and welfare expenditures as well as anti-smoking legislation. I outlined three models of responsiveness: the simply majority rule model, the competitive elitism model, and the thermostatic model of policy responsiveness.

The main difference between these models is the direction of causation from opinion to policy. The simple majority rule model suggests that opinion should positively influence changes in policy and not vice versa; this is a traditional model of democratic governance. On the other hand, the competitive elitism model argues that policy changes should negatively influence changes in opinion; political elites drive changes in public opinion instead of vice versa. Finally, the thermostatic model of responsiveness is a two-directional model in which opinion and policy continuously react to each other over time. More specifically, the thermostatic model of policy responsiveness posits that policy changes follow changes in public opinion; however, public opinion also reacts to policy changes across time. However, unlike the competitive elitism model, public opinion reacts negatively to policy changes over time. When policy output increases, the public’s preference for more policy decreases; when policy decreases, the public’s preference for more policy increases. The result is a reactive system of governance where public opinion and policy constantly adjust and readjust to each other over time.

I specifically test the thermostatic model of policy responsiveness in Chapter 5 using time series analyses. For all three issue areas, there is evidence that policy changes respond in the expected direction to changes in public opinion. For instance, the model predicts that just a 3 point increase in support for education spending results in an additional $500 spent per classroom in the following time period (assuming 25 students per class). However, the way in which public opinion responds to policy changes varies across issue areas. For both education and welfare,
public opinion responds to expenditures in the long run and in a negative way. For anti-smoking legislation, public opinion responds to additional restrictions in both the short and long run in a positive way.

The analyses in Chapter 5 are novel for two reasons. First, the evidence suggests that dynamic policy responsiveness in the states functions in ways that are consistent with our expectations of a successful democracy. When public opinion changes, state policies follow. Second, although the direction varies across issues, when policy changes, the public responds in ways that are consistent with a “rational” public. The results suggest that even though questions of rationality abound at the individual level (e.g., Converse 1964), when state opinion is aggregated, state residents respond in reasonable ways to policy changes. The fact that state opinion responds to policy changes is necessary for policy representation; policy representation ultimately requires that the public notices and responds to what policy makers do. Otherwise, there would be little incentives for policy makers to represent what the public wants. In this sense, we would conclude that democracy works at the sub-national level and works much better than many of us may have expected.

While the analyses in Chapter 5 has taken an important step in exploring the dynamic relationship between opinion and policy in the states, there are three areas of future research, which I believe are particularly fruitful. The first is to identify the mechanisms through which dynamic representation occurs. The second is to explore possible mediating factors that may condition the influence that opinion has on policy and vice versa. Finally, scholars can begin to decipher how issue characteristics influence dynamic responsiveness by looking at variations across issue areas. I talk in more detail about all of these areas below.

Mechanisms of Dynamic Responsiveness: The Influence of Opinion on Policy

In Chapter 5, I outlined various mechanisms through which policy may respond to public opinion over time. Policy responds to public opinion primarily through the elections, which serve
as the main link between state opinion and policymakers. Elections lead to two mechanisms that explain the responsiveness of policy changes to mass public preferences: electoral turnover and political expediency (Erikson, MacKuen, and Stimson 2002). Electoral turnover accounts for the fact that the public elects elites who are in line with their policy preferences who then enact similar policies; for instance, a liberal public elects Democrats into office who then enact liberal policies. At the same time, however, elected officials catch wind of changing public opinion and adjust their behavior accordingly because they are motivated by re-election; this is political expediency. Both of these mechanisms have been found to explain the relationship between public opinion and policy at the national level (Erikson, MacKuen, and Stimson 2002).

What we do not know is whether these same mechanisms are at work at the sub-national level. And, in fact, the evidence presented in Chapter 5 is merely suggestive that elections play a critical role in the way in which policy responds to opinion. Should we expect the same mechanisms to account for the public opinion policy linkages found across the states? The answer depends on whether (1) elections are tools that state electorates use to influence policy outputs and whether (2) state political elites are rational actors who adjust their behavior in order to be re-elected. With the first point, liberal state electorates are expected to elect Democrats to office while conservative state electorates are expected to elect Republicans to office, similar to the national level. While this makes both theoretical and intuitive sense, the empirical evidence is quite weak. Many early studies found that the relative strengths of the Republican and Democratic parties in state politics were statistically unrelated to the policy directions within the states (Dye 1969). The seemingly unimportance of parties in state elections was reconciled by Erikson, Wright, and McIver (1993) who acknowledged the wide variation in the ideological orientations of state political parties. This variation is a result of state electorates; liberal state electorates tend to have state parties that are liberal while conservative state electorates produce
parties that are conservative. The flexibility that the parties have in their ideological stances across the states leads to the mismatch between electoral partisanship and policy output.

Erikson, Wright, and McIver (1993) show that party elite liberalism is an intervening variable between state opinion liberalism and legislative party strength. Liberal state electorates cause liberal parties, which over time contribute negatively to Democratic partisanship. This negative relationship is due to the fact that state parties and elites moderate their positions when running for office; in ideologically similar states, Republicans gain votes by moving to the left while Democrats gain votes by moving to the right. Indeed empirical evidence presented by Erikson, Wright, and McIver (1993) show that state opinion liberalism is positively related to policy liberalism, but negatively related to Democratic legislative strength. Again, this negative relationship is a function of Democratic parties moderating their policy preferences to the right in states in which both parties are liberal. Nonetheless, the results provide strong evidence that state electorates use elections to influence policy outputs.

While we expect for state electorates to elect political elites that are ideologically similar, we also expect for state political elites to modify their behavior once in office. As with national political elites, we expect state elites to be rational actors who are primarily interested in reelection; we expect state political expediency. Erikson, Wright, and McIver (1993) find strong evidence that politicians—once in office—adjust their behavior to be in line with state electorates. In fact, their results suggest that the partisan division of the legislature is of little relevance. Once in office, Democrats and Republicans act in similar ways that “one cannot tell the difference” (Erikson, Wright, and McIver 1993 137). Again, this is a result of the variations across the states in party labels. Liberal electorates produce liberal parties, so regardless of partisan control, politicians enact liberal policies. Just as candidates moderate their policy preferences to gain office, they also moderate their preferences once in office. In ideologically similar states, Republican elected politicians move to the left while Democratic elected politicians
move to the right such that partisan identification is basically unrelated to policy liberalism. Given past research, it is reasonable to assume that state politicians adjust their preferences to changing public opinion.

Yet, there is more work to be done. In particular, how do state politicians gain information about the changing preferences of residents and are the ways in which state politicians gain this information different from national elites? Politicians may simply receive information via interaction with constituents (Fenno 1978), thus suggesting that state politicians may have a better idea of what their residents want since they interact on a much more personal level and have more frequent interactions compared to national politicians. It may be that state politicians have less uncertainty about changing public opinion, and thus, are more likely to respond in the short-term compared to national politicians.

Recent research also suggests that polls are particular important for politicians (Geer 1996; Jacobs and Shapiro 1995). But, little is known about how much state politicians use state polls in their decision-making or even whether state politicians are actively engaging in polling activity. Or do state politicians rely on national or regional surveys of public opinion because of the cost associated with more localized polls? Finally, interest groups may provide ample amount of information to politicians about the changing political winds. We know that there is large variation in the diversity and density of interest group activity across the states (Gray & Lowery), but little is known about how these variations translate into policymaking. And, in particular, we know little about how interest groups play a role in the response of state politicians to public opinion over time.

