IDENTIFYING AND EXPLAINING INSTABILITY IN THE GENERAL MODEL OF POLICY INNOVATION DIFFUSION

A Dissertation in
Political Science
by
Daniel J. Mallinson

© 2015 Daniel J. Mallinson

Submitted in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy

May 2015
The dissertation of Daniel J. Mallinson was reviewed and approved* by the following:

David Lowery  
Bruce R. Miller and Dean D. LaVigne Professor of Political Science  
Dissertation Advisor  
Chair of Committee

Michael Berkman  
Professor of Political Science

John Gastil  
Head and Professor of Communication Arts and Sciences

Peter K. Hatemi  
Associate Professor of Political Science, Microbiology, and Biochemistry

Christopher Zorn  
Liberal Arts Research Professor of Political Science and Sociology

James Piazza  
Associate Professor of Political Science  
Director of Graduate Studies

*Signatures are on file in the Graduate School
Policy diffusion research has deep roots in political science and continues to grow as a research program. Over the last 25 years, scholars assembled a body of knowledge one piece at a time using event history models that focus on the adoption of a single innovation. This approach generated new knowledge about specific predictors of adoption; however it also created a fractured testing of the general model of policy diffusion. In response, scholars recently began returning to an older approach of aggregating adoption data in order to determine the generalizability of the policy diffusion model. This dissertation bridges the two approaches and further builds on the macro-level approach by testing the general patterns of innovation adoption while also pushing forward our understanding of the causal mechanisms underlying the process.

The first chapter of this dissertation pulls together the extant evidence, i.e., the existing trees, through a systematic review and synthesis of the last 25 years of diffusion findings. The goal is to understand the weight of evidence for theoretically important diffusion predictors, as well as the varied modeling approaches for spatial effects and duration dependence. Doing so reveals great diversity not only in scholars’ approaches to modeling diffusion, but also their findings regarding some of its most important predictors (e.g., the influence of neighbor adoptions). The subsequent chapters test potential explanations for the diversity in these findings.

First, chapters 3 and 4 test the generalizability of the policy diffusion model and examine how its elements change across time and throughout the diffusion lifecycle. Specifically, using a large dataset of innovations adoptions from 1960 through 2010, chapter 3 tests how the association between external influences, internal characteristics, and innovation attributes changes from 1960 through 2010 and chapter 4 examines how they change during different stages of the diffusion process (i.e., innovation, early adoption, early majority adoption, late majority adoption, and laggard adoption). While many of the important predictors exhibit general effects when all data are pooled, those effects are not stable across time. For instance, there is evidence to suggest that the effect of regional pressure declined over the last 50 years, while ideological similarity is increasingly important. This comports with an emerging understanding of increasingly polarized politics in the states.

Chapter 5 views adoption from a different angle by offering a new continuous measure of policy adoption speed. In this case, the policy becomes the unit of analysis so that researchers can examine how innovation attributes shape how quickly policies are taken up by the states. This is an important development for sorting out when learning is the primary causal mechanism driving the diffusion of a policy versus other mechanisms that are typically faster or slower.
Understanding macro-level diffusion dynamics is important; however researchers also must advance our understanding of the micro-level causal mechanisms that drive innovation adoption. To that end, Chapter 6 offers a theoretical construct for sorting and testing these mechanisms, as well as the foundation for and experimental paradigm for the purpose of understanding the elite socialization mechanism. Specifically, this mechanism focuses on how social pressure from elites’ interpersonal relationships influences the propensity to adopt new ideas. While the experiment does not yet directly test this theory among an elite population, it demonstrates that public compliance pressure and private acceptance underlie conformity behavior in the political realm. This successful experimental protocol provides a foundation for additional incremental advancements that will help us understand how the personal interactions of state legislators shape their search for and use of policy information.
# Table of Contents

List of Figures.............................................................................................................................. vii

List of Tables................................................................................................................................. ix

Acknowledgements ........................................................................................................................ x

Chapter 1 Introduction...................................................................................................................... 1
   The General Model of Policy Diffusion .......................................................... 3
   Analytical Approach ...................................................................................... 5
   Data and Methods ......................................................................................... 10
   Contribution .................................................................................................... 12

Chapter 2 Twenty-Five Years of Evidence: A Systematic Review and Synthesis of the Policy Diffusion Literature .................................................................................................................. 15
   Methodology ..................................................................................................... 18
   Results of the Systematic Review ................................................................. 23
   Research Synthesis Results ............................................................................. 36
   Conclusion .......................................................................................................... 43