**Mechanisms of Dynamic Responsiveness: The Influence of Policy on Opinion**

The mechanisms that account for the public’s reaction to policy changes are less understood. Yet, we can deduce that the way in which the public responds to policy changes rests on the acquisition and availability of political information. State residents have to know about
policy changes in order to react to them. First, public opinion may respond to policy almost immediately as political information is transmitted by majority and opposition groups. In this scenario, public opinion responds to political rhetoric and discourse as transmitted by the media and political elites (Jacobs and Shapiro 2000; Zaller 1992; Stimson 1991). Indeed, there is evidence that newspaper and television exposure influences opinions at the individual (Bartels 1993; Mutz and Martin 2001) and aggregate levels (MacKuen, Erikson, and Stimson 1992). And, while the public may not know the specifics about the policy changes, they will be informed enough to understand the direction and scope of the change (Page and Shapiro 1992; Erikson, Wright, and McIver 2002; Burstein 2003).

But, public opinion may also respond to policy changes gradually over time as citizens experience the effects of those changes directly. This second, long term mechanism may mean that citizens are gradually learning about the new policy through their own experiences; for instance, residents may learn about a smoking ban in restaurants as they go out to eat in restaurants. But, public opinion may also respond to policy changes gradually over time through cohort replacement. I suspect that citizens who come of age under a new policy will react differently towards that policy compared with earlier born cohorts. What I am suggesting is that through cohort replacement, public opinion may gradually fall in line with policies that are enacted.

Again, the analyses in Chapter 5 are merely suggestive of the mechanisms by which state residents learn about policy changes. Scholars can begin to assess how information about policy changes is disseminated into the public via projects that look at how state media outlets respond to specific policy changes. For instance, does the public respond differently to policy changes, in the short term, when state media outlets have a consensus about the policy outcome compared to when there are large disagreements? How do state residents reconcile information received from local media outlets compared to national media outlets? Moreover, because information is
largely contingent on being transmitted via word of mouth, what role do social networks and communities play in the diffusion of information across a state? Finally, what role does cohort replacement play in the gradual reaction of opinion to policy changes? Are people who came of age under a certain state policy different from people who came of age earlier without that policy? Answering questions like these will help us understand how state publics respond to policy changes, which is a critical aspect of a functional democracy.

**Mediating Factors of Dynamic Responsiveness**

As stated in the introductory chapter, the states provide a prime laboratory for studying how public opinion is translated into policies and vice versa because of the variations in possible mediating factors. These factors allow scholars to identify variables that may condition the impact of public opinion on the policy process. While these specific types of analyses are beyond the scope of this project, the results presented here offer scholars a baseline from which to develop additional theories and empirical projects. In particular, we can begin to theorize how mediating factors may condition the way state opinion is translated into policy changes. We can also identify mediating factors that may condition the way in which state citizens respond to policy changes. I provide some ideas for future research on both of these areas below.

**Mediators on the Effect of Public Opinion on Policy**

Because the mechanism by which policy reacts to opinion rests with the political elites, the extent to which policy reacts to opinion should be dependent on *institutional characteristics*. Two important institutional characteristics that have been found to condition policy responsiveness include the presence of the initiative and legislative professionalism. Initiatives are a form of direct democracy where citizens can directly propose laws and policies to the legislature. Several studies have shown that initiatives heighten policy responsiveness to public opinion on a variety of issues including abortion (Areceneaux 2002; Bowler and Donovan 2004; Gerber 1999), government spending (Matsusaka 2004), the death penalty (Gerber 1996), and gay
rights (Gerber and Hug 2001). Why does the presence of initiatives increase policy responsiveness? One theory is that legislators take into account public opinion when drafting legislation in anticipation of future initiatives (Gerber 1996). Hence, the mere “threat” of an initiative is enough for elected officials to respond to changing levels of public opinion. Another theory is that initiatives give legislators more accurate information about voter preferences (Romer and Rosenthal 1979; Matsusaka 2004). The presence of initiatives, thus, gives legislators an extra information source from which to gauge changing public opinion. Both of these theories imply that initiatives will influence the political expediency of state legislators. Because political expediency explains the short term influence of public opinion on policy, we should expect the presence of initiatives to mediate the short term relationship between public opinion and policy.

Legislative professionalism also has been shown to increase policy responsiveness. Professional legislatures are those in which legislators meet in unlimited session, are paid well, and are provided with superior staff resources and facilities (Squire 1992). These increased resources allow professional legislators to have more contact with their constituents (Squire 1993), monitor changing preferences better, and, therefore, be more attentive to constituent concerns (Maestas 2000). Hence, in the short term, legislative professionalism increases the policy responsiveness to public opinion, again, because it allows legislators to monitor and react quicker to changing public opinion through political expediency.

However, the effect of legislative professionalism on policy responsiveness can also have long term effects. Legislative professionalism creates an environment that attracts highly skilled politicians who vie for elected office; individuals seeking office in professional legislators are more likely to be “career” or professional politicians (Berkman 1994; Squire 1992; Thompson and Moncrief 1992) who have ambitious long term goals of higher office (Maestas 2000; 2003). Because professional legislatures attract higher quality politicians, responsiveness through electoral turnover is also expected to be higher in these legislatures. Hence, legislative
professionalism should mediate both the short and long term components of the effect of public opinion on policy as (1) professional legislators are better equipped to monitor changing preferences in the short term and (2) citizens have a higher quality pool of candidates from which to elect in the long term.

**Mediators on the Effect of Policy on Public Opinion**

The extent to which policy changes influence public opinion should be dependent on citizen characteristics and aspects of the broader political environment. The primary premise of a two directional model of policy responsiveness is that citizens are attentive to policy changes over time. Hence, factors that influence the amount of political awareness of the mass public should mediate the influence of policy on aggregate preferences. One factor that influences political attentiveness and sophistication more broadly is educational attainment; at the individual level, educational attainment is positively associated with political information acquisition, political knowledge (Delli Carpini and Keeter 1996), and political interest (Brady, Verba, and Schlozman 1995). We should expect the same relationship at the aggregate; the more educated a public is the more politically sophisticated and responsive to what policy makers are actually doing. I theorized that the public can respond to policy changes in the short term via information or in the long run in response to tangible policy outcomes. Regardless, the more attentive or political sophisticated the public is, the more responsive it will be to changing policies in both the short and long term.

The broader political environment can also condition the influence of policy changes on public opinion. There are many aspects of the political environment, which may influence the amount of information the public has about policy changes; however, one particularly important factor is political competition. How might party competition increase the public’s response to policy changes? Increased party competition may simply lead to more political information in the environment causing individuals to be more aware of policy changes (Nicholson 2003; Delli
Carpini, Keeter, and Kennamer 1994). Increased party competition may also cause politicians to be more likely to use the media to win public support for the policy changes that they desire (Jacobs and Shapiro 2000). Whether due to an increase in political information or an increase in “crafted talk” by political elites (Jacobs and Shapiro 2000), political competition is expected to increase the public’s response to policy changes. And, because the public responds to the information of policy changes immediately, political competition will mediate the effect of policy changes on public opinion in the short term.

In short, while looking at the mediating factors of dynamic policy responsiveness is beyond the scope of this project, there are several avenues for future research. In particular, I’ve suggested that institutional factors should mediate the way in which political elites respond to changing political preferences. Similarly, the way in which state residents respond to policy changes should depend on factors that influence the amount of information in the political environment. These are simply a few of the many possible factors that may mediate the dynamic relationship between opinion and policy over time at the sub-national level. The beauty of studying dynamic policy responsiveness at the sub-national level is that we can use the variations across the states to identify these mechanisms, thereby improving upon our theoretical models of responsiveness more generally.

**Variations across Issues**

Finally, an important avenue for future research is to explore how dynamic policy responsiveness varies across issues and to answer why these variations exist. The analyses in Chapter 5 identify important way in which the dynamic relationship between opinion and policy varies across issues. In particular, I find that while preferences towards education and welfare spending respond negatively to state expenditures, state attitudes towards anti-smoking legislation actually becomes more supportive as restrictions increase.
The question for future research then, is why does public opinion respond differently to anti-smoking legislation compared to expenditures? It may be that public health issues are simply different from other issues. Because the goal of the policy outcome (i.e., to improve public health of state residents) is generally agreed upon among citizens, there may be more of an acceptance of policies compared to when the goal of the policy outcome causes large political divisions. It may also be that public opinion responds differently to incremental policy changes, such as expenditures, compared to more episodic policy changes, such as anti-smoking legislation.

The point is that there are various issue characteristics which may influence the dynamic relationship between opinion and policy. Issues vary on a number of different factors that may influence the ways in which policy reacts to opinion changes and vice versa. At a basic level, issues vary in saliency or how important the issue is to the public. Some issues, such as abortion and pornography regulation, gambling, the death penalty, and sex education, are more sensitive to public opinion because they are non-technical, highly salient, and easily understood by residents (Mooney & Lee 1995; Carmines & Stimson 1989). Because of these characteristic, citizens have both the ability and the incentives to make their views known to their representatives (Carmines & Stimson 1980). Moreover, because citizens are louder in their policy preferences for highly salient policies, it is probably easier for political officials to gauge and respond to public opinion. These issues are also likely to form the subject of political debate (Graber 1989) and candidates are likely to pay more attention to public opinion on these issues (Hill and Hurley 1999). Indeed several scholars have found that politicians respond more directly to citizen preferences on salient, non-technical policies, such as the death penalty (Haider-Markel and Meier 1996; Mooney and Lee 1995). And while few studies looking at the impact of opinion on policy include direct measures of issue salience, those that do suggest that public opinion has a stronger impact on policy for highly salient issues (Burstein 2003; Wlezien and Soroka 2007). These same studies also imply that the public will be more likely to respond to policy changes on those
issues that they care more about (Wlezien and Soroka 2007), yet it is unclear how exactly the public should respond to policy changes (e.g., in a positive or negative way).

The fact that issues vary on characteristics not only implies variation in representation across issue areas, but also variation in responsiveness across time as issues wax and wane in importance (Wlezien and Soroka 2007). Hence, an additional avenue for future research is to assess how issue saliency varies across time and whether the relationship between opinion and policy varies as issue characteristics change. The expectation is that as saliency increases, the relationship between opinion and policy should also increase (Jones 1994; Franklin and Wlezien 1997; Soroka 2003), yet there is little research in this area to confirm that expectation (Wlezien 2005; Burstein 2003). And, we know even less about how issue saliency varies across the states and how that variation impacts dynamic responsiveness at the sub-national level.

The Role of Public Opinion on Policy Innovation

Finally, in Chapter 6, I explored the role that state preferences towards smoking bans in restaurants played in the adoption of smoking bans in restaurants across the states. Specifically, I analyzed the role of public opinion on state policies from the perspective of state innovation and diffusion. Via this approach, states adopt a new policy (in this case, smoking bans in restaurants), but at different times. By using event history analysis, I can explore the role that public opinion plays in the timing variations in state adoption of smoking bans. This is different from the analyses in the Chapter 5 in which I explored the role of public opinion on a continuous measure of anti-smoking legislation that can (potentially) change every year.

Through a variety of models, I find that state preferences play a key role in the probability that a state innovates. As public opinion becomes more supportive of smoking bans in restaurants, a state is more likely to enact a smoking ban in restaurants. This finding is consistent with traditional notions of democracy and is not unexpected. What is novel about these findings, however, is that public opinion plays an important role in the adoption of policies
even after controlling for policy enactments of neighboring states. The majority of past research has found that neighboring states have a large effect over the adoption of innovations (e.g., Berry and Berry 1990). And, scholars have hypothesized that the mechanism through which neighboring states influence innovation is economic competition or social learning (e.g., Berry and Baybeck 2005).

The results presented in Chapter 6 suggest a different mechanism through which neighboring states influence innovation. In particular, the results suggest that states look towards neighbors when making decisions about innovating because it provides information about the level of public support within their own borders. State legislators view the adoption of policies in neighboring states as a resource through which to learn about the public support in their own state for similar policies. If neighboring states that are similar in culture, demographics, and ideology have enacted certain policies, then public support is ripe for similar policies in a legislator’s own state.

More research is needed, however, to confirm these conclusions. Are the results presented in Chapter 6 unique to anti-smoking legislation or do they characterize the role that public opinion plays in the adoption of innovations more generally? Perhaps state legislators use neighboring states as a resource to learn about public opinion in their own borders only on issues that are less visible in the media, such as support for smoking bans in restaurants. Are there factors that mediate the impact that public opinion has on innovation? For instance, are legislators that are more professional more likely to respond to changing public preferences compared to other legislators? And, are state legislators actually using neighboring policies to inform them about opinion within their own borders? Elite surveys of state legislators that ask about the ways in which officials gauge public opinion could be helpful in answering this last question. Regardless, the results presented in Chapter 6 suggest that the impact that neighboring
states and public opinion play in the innovation and diffusion of policies across states is more complex than originally thought.

**Concluding Remarks**

I started this project with a simple question: does public opinion matter? After various analyses, the answer seems to be an emphatic “yes”; public opinion does matter at the sub-national level. Variations in state policies reflect differences in state opinion. And, public opinion does not just matter in a static way; the manner in which state preferences change plays an important role in how state policies are made over time. The relationship between opinion and policies at the state-level is not just contemporaneous; instead there is a causal relationship between state preferences and policy changes. Public opinion influences changes in state policies, but state policies also influence changes in state opinion. The fact that state opinion responds to policy changes is important. After all, the very idea of policy responsiveness implies that citizens respond in a rational way to policy changes. As Wlezien and Soroka (2007) state “the existence of each connection between opinion and policy—indeed, the existence of both connections—is critical to the functioning of a representative democracy” (812-813). And, in light of this, it seems from these analyses that representative democracy is functioning quite well in the American states.
References for Chapter 7


Appendix A

Details on Surveys and Question Wording for Public Opinion Measures

In Appendix A, I provide detailed information about the surveys used to create the public opinion measures in Chapters 2 and 3. More specifically, information on survey organization, question wording, and the coding for each issue area is shown in Table A1. All surveys were collected using Penn State’s *iPoll* database. As shown in Table A1, numerous surveys were compiled to create the public opinion measures. For instance, to create state public opinion towards the death penalty, over 55 different surveys across 3 survey organizations were used. It was important to use as many surveys as possible to expand the time frame, ensure that certain states had enough information, and increase the amount of information per state. In order to pool responses across organizations for a given year, I assume that each survey is measuring the same latent opinion; that bias is not introduced due to the survey design or survey implementation, such as question ordering or interviewer characteristics.