Chapter 3 The Decline of Neighbors and Rise of Ideology: Changes in Policy Diffusion Predictors from 1960 to 2010 ......................................................................................................................... 46
   The General Diffusion Model through Time .................................................. 48
   Expectations ....................................................................................................... 51
   Methods and Data ............................................................................................ 56
   Results ............................................................................................................... 60
   Discussion ........................................................................................................ 73
   Conclusion .......................................................................................................... 77

Chapter 4 Predictors of Policy Diffusion across the Stages of Adoption.......................................................................................................................... 80
   Leaders and Laggards ...................................................................................... 82
   Theory of the Diffusion Lifecycle .................................................................... 85
   Data and Methods ............................................................................................ 93
   Results ............................................................................................................... 98
   Discussion ........................................................................................................ 103

Chapter 5 Measuring Policy Adoption Speed in the American States .......................................................................................................................... 107
   Adoption Speed and Its Predictors ............................................................... 110
   Measuring and Testing Adoption Speed ....................................................... 116
   Results of the Adoption Speed Model .......................................................... 128
   Conclusion ...................................................................................................... 133
Chapter 6 The Causal Mechanisms Underlying Policy Innovation Diffusion:
   Understanding Socialization Diffusion .......................................................... 137
   Mechanisms of Diffusion .............................................................................. 140
   A Typology of Diffusion Mechanisms .......................................................... 149
   Laying the Foundation for Understanding Elite Socialization .................... 153
   Evidence of Conformity Pressure in the Mass Public and Beyond ............ 156
   Anecdotal Evidence of Conformity Pressure and Elite Behavior ............... 160
   Variation in Conformity Behavior and Expectations for the Experiment .... 163
   Study Design .................................................................................................. 165
   Results ........................................................................................................... 175
   Discussion ....................................................................................................... 188

Chapter 7 Conclusion ....................................................................................... 191
   Limitations .................................................................................................... 195
   Implications for Policy Diffusion Research .................................................. 199
   Broader Implications .................................................................................... 201
   Future Directions .......................................................................................... 203

Appendix A Description of adoption data collected by the author .................. 207

Appendix B Full output for pooled multi-level model of policy adoption and alternative specifications from Chapter 3 ................................................. 208

Appendix C Summary statistics for Chapter 5 ................................................. 209

Appendix D Full results of adoption speed OLS models ................................. 210

Appendix E Influence of law policies in Chapter 5 ......................................... 211

Appendix F Information sheet provided to both treatment and control groups .... 214

Appendix G Confederate talking points: Pro-firing ....................................... 215

Appendix H Confederate talking points: Anti-firing ...................................... 216

Appendix I Randomization ............................................................................. 217

Appendix J Use of deception in the study design .......................................... 219

Appendix K Details for Behavioral Measures ................................................. 221

Appendix L Breakdown of opinion change in the treatment and control groups... 222

References ....................................................................................................... 226
List of Figures

Figure 1.1: Simplified general model of policy diffusion .................................................. 5
Figure 2.1: Count of included articles by publication year from 1990 to 2013 ........ 24
Figure 2.2: Count of major topics for each included model........................................... 26
Figure 2.3: Spans of first and last adoption for each included diffusion model........ 28
Figure 2.4: Count of models by year of publication and type (logit, probit, or other) ................................................................................................................................. 30
Figure 2.5: Count of models by year of publication and duration dependence method .............................................................................................................................. 31
Figure 2.6: Measurement of contiguous neighbor adoption for the 70 percent of models that included such a measure ................................................................. 34
Figure 3.1: Policies adopted in each decade included in the analysis, by major topic ........................................................................................................................................... 59
Figure 3.2: Coefficient plot for the completely pooled analysis, includes random effects for policy and state .................................................................................................................. 63
Figure 3.3: Plot of Predicted probability of innovation adoption for non-complex and complex policies as salience increases, as measured by Gallup's Most Important Problem Poll ....................................................................................................................... 64
Figure 3.5: Predicted probability of adoption and 95% confidence intervals for percent neighbors in 1990s and relative ideology in 2000s ........................................ 68
Figure 3.6: Change in the odds ratios and 95% confidence intervals for the effects of citizen liberalism and legislative professionalism on innovation adoption from 1960 to 2010 ......................................................................................................................... 69
Figure 3.7: Change in odds ratios and 95% intervals for the effects of population size and per capita income on innovation adoption from 1960 to 2010......... 70
Figure 3.8: Predicted probability of innovation adoption for complex and non-complex policies as public salience increases ...................................................................................... 72
Figure 4.1: Reproduction of adoption categories from Rogers (2003) ...................... 86
Figure 4.2: Count and density of state lottery adoptions across time broken into five adopter categories: innovators, early adopters, early majority, late majority, and laggards ......................................................................................................................... 96
Figure 4.3: Distribution of policy types within each category of adoption .......... 97
Figure 5.1: Plot of the cumulative number of adoptions across time since the first adoption for a fast-adopted, slow-adopted, and average policy with the calculated speed measure included in parentheses ........................................ 120
Figure 5.2: Scatterplot of adoption speeds across time with a LOESS line demonstrating the increase in adoption speed after 1965........................................ 122