A large part of overcoming this bias was to limit my analyses to surveys that employed similar question wording. For instance, abortion attitudes vary a great deal based on the question asked; consequently, I only used surveys that asked about abortion in an absolute sense instead of in about specific situations (e.g., in cases of incest). The exception is with attitudes towards anti-smoking legislation. As stated in Chapter 3, there are large differences between the way people answered the question in the CPS compared to the Gallup polls. This difference was no doubt due to question wording; the CPS-TUS asked whether respondents thought that smoking “should not be allowed” in various public places, while the Gallup polls asked respondents about “bans” in various public places. Naturally, respondents are less likely to support bans compared to simple restrictions. To account for this difference in question wording, an additional covariate measuring the survey was included in the model (see Chapter 3 for details).
Table A1 Survey Organization, Question Wording, and Coding of State Public Opinion for Each Issue Area

<table>
<thead>
<tr>
<th>Issue Area</th>
<th>Question Wording</th>
<th>Years of Survey</th>
<th>Coding at Individual Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideology</td>
<td>How would you describe your views on most political matters? Generally do you think of yourself as liberal, moderate, or conservative? 1977-2007</td>
<td>1=liberal, 0=moderate, conservative</td>
<td></td>
</tr>
<tr>
<td>Partisanship</td>
<td>Generally speaking, do you usually consider yourself a Republican, a Democrat, an Independent, or what? 1977-2007</td>
<td>1=Democrat, 0=Republican, Independent</td>
<td></td>
</tr>
<tr>
<td>Abortion</td>
<td>Please tell me which one of the opinions best agrees with your view. 1. By law, abortion should never be permitted 2. The law should permit abortion only in case of rape, incest, or when the woman's life is in danger 3. The law should permit abortion for reasons other than rape, incest, or danger to the woman's life, but only after the need for the abortion has been clearly established. 4. By law, a woman should always be able to obtain an abortion as a matter of personal choice. 1980, 1982, 1984, 1986, 1988, 1990, 1992, 1994, 1996, 1998, 2000, 2004</td>
<td>1=women should always be able to obtain an abortion as a matter of personal choice, 0=else</td>
<td></td>
</tr>
</tbody>
</table>

General Social Survey

National Election Survey

CBS/New York Times

Gallup
<table>
<thead>
<tr>
<th>Question Wording</th>
<th>Years of Survey</th>
<th>Coding</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Education Spending</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount. g. improving the nation’s education system.</td>
<td>1973-1980, 1982-1991, 1993, 1994, 1996, 1998, 2000</td>
<td>1=too little, 0=too much, about right</td>
</tr>
<tr>
<td>National Election Survey</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If you had a say in making up the federal budget this year, for which programs would you like to see spending increased and for which would you like to see spending decreased: Should federal spending on public schools be increased, decreased or kept about the same?</td>
<td>1979, 1988, 1990, 1992, 1994, 1996, 2000, 2002, 2004</td>
<td>1=increased, 0=decreased, kept about the same</td>
</tr>
<tr>
<td>Gallup</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(I am going to ask you several additional questions about government spending. In answering, please bear in mind that sooner or later all government spending has to be taken care of out of the taxes that you and other Americans pay. As I mention each program, tell me whether the amount of money now being spent for that purpose should be increased, kept at the present level, reduced, or ended altogether.) How about spending for...federal money to improve the quality of public education?</td>
<td>1984, 1986, 1989, 1991, 1998</td>
<td>1=increased, 0=decreased, kept about the same</td>
</tr>
<tr>
<td>CBS/New York Times</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Should federal spending on education be increased, decreased, or kept about the same?</td>
<td>1979, 1988, 1990, 1996</td>
<td>1=too little, 0=too much, about right</td>
</tr>
<tr>
<td>Roper</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount)....improving the nation’s education system</td>
<td>1974-1977, 1979-1986</td>
<td>1=too little, 0=too much, about right</td>
</tr>
<tr>
<td><strong>Welfare Spending</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount. k. Welfare</td>
<td>1973-1980, 1982-1991, 1993, 1994, 1996, 1998, 2000</td>
<td>1=too little, 0=too much, about right</td>
</tr>
<tr>
<td>National Election Survey</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If you had a say in making up the federal budget this year, for which programs would you like to see spending increased and for which would you like to see spending decreased: Should federal spending on welfare programs be increased, decreased or kept about the same?</td>
<td>1992, 1994, 1996, 2000, 2002, 2004</td>
<td>1=increased, 0=decreased, kept about the same</td>
</tr>
<tr>
<td>Gallup</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount)... Are we spending too much, too little, or about the right amount... on welfare?</td>
<td>1980</td>
<td>1=more money, 0=less money, the same amount</td>
</tr>
<tr>
<td>CBS/New York Times</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount)... on welfare?</td>
<td>1992</td>
<td>1=too little, 0=too much, about right</td>
</tr>
<tr>
<td>Roper</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount)... on welfare?</td>
<td>1974-1986</td>
<td>1=too little, 0=too much, about right</td>
</tr>
<tr>
<td>Smoking Bans in Restaurants</td>
<td>Question Wording</td>
<td>Years of Survey</td>
</tr>
<tr>
<td>-----------------------------</td>
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<td>----------------</td>
</tr>
<tr>
<td>Gallup</td>
<td>What is your opinion regarding smoking in public places? First, in restaurants should they set aside certain areas, should they totally ban smoking, or should there be no restrictions on smoking?</td>
<td>1990, 1991, 1994, 1999, 2000, 2001, 2003, 2005, 2007</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Smoking Bans in Workplaces</th>
<th>Question Wording</th>
<th>Years of Survey</th>
<th>Coding</th>
</tr>
</thead>
</table>
Appendix B

Imputation of Public Opinion Measures used in Chapter 5

In Appendix B, I describe the measurement techniques for estimating dynamic public opinion on education spending, welfare spending, and anti-smoking preferences at the state level. In Section I, I describe three techniques used to impute estimates for the spending preferences for three time points (1995, 1997, and 1999) that are missing for all states. In Section II, I describe similar techniques used to impute estimates for the anti-smoking preferences for two time points (1994 and 2004) that are missing for all states. In the final section, I re-estimate the dynamic models reported in Chapter 5 using the various public opinion measures as described in Sections I and II.


For public opinion on education spending, the aggregate state level dataset spans from 1974-2000 while the aggregate state level data on public opinion on welfare spending span 1975-2000. For both datasets, there are three years in which all states are missing: 1995, 1997, and 1999. There are three techniques that I use to recover public opinion estimates for the states in 1995, 1997, and 1999. These techniques include mean interpolation, multiple imputation (MI) at the state-year level, and multiple imputation (MI) at the individual level prior to MRP. A fourth option is to estimate models using listwise deletion and ignoring the missing data from the three years, as I describe in the last section.

Mean Interpolation

Once I have state-level public opinion measures across time, I can impute data for 1995, 1997, and 1999 by using mean interpolation. Mean interpolation is used simply by taking the mean of the estimates prior to and after the missing data year. For instance, to get estimates on
public opinion for education in 1995, I simply take the state estimate for 1994, add it to 1996 and divide by two.

A major advantage of mean interpolation is its ease of execution. Mean interpolation, however, overestimates the certainty of the values, which can cause the standard errors in models to be too small (King, Honaker, Joseph, and Scheve 2001). Hence, even though mean interpolation is intuitively sensible, it can lead to additional statistical problems when using these values in subsequent models.

Mean interpolation can also cause bias towards linearity in our public opinion measures. We are assuming that nothing occurs to make public opinion estimates “spike” in a certain year; instead there is a linear progression of change in public attitudes towards education and welfare spending. At the national level, public opinion towards education and welfare spending does exhibit a sense of linearity and stability across time (Page and Shapiro 1992), so this assumption seems valid. Additionally, there is nothing a priori to suspect that public opinion towards education or welfare spending would exhibit large shifts in 1995, 1997, or 1999.

Multiple Imputation at the State-Year Level

Multiple imputation (MI) is a general approach for handling unit and item non-response in sample surveys and has been applied with increasing frequency in the past two decades (Schafer and Olsen 1998; King et al. 2001; Gelman, King, and Liu 1999; Allison 2002). It has also been used for pooled times series cross sectional (TSCS) datasets (Honaker et al. 2009; Honaker and King 2010). MI methods use information from other non-missing variables in the data to predict a value for a missing variable. An advantage of MI is that it models the uncertainty associated with the predictions directly by iterative estimations, effectively creating $j$ number of imputed datasets. The completed datasets will differ in their predicted values of the missing variables, due to the random error associated with each prediction and, thus, reflect
uncertainty levels. Analysts can apply statistical methods to each imputed dataset separately or use a simple procedure to combine the results across the $j$ datasets (King et al. 2001).

An assumption of MI is that the data are *missing at random* (MAR) (Honaker et al. 2009). This assumption means that the pattern of missingness only depends on the observed data, not the unobserved data. When missingness is not dependent on the data at all, the data are *missing completely at random* (MCAR). Is it realistic to assume that the missing data for 1995, 1997, and 1999 are MAR (or MCAR)? This is a reasonable assumption since the missingness is due to unasked questions (Gelman, King, and Liu 1999).

When performing MI, the first step is to decide what to include in the models. As Honaker et al. (2009) suggest, it is crucial to include at least as much information as in the analysis model. Moreover, because the model is *predictive* and not *causal* it is defensible to use as many variables as possible as well as lag and lead variables in the pooled TSCS case. The following variables are included to impute education preferences at the state-year level for 1995, 1997, and 1999: lag and lead values of education preferences, % Democrat, of % Liberal, % college educated, per pupil spending on elementary and secondary education in constant 2000 dollars, population density logged, population logged, and per capita income in constant 2000 dollars. The following variables are included to impute welfare preferences at the state-year level for 1995, 1997, and 1999: lag and lead values of welfare preferences, AFDC benefits for a family of four with no income adjusted by state-CPI rates (see Chapter 5 for more detail), % Democrat, % Liberal, % African American, unemployment rate, poverty rate, population logged, population density logged, and per capital income in constant 2000 dollars. And, because states may exhibit different dynamic patterns, each of these variables is interacted with the state variable for both education and welfare. Mean estimates are then calculated by taking the mean estimate for each state across the 5 imputed datasets.
Because we are using other variables to impute values for 1995, 1997, and 1999, this technique has the potential to bias the public opinion estimates towards instability. This is tempered by including lags and leads of both public opinion measures, however, this potential is still more of a risk compared to mean interpolation.

Multiple Imputation at the Individual Level prior to MRP

The final technique used to recover estimates for 1995, 1997, and 1999 is MI on individual level data prior to executing MRP. The first step in imputing public opinion at the individual level is to create an “empty” dataset for each of the three missing years. I simply create three empty datasets with 3,264 cells (to correspond to the 3,264 “person-types” based on age, education, race, gender, and state used in MRP) where all respondents are missing on the particular public opinion measure. I then merge these empty datasets with individual level data from the previous year. For instance, the 1995 empty dataset is merged with individual level data from 1994. This is done so that a person’s propensity to endorse a particular opinion based on education, age, gender, race, and state can be imputed based on the response patterns from the previous year.

Similar to MI on TSCS data, a crucial step is to decide what to include in the imputation models. I use gender (0=male, 1=female), race (0=non-black, 1=black), age (four categories: 18-29, 30-44, 45-64, and 65+), education (four categories: no high school degree, high school degree, some college, and college+), region (four categories: northeast, south, west, and Midwest), ideology (two dummy variables indicating liberal or conservative), partisanship (two dummy variables indicating Democrat or Republican), and state (dummy variables) to impute values for education and welfare spending for each of the three missing years. This creates 5

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32 Of course, the “empty” dataset is missing on ideology and partisanship. The MI, however, cycles through and creates imputations for these variables as well. Once these variables are imputed, they are then used to impute values for the public opinion measures. I conduct 10 cycles for each imputed dataset.

At this point, I randomly sample 1,500 observations from the imputed datasets to use for the missing years. This causes each of the states to have a roughly equal number of respondents (usually less than 100) for each of the three missing years. Hence, while each state has valid data for the three missing years, the N is small and overwhelmed by the “real” data when performing MRP.

I then perform the MRP technique to obtain yearly state level estimates on education and welfare spending, as described above. The difference from the above explanation, however, is that the 1,500 imputed estimates for 1995, 1997, and 1999 are included prior to performing MRP. This creates different estimates for the years 1993-2000 between the “raw” estimates in which no imputation took place and the “imputed” estimates based on individual level data. For instance, in the “raw” data, 1993 public opinion measures were estimated using individual level data from 1991, 1992, 1993, 1994, and 1996; in the “imputed” data, 1993 public opinion measures were estimated using individual level data from 1991, 1992, 1993, 1994, and 1995.

Because I am still using a five year window to estimate the public opinion measures, this approach biases towards stability. In smoothing over five years, we are potentially smoothing over shocks that may appear in the data. Moreover, because the missing years only have 1500 observations, which are spread across the 51 states, the estimates in 1995, 1997, and 1999 are overwhelmed by other years in the five year window that has a greater number of observations. This is particularly true of the most populated states, which may have several hundred respondents in any one year and only an average of 30 observations in 1995, 1997, or 1999.

**Relationship between Various Measurement Techniques for Education and Welfare**

In the end, I have three different public opinion measures for both education and welfare spending across the states for 1995, 1997, and 1999. The first uses mean interpolation based on
the aggregate estimates of state public opinion across time. The second technique uses MI at the state-year level based on various state level covariates. Finally, the third technique uses MI at the individual level prior to the estimation of state level public opinion via MRP. Table B1 shows the means and standard deviations of each of the three measures across states for 1995, 1997, and 1999.

Table B1 shows that there are few differences between the three public opinion measures for education and welfare spending for 1995, 1997, and 1999. We can see, however, how on average, the standard deviation from mean interpolation is smaller compared to MI at the state and individual levels. This is because mean interpolation tends to overestimate the amount of certainty in the estimates.

Table B2 shows the correlations between the three different public opinion measures for education and welfare spending in 1995, 1997, and 1999. The public opinion estimate for education spending based on mean interpolation is highly correlated with the estimate obtained from MI at the individual level \( (r=.83) \) and the estimate obtained from MI at the state level \( (r=.70) \). Estimates using MI at the individual level are modestly correlated with estimates using MI at the state level \( (r=.59) \). This general pattern is also true for attitudes towards welfare spending. The public opinion estimates for welfare spending based on mean interpolation is highly correlated with the other two estimates \( (r=.70 \text{ for MI at the state level and } r=.76 \text{ for MI at the individual level}) \). Estimates using MI at the individual level are poorly correlated, comparatively speaking, with estimates using MI at the state level \( (r=.41) \).

Finally, Figures B1-B3 check the plausibility of each of the measurement techniques by seeing how each predicts missing values in a time series for specific states. If a measurement technique produces estimates that are drastically higher in 1995 compared with observed data from 1994 and 1996, we might worry that there is a problem with the estimates; in other words, a certain technique may bias time trends towards instability. I chose three different sized states to
explore time trends: Delaware, the fifth least populated state, is shown in Figure B1, Kentucky, the median populated state is shown in Figure B2, and Indiana, the fifth most populated state, is shown in Figure B3. In each figure, I present scatterplots of the public opinion estimates from 1992-2000. Each of the estimates can be compared with raw data; that is data that has no manipulation beyond the MRP technique described in the Chapters 2 and 3.