Figure 5.3: Plot of mean speeds and 95% confidence intervals for fifteen policy domains (assigned based on the Policy Agendas Project coding scheme)........ 123

Figure 5.4: Plot of OLS coefficients and confidence intervals for model of innovation adoption speed. Thick confidence bars = 90% interval and thin = 95% interval. .................................................................................................................. 129

Figure 5.5: Plot of the moderating effect of policy complexity on the positive effect of salience (MIP) on the predicted speed of adoption.................................. 131

Figure 6.1: Concept map of state policy innovation mechanisms.......................... 141
Figure 6.2: Picture of treatment environment.......................................................... 172
Figure 6.3: Discrete change of opinion in control and treatment groups................. 176
Figure 6.4: Distribution of conservatism for pro- and anti-firing groups of participants .................................................................................................................. 180
Figure 7.1: Full output for pooled adoption model and alternative specifications..... 208
Figure E.1 Plot of COVRATIOs with law policies highlighted red............................ 212
Figure E.2 Plot of DFBETASs for Most Important Problem with law policies highlighted red............................................................................................... 213
Figure L.1: Opinion changes for control group participants by subcategory......... 223
Figure L.2: Opinion changes for treatment group participants by sub-category..... 225
# List of Tables

Table 2.1: Data collected from included diffusion articles ........................................... 22
Table 2.2: Inclusion and exclusion of key diffusion predictors ................................. 37
Table 2.3: Summary of effect direction for key diffusion predictors ......................... 41
Table 3.1: Models of policy adoption for each decade from 1960 through 2010 ........ 65
Table 4.1: Multi-level models of policy adoption for each stage of the diffusion process (Rogers 2003), with random effects for policy and state ....................... 99
Table 5.1: Innovation attributes, their measures, and expected effects on adoption speed........................................................................................................................................ 127
Table 6.1: Categorization of diffusion mechanisms by level of analysis and direction of idea movement .......................................................................................... 152
Table 6.2: Percentage of treatment group participants that changed their opinion due to a desire to be liked, right, both, or did not change ........................................... 178
Table 6.3: Comparison of participants who indicated support or opposition for the firing of Paterno in their pre-test survey, including t-tests........................................ 181
Table 6.4: Comparison of participants in both treatment and control conditions who changed their opinion, including t-tests......................................................... 182
Table 6.5: Comparing the behavior of participants that changed their opinion and those that did not in the treatment condition ......................................................... 185
Table 6.6: Difference in means for behavioral variables in each category of opinion change using no opinion change as the baseline .............................................. 186
Table A.1: Policy name, year of first and last adoption, total count of adoptions, description, and source for additional adoptions collected by the author ........ 207
Table C.1 Descriptions and summary statistics for innovation adoption speed analysis ...................................................................................................................... 209
Table D.1 Full results for innovation adoption speed analysis .................................. 210
Table I.1 Comparison of demographic and dispositional traits for non-randomized and randomized subgroups with the treatment group .............................. 218
Acknowledgements

Graduate school, and dissertating especially, is not possible without the support of others. I would not be here today without the support of my faith, family, friends, and mentors that coached, challenged, and pushed me along the way. A word of thanks seems like not enough, so I hope to thank you all in person when this document is finally filed.

I am most thankful for a faith that kept me grounded throughout the ups and downs of graduate school. While I agree with the Apostle Paul that the source of true contentment is Christ (Philippians 4:12), I cannot say that I kept that in focus each and every day. That being said, God walked with me and grew my faith and trust during graduate school, as painful as that can be at times. I am especially thankful for the community at State College Evangelical Free Church, particularly Sandy and Patty, for loving and supporting Rebecca and me during our time in State College and helping us grow. I also have to thank Ash and Heather for their friendship, encouragement, and leadership of Penn State Christian Grads. Without you, Becca and I would have never met and I would not have wrestled with how to merge faith and calling in academia. Ash, thank you for the countless lunches and sound advice.