On average and across all three states, the MI at the state level approach produces the most instability in the public opinion estimates whereas the mean interpolation approach produces the most stability. The estimates from the MI at the individual level approach tends to systematically bias welfare spending preferences downward, particularly for Delaware and Indiana, although the dynamics of the welfare spending preferences are fairly similar for both the mean interpolation and MI at the individual level approaches.

**Error Correction Models from Chapter 5 using Alternative Estimates**

In this section, I replicate the models presented in Tables 5.1 and 5.2 using the alternative estimates of education and welfare opinion. I compare the results reported in Chapter 5 from those using the estimates from mean interpolation and MI at the individual level. Tables B5 and B6 show the results of estimating an ECM predicting changes in state policy on per pupil spending and AFDC benefits from changes in state public opinion on education spending and welfare spending, respectively. Tables B7 and B8 show the results of estimating an ECM predicting changes in public opinion on education and welfare spending on changes in state policy in per pupil spending and AFDC benefits. See Chapter 5 for details on the control variables.

As can be seen from Tables B3 and B4, the inferences regarding the short and long term effects of public opinion on state policy changes are similar across the different measures of public opinion. The exception is with the short term effect of public opinion towards welfare spending on AFDC benefits, which is insignificant at the .05 level when using the estimates from
MI at the individual level. Overall, however, the models are quite similar across the various estimates of state public opinion.

Table B5 also shows that inferences about the long term effect of changes in per pupil spending on changes in attitudes towards education spending are nearly identical across the three model specifications. Unfortunately, Table B6 suggests that the results concerning the effects of AFDC benefits on opinion towards welfare spending should be taken with caution. Using mean interpolation, AFDC benefits appear to have an insignificant short and long term effect on changes in attitudes towards welfare spending. And, the model using MI at the individual level also suggests that AFDC benefits have an insignificant effect on public attitudes towards welfare.

In results available upon request, models using the raw estimates on state public opinion towards welfare spending suggest similar inferences as reported in Chapter 5; there is a significant long term effect of AFDC benefits, but an insignificant short term effect of AFDC benefits on welfare attitudes. More research is needed to indicate whether AFDC benefits have a positive impact on welfare attitudes at the state level and whether these effects have short or long term components.

**Recovering Missing Data on Anti-smoking Preferences in 1994 and 2004**

The public opinion measure towards smoking restrictions in restaurants spans from 1991 to 2006 for all 50 states and DC. All states, however, have missing data in 1994 and 2004 since questions were not asked in these two years. Similar to the above analyses, I use mean interpolation, MI at the state-year level, and MI at the individual level to impute public opinion towards smoking restrictions in restaurants.

**Multiple Imputation at the State-Year Level for Anti-smoking Legislation**

When performing MI, the first step is to decide what to include in the models. As Honaker et al. (2009) suggest, it is crucial to include at least as much information as in the analysis model. Again, because the model is predictive and not causal it is defensible to use as
many variables as possible as well as lag and lead variables in the pooled TSCS case. The following variables are included to impute preferences towards smoking restrictions in restaurants at the state-year level for 1994 and 2004: lag and lead values of % Democrat, of % Liberal, % college educated, % black population, population density logged, population logged, per capita income in constant 2000 dollars, policy restrictions in restaurants, policy restrictions in hotels/motels, policy restrictions in government workplaces, state taxes on cigarettes, % smokers, % support abortions in any circumstances, % of residents who support smoking bans in restaurants, and % of residents who support smoking bans in workplaces. And, because states may exhibit different dynamic patterns, each of these variables is interacted with the state variable for both education and welfare. Mean estimates are then calculated by taking the mean estimate for each state across the 5 imputed datasets.

**Multiple Imputation at the Individual Level for Anti-smoking Legislation**

MI at the individual level prior to MRP is performed in a similar manner to the above analyses. I simply create two empty datasets with 3,264 cells (to correspond to the 3,264 “person-types” based on age, education, race, gender, and state used in MRP) where all respondents are missing on the anti-smoking public opinion measure. I then merge these empty datasets with individual level data from the previous year. For instance, the 1997 empty dataset is merged with individual level data from 1996. This is done so that a person’s propensity to endorse a particular opinion based on education, age, gender, race, and state can be imputed based on the response patterns from the previous year. Also included in the empty dataset for 1997 is a survey variable which is equal to 1 to indicate that the respondents are from the CPS-TUS survey since all respondents in 1996 are from the CPS-TUS survey. This is important to include since the two surveys differ substantially on the public opinion measures and since the aggregate data is estimated as if all responses are from the CPS-TUS (see Chapter 3 for details). In 2004, when pooled using 2003, 2004, and 2005 data, there is no information from the CPS-
TUS survey. Hence, the imputed estimates for 2004 are unusually low due to question wording. I discuss how I adjust these estimates in the next section.

Similar to MI on TSCS data, a crucial step is to decide what to include in the imputation models. I use gender (0=male, 1=female), race (0=non-black, 1=black), age (four categories: 18-29, 30-44, 45-64, and 65+), education (four categories: no high school degree, high school degree, some college, and college+), region (four categories: northeast, south, west, and Midwest), survey (dummy variable indicating Gallup or CPS-TUS survey; only in 2004) and state (dummy variables) to impute values for smoking preferences towards restaurants for the two missing years. I also include variables for smoker status; this is important to include since one of the largest predictors of public support for smoking legislation is smoker status. From the Gallup surveys, this includes a dummy variable measuring whether the respondent smoked any cigarettes in the past week. From the CPS-TUS, this includes a dummy variable measuring whether the respondent has smoked 100 cigarettes (roughly 5 packs) in their lifetime. This creates 5 imputed datasets with 3,264 observations with valid data on the public opinion measures for 1997 and 2004.

At this point, I randomly sample 1,500 observations from the imputed datasets to use for the missing years. This causes each of the states to have a roughly equal number of respondents (usually less than 100) for each of the three missing years. Hence, while each state has valid data for the two missing years, the N is small and overwhelmed by the “real” data when performing MRP.

I then perform the MRP technique to obtain yearly state level estimates on attitudes towards smoking restrictions in restaurants, as described above. Because I am still using a three year window to estimate the public opinion measures, this approach biases towards stability. In smoothing over three years, we are potentially smoothing over shocks that may appear in the data. Moreover, because the missing years only have 1500 observations, which are spread across
the 51 states, the estimates in 1997 and 2004 are overwhelmed by other years in the three year window that has a greater number of observations. This is particularly true of the most populated states, which may have several hundred respondents in any one year and only an average of 30 observations in 1997 or 2004.

As stated earlier, the estimates for 2004 are exceptionally low due to question wording differences between the CPS-TUS and Gallup surveys. Recall from Chapter 3, that all of the opinion measures are estimated as if respondents all responded to the CPS-TUS Survey. To adjust the 2004 imputed estimates to match and to not artificially inflate any dynamics, I use the 2003 “raw” data to estimate the question wording effect. More specifically, I estimate public opinion towards restaurants when the dummy variable for question wording is equal to 0 and then compare it to estimates when the dummy variable for question wording is equally to 1 (recall from Chapter 3 that a question wording covariate is included in the multi-level model where 1=CPS-TUS and 0=Gallup). I then measure the difference between state estimates when the CPS-TUS survey is used compared to the Gallup survey. To adjust the estimates for 2004, I simply add the difference between the surveys. On average, the difference between state estimates from the CPS-TUS were about 5% higher compared to estimates using the Gallup surveys.