Naturally, the next person to thank is the love of my life, Rebecca. The dual academic life is a challenging one, but I appreciate that we can understand each other’s worlds, as well as commiserate and support each other during the difficult challenges that arise. Bec, thank you for your support and for being a source of joy as I completed this work and found a new job. I cannot wait to see what God has in store for us next. And to Peanut, thank you for waiting just long enough for me to defend this dissertation before you made your debut.

To my family, particularly my mom, I want to thank you for supporting me throughout the long journey from high school to higher education. You first started hearing of my dream to be a professor of political science in 2004 and never stopped encouraging me in that pursuit. Your love and support mean so much.
I also want to thank my fellow graduate students in political science for their help along the way. We were all in this together, and it was a joy to see you develop as scholars and to be a small part of that. To Amanda, Ben, Chris, and Lee – I could not think of a better group of Americanists with which to journey through the ups and downs of graduate school. I cannot wait to see where we all end up. To Joe and Mike – thank you for compelling conversation and friendship, and particularly to Joe and Dee for opening your home and lives to Becca and I on multiple occasions. Finally, special thanks are reserved for Charles. Thank you for your tireless encouragement and support as I finished this project and went on the job market, as well as your constant willingness to help with details like proofreading. Your friendship means so very much.

This dissertation and my development as a scholar were not possible without the mentorship of the great faculty in Penn State’s Department of Political Science. Dave, thank you for your hands-on-when-necessary approach to my work. You recognized my preference towards independence, while always stepping up and offering sound and quick wisdom when it was necessary. I look forward to working together more in the future. To Pete, thank you for mentoring me through my foray into laboratory experiments and behavioral genetics. Your advice, humor, and support continue to be invaluable. To Michael, thank you for your keen insight as a member of my committee and for kick starting this entire project. This all started in your State Politics graduate seminar in my very first semester at Penn State. To Chris, thank you also for your keen insight as I shaped and formed the ideas for this project, as well as for the hours you spent with me on methods. To John, I could not have asked for a more kind, helpful, and insightful outside member.

Finally, to Kristy, thank you for all of your help during the most important of my graduate school years. Nothing would be possible in our grad program without your work.
Chapter 1

Introduction
It is one of the happy incidents of the federal system that a single courageous state may, if its citizens choose, serve as a laboratory; and try novel social and economic experiments without risk to the rest of the country. (Supreme Court Justice Louis Brandeis)

Since his 1932 dissent in *New State Ice Co. v. Lieberman*, Justice Brandeis’s commentary on the American states as laboratories of democracy frames much of the scholarly work on federalism and state policymaking. In fact, it is nearly a normative requirement to mention the phrase in a dissertation about policy innovation diffusion. This is because researchers have been trying to unpack the normative and empirical meaning of that phrase for the better part of a century. In doing so, they seek to answer fundamental questions, such as why do some states adopt innovative policies early and others late? Why are some states more likely to be the first to act while others are often late to the party? What forces internal and external to the states drive the spread of an innovation? To what extent are some adoptions coincidental, due to common internal characteristics, while others are the result of cross-state influence? Do the best policies spread? How do a policy’s attributes affect its chances of spreading quickly and widely? These are the questions that motivate different parts of this dissertation. The core question that they all link to, however, is why do states innovate?

Much has been written on this topic (Graham, Shpan, and Volden 2013); however substantial gaps in understanding still remain. One of the most fundamental is the unanswered question of whether the “general” model of policy diffusion offered by Berry and Berry (1990, 2007) and expanded upon by others is actually generalizable across time and policy domains. For 25 years, much of the development and testing of
that model occurred through high-context models of the spread of a single innovation, from lotteries (Berry and Berry 1990) to human trafficking prevention (Bouché and Wittmer 2014). The purpose of each study is often to test a newly identified predictor of adoption; however, its importance is rarely tested in other domains.

Thus, there are diminishing returns to using this approach (Boehmke 2009a). It generates a rich understanding of specific policies, but also a plethora of inconsistent results for theoretically important covariates without a systematic understanding of why the effects vary. Thus, we know a great deal about the individual trees, but we have not yet stepped back to observe the broader make-up of the forest. In sum, there is a fundamental assumption of generality in the policy diffusion model that remains to be tested. Furthermore, the fractured nature of the existing scholarship inhibits researchers from drawing conclusions about whether policy diffusion dynamics change over time and how those changes relate to broader patterns of change in American society and politics.

Before describing how this dissertation approaches the motivating questions presented above and advances the research on policy innovation diffusion, it is first important to explicate the theoretical model motivating this work.