**Relationship between Various Measurement Techniques for Anti-smoking Legislation**

In the end, I have three different public opinion measures for attitudes towards smoking bans in restaurants across the states for 1997 and 2004. The first uses mean interpolation based on the aggregate estimates of state public opinion across time. The second technique uses MI at the state-year level based on various state level covariates. Finally, the third technique uses MI at the individual level prior to the estimation of state level public opinion via MRP. Table B7 shows the means and standard deviations of each of the three measures across states for 1997 and 2004.
Table B8 shows that there are few differences between the public opinion estimates for 1997 and 2004. The standard deviations are also all relatively similar. Table B4 shows the correlations between the three different public opinion measures for preferences towards smoking bans in 1997 and 2004. The public opinion estimate based on mean interpolation is highly correlated with the estimate obtained from MI at the state level ($r = .91$). Estimates using MI at the individual level are modestly correlated with estimates using MI at the state level ($r = .64$) and estimates based on mean interpolation ($r = .62$). In all, the three estimates are highly correlated.

Finally, Figure B4 checks the plausibility of each of the measurement techniques by seeing how each predicts missing values in a time series for specific states. If a measurement technique produces estimates that are drastically higher in 1997 compared with observed data from 1996 and 1998, we might worry that there is a problem with the estimates; in other words, a certain technique may bias time trends towards instability. As before, I chose three different sized states to explore time trends: Delaware, the fifth least populated state, Kentucky, the median populated state and Indiana, the fifth most populated state. I present scatterplots of the public opinion estimates from 1996-2005. Each of the estimates can be compared with raw data; that is data that has no manipulation beyond the MRP technique described in Chapters 2 and 3.

On average and across all three states, the MI at the individual level approach produces the most instability in the public opinion estimates, particularly for a small state, such as Delaware, whereas the MI at the state level approach produces the most stability. The estimates from the MI at the individual level approach tends to systematically bias smoking preferences downward, particularly for Delaware, in 2004 as a result of the difference in question wording from just using Gallup questions. Based on these analyses, I decide to used the MI at the state level estimates for 1997 and 2004 in the empirical models for Chapters 5 and Chapter 6.
Error Correction Models on Anti-Smoking Legislation from Chapter 5 using Alternative Estimates

In this final section, I replicate the models presented in Tables 5.3 and 5.4 using the alternative estimates of preferences towards smoking bans in restaurants. I compare the results reported in Chapter 5 from those using the estimates from mean interpolation and MI at the individual level. Table B9 shows the results of estimating an ECM predicting changes in state policy on anti-smoking legislation from changes in state public opinion on smoking bans in restaurants. Table B10 shows the results of estimating an ECM predicting changes in public opinion on smoking bans on changes in state policy in anti-smoking legislation. See Chapter 5 for details on the control variables.

As can be seen from Table B9, the inferences regarding the short and long term effects of public opinion on state policy changes are similar across the different measures of public opinion. The exception is with effect of public opinion towards smoking bans on anti-smoking legislation, which is insignificant at the .10 level when using the estimates from MI at the individual level. Recall, however, that the MI at the individual level approach produced the most instability in the estimates. Hence, I think this is more proof that MI at the individual level is not a valid approach to recovering missing data for preferences towards smoking bans.

Table B10 also shows that inferences about effect of changes in anti-smoking legislation on changes in attitudes towards smoking bans are nearly identical across the three model specifications. Again, there is an exception when using the MI at the individual level approach; the long term effect of legislation on public opinion is not significant using the MI at the individual level approach. Again, I think this is evidence that the MI at the individual level approach is not appropriate to recover missing data for anti-smoking preferences. This is further evidenced by the fact that when using these estimates, the effect of the percentage of adult smokers, which is highly related to public opinion on smoking bans, increases. Hence, it may be
that the percentage of adult smokers is picking up on public preferences towards anti-smoking legislation that is not captured by the MI at the individual level estimates.
References for Appendix B


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### Table B3 Error Correction Model Predicting Changes in Per Pupil Spending (N=950)

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Note: Newey-West Standard Errors in parentheses. Significance levels: **.05, ***.01 with a two-tailed test
### Table B4 Error Correction Model Predicting Changes in AFDC Benefits (N=898)

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Note: Newey-West Standard Errors in parentheses. Significance levels: **.05, ***.01 with a two-tailed test
Table B5 Error Correction Model Predicting Changes in State Opinion on Education Spending (N=989)

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<td>(.03)</td>
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<td>Proportion Liberal (t-1)</td>
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<td>.03</td>
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<td>.03 ***</td>
<td>.01</td>
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<td>(.02)</td>
<td>(.01)</td>
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<td>Proportion African American (t-1)</td>
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<td>∆ Proportion African American</td>
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Note: Newey-West Standard Errors in parentheses. Significance levels: **.05, ***.01 with a two-tailed test
Table B6 Error Correction Models Predicting Changes in State Opinion on Welfare Spending (N=909)

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<th>MI at Individual Level</th>
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<td>Welfare Spending (t-1)</td>
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<td>-.30 ***</td>
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<td>(.04)</td>
<td>(.03)</td>
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<td>AFDC Benefits (t-1)</td>
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<td>-.000001 ***</td>
<td>-.000005</td>
</tr>
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<td></td>
<td>(.000002)</td>
<td>(.000004)</td>
<td>(.000003)</td>
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<td>Δ AFDC Benefits</td>
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<td>.00002</td>
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<td>(.000010)</td>
<td>(.00002)</td>
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<td>Per Capita Income (t-1)</td>
<td>.00</td>
<td>.00</td>
<td>-.000001 **</td>
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<td>(.00)</td>
<td>(.00)</td>
<td>(.00)</td>
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<td>Δ Per Captia Income</td>
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<td>.00</td>
<td>.000002 **</td>
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<td>(.00)</td>
<td>(.00)</td>
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<td>National Opinion on Welfare</td>
<td>.14 ***</td>
<td>.41 ***</td>
<td>.22 ***</td>
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<td>Spending (t-1)</td>
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<td>(.05)</td>
<td>(.04)</td>
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<td>.52 ***</td>
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<td>Spending</td>
<td>(.04)</td>
<td>(.05)</td>
<td>(.04)</td>
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<td>.01</td>
<td>.06 ***</td>
<td>.08 **</td>
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<td>(.03)</td>
<td>(.04)</td>
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<td>-.08</td>
<td>-.49</td>
<td>-1.27 **</td>
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<td>(.55)</td>
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<td>(.02)</td>
<td>(.03)</td>
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<td>Δ Proportion Liberal</td>
<td>.00</td>
<td>-.04</td>
<td>.18 ***</td>
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<td>(.04)</td>
<td>(.05)</td>
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<td>.03 ***</td>
<td>.03 ***</td>
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<td>(.01)</td>
<td>(.01)</td>
</tr>
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<td>Δ Proportion Democrat</td>
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<td>-.01</td>
<td>-.04</td>
</tr>
<tr>
<td></td>
<td>(.02)</td>
<td>(.03)</td>
<td>(.03)</td>
</tr>
<tr>
<td>Proportion African American (t-1)</td>
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<td>.06 ***</td>
<td>.02</td>
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<td>(.01)</td>
<td>(.02)</td>
<td>(.02)</td>
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<td>Δ Proportion African American</td>
<td>-1.07 **</td>
<td>-.16</td>
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<td>(.86)</td>
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<td>(.01)</td>
<td>(.01)</td>
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Note: Newey-West Standard Errors in parentheses. Significance levels: ** .05, *** .01 with a two-tailed test
Table B7 Mean for Public Opinion Measures on Smoking Bans in Restaurants for 1997 and 2004. Standard Deviations in Parentheses