**The General Model of Policy Diffusion**

Equation 1 provides a modified version of Berry and Berry’s (1990, 2007) general model of policy diffusion. In it, state adoption of a policy innovation is a function of five components: legislator motivation, resources and obstacles, other policies, external forces, and attributes of the policies. The first three components capture important
internal characteristics of the states, such as their motivation for innovating (e.g., the severity of the problem it addresses), the resources available to them for legislating and obstacles to adoption, and competition among policies for space on the agenda. External influences recognize that the states are part of a federal system where they are influenced by mandates and incentives from the federal government; competition, pressure, and new ideas from peer states; and pressure and ideas from local governments.

Equation 1: The Modified General Model of Policy Diffusion

\[ \text{ADOPT}_{i,t} = f(\text{MOTIVATION}_{i,t}, \text{RESOURCES}/\text{OBSTACLES}_{i,t}, \text{OTHER POLICIES}_{i,t}, \text{EXTERNAL}_{i,t}, \text{POLICY ATTRIBUTES}_{i,t}) \]

Berry and Berry’s original model did not include innovation attributes as a distinct component, however they are added here because recent research formally incorporates Rogers’ (2003) five innovation attributes (relative advantage, observability, complexity, trialability, and compatibility) into the model of policy innovation diffusion (Makse and Volden 2011; Nicholson-Crotty 2009). Doing so recognizes that all policies are not equal in terms of their advantage over the status quo, salience, complexity, ease of abandonment, and compatibility with state values and culture. These features shape the likelihood and speed at which states decide to take up and pass innovations.

Adding the attributes, however, is not a simple prospect, as there is overlap between some of them (particularly relative advantage) and the “Other Policies” element of the original model. Therefore, I have simplified this model into three main
components: internal characteristics, external influences, and policy attributes. Figure 1.1 provides a graphical depiction of the simplified theoretical model that provides the motivation for each subsequent chapter in this dissertation. While the next four chapters explicitly test different aspects of this model, Chapter 6 addresses the causal mechanisms that operate below the macro-level model. I will now lay out the analytical approach and purpose of each of these chapters.

Figure 1.1: Simplified general model of policy diffusion

Analytical Approach

The first step to evaluating the forest is to examine what we have learned from the collection of trees. In Chapter 2, I gather the existing single-policy studies that test Berry and Berry’s (1990, 2007) general model. I first evaluate the methodological consistency and rigor of these studies, including the types of statistical models used and measurement
of important variables, like neighbor adoptions. Then, I synthesize the findings of these studies for five important elements of the general model: neighbor previous adoption, state liberalism, legislative professionalism, slack resources, and federal intervention.

While Chapter 2 provides a sense of the consistency of past findings regarding two of the categories of adoption predictors from Figure 1.1, it does not explicitly test their generality. Furthermore, the studies of individual adoptions do not allow for the testing of innovation attributes, nor do they provide any understanding of how the components of the simplified general model change over time. Chapter 3 first tests the generality of this model using a large pool of 119 innovations that were adopted between 1960 and 2010. Essentially, it tests which components of the diffusion model relate to the likelihood that a state will adopt any given innovative policy. It then provides an important advancement on policy diffusion theory by examining the extent to which the predictors of diffusion change over time. First, expectations are developed based on broader changes in state politics and American society over the past 50 years. I then test these expectations by evaluating the general model in five different decades (i.e., the 1960s, 1970s, 1980s, 1990s, and 2000s). This provides initial intuition into how diffusion dynamics change over time.

Chapter 4 develops and tests a theory for how these predictors change across the diffusion lifecycle. By diffusion lifecycle I mean the five stages of adoption (i.e., adopter categories) identified in Rogers’ (2003) broader theory of innovation adoption: innovation, early adoption, early majority adoption, late majority adoption, and laggard adoption. This essentially answers the question of whether states falling into these categories respond to the same factors in adopting an innovation, or if there is variation in
the effects of the components of the general model across the categories. It also recognizes that while internal characteristics, external influences, and policy attributes associate with the likelihood that an innovation is adopted, not all adopters respond to these factors in the same way. The diffusion process necessarily unfolds over time and adopters respond to different influences depending on when they adopt.

Building on the idea that states respond to different stimuli depending on how quickly or slowly they adopt, Chapter 5 addresses the temporal (in)stability of policy diffusion from a different perspective. Instead of focusing on the likelihood/risk that a state will adopt an innovation, this chapter examines how quickly states innovate and whether that changes across time and is shaped by the attributes of each policy. Shifting the focus from the likelihood to the rate of adoption is useful because they each help us learn something different about adoption patterns and how they change. The likelihood of adoption tells us something about why states adopt new ideas, whereas speed helps us understand why some innovations are acted on more quickly than others.