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<td>MI at Individual</td>
<td>Mean</td>
<td>MI at State</td>
</tr>
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<td>Interpolation</td>
<td>Level</td>
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<td>(.07)</td>
<td>(.07)</td>
<td>(.07)</td>
<td>(.08)</td>
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Table B8 Correlations Among Public Opinion Measures on Smoking Bans in Restaurants in 1997 and 2004

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<td>MI Individual Level</td>
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# Table B9 Error Correction Model Predicting Changes in Anti-Smoking Legislation (N=727)

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<th>MI at Individual Level</th>
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<tbody>
<tr>
<td>Anti-smoking Legislation (t-1)</td>
<td>-0.09 **</td>
<td>-0.09 ***</td>
<td>-0.08 ***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Percentage Favor Smoking Bans in Restaurants (t-1)</td>
<td>0.09 *</td>
<td>0.01 **</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Δ Percentage Favor Smoking Bans in Restaurants</td>
<td>0.02 *</td>
<td>0.04 **</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.018)</td>
<td>(0.01)</td>
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<tr>
<td>Ratio Tobacco Lobbyists</td>
<td>3.15</td>
<td>1.83</td>
<td>3.38</td>
</tr>
<tr>
<td></td>
<td>(3.24)</td>
<td>(3.16)</td>
<td>(3.28)</td>
</tr>
<tr>
<td>Ratio Health Lobbyists</td>
<td>-0.10</td>
<td>-0.01</td>
<td>-0.15</td>
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<tr>
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<td>(0.40)</td>
<td>(0.38)</td>
<td>(0.40)</td>
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<td>Power Tobacco Lobbyists</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.01</td>
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<tr>
<td></td>
<td>(0.06)</td>
<td>(0.05)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Power Health Lobbyists</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
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<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Percentage Adult Smokers (t-1)</td>
<td>-0.03 **</td>
<td>-0.02 *</td>
<td>-0.03 ***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Δ Percentage Adult Smokers</td>
<td>-0.02</td>
<td>-0.01</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Democratic Strength (t-1)</td>
<td>0.001 **</td>
<td>0.0003</td>
<td>0.001 *</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Δ Democratic Strength</td>
<td>-0.0004</td>
<td>-0.0004</td>
<td>-0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.001)</td>
<td>(0.001)</td>
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<tr>
<td>Government ideology (t-1)</td>
<td>-0.001</td>
<td>0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Δ Government ideology</td>
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<td>-0.002</td>
<td>0.0001</td>
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<tr>
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<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
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<td>Percentage Liberal (t-1)</td>
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<td>0.0003</td>
<td>0.01</td>
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<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Δ Percentage Liberal</td>
<td>-0.04</td>
<td>-0.03 *</td>
<td>-0.03</td>
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<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
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<tr>
<td>Percentage Democrat (t-1)</td>
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<td>-0.002</td>
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<td></td>
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<td>(0.004)</td>
<td>(0.004)</td>
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<td>Δ Percentage Democrat</td>
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<td>0.01</td>
<td>0.01 *</td>
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<td>(0.46)</td>
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Note: Newey-West Standard Errors in parentheses. Significance levels: * .10, ** .05, *** .01 with a two-tailed test.
Table B10 Error Correction Model Predicting Changes in State Opinion on Smoking Bans in Restaurants (N=746)

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<td>Percentage Favor Smoking Bans in Restaurants (t-1)</td>
<td>-.05 ***</td>
<td>-.08 ***</td>
<td>-.38 ***</td>
</tr>
<tr>
<td></td>
<td>(.01)</td>
<td>(.02)</td>
<td>(.06)</td>
</tr>
<tr>
<td>Anti-smoking Legislation (t-1)</td>
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<td>.17 ***</td>
<td>.32</td>
</tr>
<tr>
<td></td>
<td>(.058)</td>
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<td>(.361)</td>
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<td>.47 ***</td>
<td>.25 *</td>
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<td></td>
<td>(.102)</td>
<td>(.162)</td>
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</tr>
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<td>Tobacco Producer</td>
<td>-.32 **</td>
<td>-.45 ***</td>
<td>-.61 *</td>
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<tr>
<td></td>
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<td>(.15)</td>
<td>(.32)</td>
</tr>
<tr>
<td>Percentage Adult Smokers (t-1)</td>
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<td>-.11 ***</td>
<td>-.46 ***</td>
</tr>
<tr>
<td></td>
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<td>(.04)</td>
<td>(.11)</td>
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<td>Δ Percentage Adult Smokers</td>
<td>-.05</td>
<td>-.10 **</td>
<td>-.08</td>
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<td>(.26)</td>
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<td>(.71)</td>
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<td>.03 *</td>
<td>.05 **</td>
<td>.11 **</td>
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<td>(.02)</td>
<td>(.02)</td>
<td>(.05)</td>
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<td>(.14)</td>
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<td>.24 ***</td>
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<td>(.02)</td>
<td>(.06)</td>
</tr>
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<td>.06</td>
<td>.68 ***</td>
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<td>(.06)</td>
<td>(.13)</td>
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<td>-.02 **</td>
<td>-.02 **</td>
<td>-.07 ***</td>
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<td>(.01)</td>
<td>(.02)</td>
</tr>
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<td>Δ Percentage Democrat</td>
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<td>-.01</td>
<td>-.31 ***</td>
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<td>(.04)</td>
<td>(.11)</td>
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<td>(1.42)</td>
<td>(3.42)</td>
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</table>

Note: Newey-West Standard Errors in parentheses. Significance levels: * .10, **.05, ***.01 with a two-tailed test
Figure B1 Scatterplots of Estimates for State Opinion on Education and Welfare Spending for Delaware

Delaware Education Spending

Delaware Welfare Spending

Legend:
- Education Mean Interpolation
- Education MI State Level
- Education MI at Individual Level
- Education Raw Data

Legend:
- Welfare Mean Interpolation
- Welfare MI State Level
- Welfare MI Individual Level
- Welfare Raw Data
Figure B2 Scatterplots of Estimates for State Opinion on Education and Welfare Spending for Kentucky

Kentucky Education Spending

Kentucky Welfare Spending
Figure B3 Scatter plots of Estimates for State Opinion on Education and Welfare Spending for Indiana

Indiana Education Spending

Indiana Welfare Spending

Legend:
- Education Mean Interpolation
- Education MI State Level
- Education MI at Individual Level
- Education Raw Data

Legend:
- Welfare Mean Interpolation
- Welfare MI State Level
- Welfare MI Individual Level
- Welfare Raw Data
Figure B4 Scatterplots of Estimates for State Opinion on Smoking Bans in Restaurants for Delaware, Kentucky, and Indiana

Delaware Anti-Smoking Legislation

Kentucky Anti-Smoking Legislation

Indiana Anti-Smoking Legislation
VITA

JULIANNA PACHECO

ACADEMIC EMPLOYMENT
Robert Wood Johnson Foundation Health & Society Scholar, University of Michigan (2010-2012)

EDUCATION

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Outstanding Graduate Student Award, Penn State Department of Political Science (2006 & 2008)
Miller Summer Research Award, Penn State Department of Political Science (2006)
Best Master’s Essay Award, Penn State Department of Political Science (2006)
Bruce R. Miller Fellowship, Penn State Department of Political Science (2005)
First Place Undergraduate Exhibition, Penn State College of Liberal Arts (2004)