Adoption speed also speaks to how fundamental changes in our society and politics may be shaping state innovation. Specifically, this focus returns to an early, but untested, hypothesis of Jack Walker (1969, 1973) that policy diffusion would occur more rapidly in the future as communication technology and interstate professional organizations develop. A single-policy approach, however, does not allow for the testing of such a hypothesis, as many policies adopted over a large span of time need to be examined. In an effort to test this theory and advance the study of innovation adoption speed, Chapter 5 presents a new continuous measure of adoption speed intended to improve upon the current dichotomization of innovations into fast and slow (Nicholson-
Crotty 2009), evaluates how the speed of innovation adoption changes across time (1912-2010) and policy domains, and then models how some innovation attributes relate to adoption speed. Given the nascent state of measuring innovation attributes, the primary contribution of this chapter is the adoption speed measure and answer to the Walker’s question of whether the average rate of innovation diffusion has increased over time.

Emerging from the results of these four chapters is a common story that the general model of diffusion is not static across time. While it does generalize across a broad range of policies and long time span when pooled in Chapter 3, there are substantial changes in specific predictors over time. The most profound is a decline in the importance of neighboring states and a rise in ideological learning, whereby states are more likely to adopt something new if previous adopters are ideologically closer to them. Chapter 4 demonstrates that states are influenced by different components in different stages of the diffusion process. Ideological pressure, in particular, appears to build as an innovation spreads. Finally, diffusion speed exhibits a sharp increase since 1965. All of these changes occur in a country with rapidly advancing communications and growing elite polarization (Shor and McCarty 2011). This work answers the question of whether change is occurring and what it looks like, however the causal processes that drive these changes remain to be tested.

While diffusion scholars have previously developed and tested, to various degrees, theories on the causal mechanisms underlying policy diffusion (see Shipan and Volden 2008), there is no theoretical structure tying these mechanisms together, which results in substantial conceptual slippage (Maggetti and Gilardi, Forthcoming) and
confusion about how the results of proceeding work provide a cogent picture of these mechanisms. Furthermore, with all of the recent methodological and measurement advancements in policy diffusion research (Boehmke 2009a; Boehmke and Skinner 2012b; Boushey 2012; Desmarais, Harden, and Boehmke, Forthcoming; Nicholson-Crotty 2009; Paterson et al. 2014; Volden 2006), there has been comparatively little attention paid to conducting experiments that allow researchers to control and directly test causal mechanisms underlying individual behavior in the innovation process (Butler et al. 2014; Elkins 2014; Tyran and Sausgruber 2005). Chapter 6 provides advancements on both of these grounds. I first present a theoretical framework for organizing five mechanisms of policy diffusion: learning, competition, coercion, social contagion, and socialization. Then, I focus on the least-developed mechanism, elite socialization. I do this for two reasons. First, it provides an excellent avenue for using experiments to understand human behavior that motivates innovation. Second, it is the mechanism that most directly relates to the broader patterns identified in Chapters 3 and 5.

Elite socialization is one potential explanation for the decline in regional learning and rise in ideological patterns of adoption identified in Chapter 3. Furthermore, the increased speed of adoption found in Chapter 5 belies a process whereby states are less often following the smooth normal adoption patterns typified by Gray’s (1973a) s-curve of cumulative adoptions. Instead, policies may be increasingly following the r-curve highlighted by Boushey (2010), which may be more often motivated by mechanisms such as competition and socialization. Thus, while the bulk of this dissertation focuses on macro-level changes in the dynamics of policy diffusion, that discussion is not complete
without addressing the underlying causal mechanisms. This is, of course, a far more ambitious proposition than can be accomplished in one dissertation, so Chapter 6 provides the groundwork for future explication of the most understudied mechanism.

Data and Methods

There are three distinct data sets, with different data collection efforts and statistical methods employed, used throughout this dissertation. Chapter 2 required me to gather the available corpus of diffusion studies (67) published between 1990 and 2013 in order to systematically assess the prevailing methodology and most important results of this body of research. Each paper was coded based on its analytical approach, data, and results.

The statistical analyses in Chapters 3, 4, and 5 rely on a common dataset of policies adopted from 1912 through 2010. Chapters 3 and 4 only use the adoptions starting in 1960, due to limitations in the measurement of the dependent variables. The dataset includes adoption data from Boehmke and Skinner (2012b), Makse and Volden (2011), and 15 policies that I collected (see Appendix A). Chapters 3 and 4 both examine the risk of a state adopting an innovation in a given year as the dependent variable, with measures of external influences, internal characteristics, and policy attributes included as predictors of adoption. They both use a similar statistical technique for this analysis: hierarchical linear modeling (Gelman and Hill 2009). They key difference is the theoretical approach to analyzing the data.
Chapter 5 utilizes the same dataset of adoptions, but instead employs a new measure of policy adoption speed as the dependent variable. It is used to first examine how diffusion speed varies across time and policy domain. For this analysis, I employ the entire dataset of adoptions from 1912 through 2010. Subsequently, an ordinary least squares model is used to examine the relationship between adoption speed and certain attributes of the innovations. This analysis is primarily exploratory, given the nascent development of good measures of Rogers’ (2003) five attributes. I address these measures in further detail within the chapter.

Given the micro-level focus of Chapter 6, a different dataset and empirical technique is necessary to examine the causal micro-process underlying conformity behavior in the political realm. Specifically, I conducted an experiment addressing whether an individual would conform to a group of peers who share a different opinion than them on a high-context, identity-laden issue. I use cross-tabulations and t-tests to examine whether participants in a political discussion group were more likely to conform than those that took an impersonal web-based survey. Furthermore, I examine whether treated participants publically complied out of a desire to be liked, privately accepted the group’s opposing opinion out of a desire to be right, or responded to a combination of the two forces. Finally, I use t-tests to examine differences in personal traits and behavior between confirming and non-conforming participants.
Contribution

Having laid out the rationale and analytical approaches used in this dissertation, it is important to address the scholarly contribution of this work. First, what does it contribute to the scholarly discourse on policy diffusion? Second, what does it teach us more broadly about politics and policymaking? The first question is perhaps more straightforward than the second. As mentioned above, the policy diffusion research program is largely fractured in its analytical approach and thus it has been difficult to develop clear advances on our understanding of the process. While strides have been made, the piecemeal approach continues to identify new avenues for exploration that are often not replicated in other domains.

Two potential explanations for the substantial variation in even the most fundamental predictors of adoption identified in Chapter 2 are the distinct probability that diffusion dynamics are heterogeneous not only across policy domain, but also across time, and the difficulty in precisely estimating small, but substantively significant effects, such as the adoption of previous neighbors, with only a handful of observed adoptions available in a single policy model (Gelman and Weakliem 2009). This dissertation addresses both of these issues by examining the generality of the “general” model of policy diffusion and how it changes based on time. Furthermore, chapters 5 and 6 address the underlying causal mechanisms that motivate innovation adoption. This is necessary in order to understand broader changes in diffusion over time. The specific contributions of each chapter are further outlined above.
This leads directly into addressing the question of what this dissertation teaches us about politics more broadly. American society and state politics have changed a great deal since the founding, and certainly so in the last 50 years. The rise in rapid communications technology, like the Internet and smartphones (File 2013), yields an abundant information environment (Bimber 1999), which has the potential to overwhelm elites. Furthermore, states have been drawn more tightly together in some ways and pushed further apart in others during the same time period. On one hand, rapid communications coupled with the increased activity of professional organizations for legislators, governors, and bureaucrats pulls geographically disparate states together. Additionally, states no longer simply compete with their contiguous neighbors for resources; they are increasingly in competition with all other states, as typified by the ability of numerous states to draw filmmaking revenue from California through tax incentives (McDonald 2007, 2011).

On the other hand, ideological organizations, like the conservative American Legislative Exchange Council (ALEC) and progressive State Innovation Exchange (SiX), coupled with the documented rise in elite political polarization (Shor and McCarty 2011) binds narrower subsets of states together due to ideological similarity. The research represented in this dissertation helps us first understand whether the specific predictors of innovation adoption captured by Figure 1.1 change across time and during the process of innovation diffusion. This helps researchers identify where to look in terms of the causal processes that led to this change. For instance, the growth of ideological

---

1 SiX was formed in 2014 from the merger of the American Legislative Issues and Campaign Exchange, Progressive States Network, and Center for State Innovation. The primary purpose of this merger was to provide a progressive counter-weight to ALEC. [https://stateinnovation.org](https://stateinnovation.org).
diffusion found in Chapter 3 could be the result of the rise of groups like ALEC and growing elite polarization. Furthermore, the marked increase in diffusion speed in Chapter 5 is likely, at least partially, the result of the increased speed of communications technology. Future research will help scholars explicate these mechanisms.

Identifying how these factors change also teaches us something about representation. Fundamentally, policy diffusion is about understanding the spread of ideas and the voices that legislators listen to. It recognizes that legislators’ reactions to policy problems are shaped not only by their constituents and other within-state factors, but also cross-state actors in the broader federal system. Thus, identifying how those predictors change tells us something about whom legislators represent. For example, if within state and/or neighbor state effects decline over time and are replaced by ideologically driven learning, it suggests that legislators may no longer be searching for the optimal policy solution for the purpose of pursuing ideologically neutral notions of good governance. In fact, this view of good governance, a legacy of the progressive movement, is an untested assumption of policy diffusion theory and the idea that states are laboratories of democracy. If policies are spreading throughout the state system less broadly, but are instead increasingly following narrower networks driven by characteristics such as ideology, this presents a fundamentally different picture of whom legislators are listening to and why they are adopting new ideas. It suggests a different purpose for why the laboratories innovate.
Chapter 2

Twenty-Five Years of Evidence: A Systematic Review and Synthesis of the Policy Diffusion Literature
Over the course of 50 years, over 700 scholarly articles have tackled the fundamental question of why innovative policies spread (Graham, Shipan, and Volden 2013). Regardless of whether the research focuses on diffusion among the American states, or within the international system, scholars seek to understand why ideas spread and what motivates a state or country to take them up. The early core of this work was largely performed in the American context (e.g., Gray 1973a; Savage 1978; Walker 1969), however there is growing interest in expanding the theory of policy innovation adoption to incorporate the cross-country spread of ideas (Braun and Gilardi 2006; Cao 2009, 2010; Gilardi 2012; Greenhill 2010). Beyond barriers to communication and sharing between scholars working in the American and comparative contexts (Graham, Shipan, and Volden 2013), there is a growing concern about the diminishing returns of the prevailing methodology used by both: single-policy event history models (Boehmke 2009a). This approach led to a fragmented testing of the general model of diffusion (Berry and Berry 1990, 2007), which yields conflicting results and sparse replication of new findings. In response, researchers recently began to accumulate large datasets of policies in order to study the macro-level dynamics of policy diffusion (Boehmke and Skinner 2012b; Boushey 2010; Nicholson-Crotty 2009). Alas, no one has yet systematically examined the existing body of single-policy studies in order to identify what has been learned, what remains to be tested, and how these models can potentially remain useful in the future in the midst of a growing push for more generalizable findings. That is the purpose of this chapter.
In 1990, Frances Stokes Berry and William D. Berry provided an important Lakatosian (1970) advancement for the policy diffusion research program. Specifically, they introduced event history analysis (EHA) as a method for merging previously disparate inquiries into the internal and external influences of state innovation adoption. To demonstrate the utility of this statistical approach, the authors chose to model state lottery adoptions. EHA allowed them to test both strands of research, while also identifying new areas for inquiry. Since 1990, many similar studies have been conducted on diverse topics, from same-sex marriage bans (Haider-Markel 2001) to stem cell research (Karch 2012). Many of these studies either test Berry and Berry’s general diffusion model (Equation 1) in a new policy area that is expected to behave differently (e.g., Mooney and Lee 1995) or to add a new, previously untested, predictor to the model (e.g., Balla 2001).

This approach has been vital for refining policy diffusion theory, however it has important limitations. While the internal validity of these studies is quite good, it is difficult to draw conclusions outside of the innovation being studied. This is because the models are often dominated by highly contextualized covariates that are not replicated, or even applicable, within other policy domains. Before testing the generalizability of policy diffusion theory across policies and time, it is important to take stock of what these single-policy studies have found. While scholars previously provided narrative reviews of the policy diffusion research program (e.g., Karch 2007b), no one has yet systematically evaluated the breadth, methodological consistency, and findings of these studies.

This chapter does just that by asking what is the policy and temporal coverage of the existing body of research? What types of modeling approaches are used and how have
researchers adapted to methodological advances in EHA over the last three decades? Finally, what have these studies found regarding the major predictors of policy innovation diffusion (i.e., neighbor adoptions, ideology, legislative professionalism, slack resources, and federal intervention)? These questions will be answered through systematically reviewing the literature that uses Berry and Berry’s (1990) analytical approach of binary time-series-cross-sectional (BTSCS) analysis and then synthesizing the key results. First, I will explain my approach for gathering and analyzing the relevant literature. Then, I will address each of these important questions about the research program.

Methodology

Conducting this systematic review of the Berry and Berry (1990) analytical approach involved five main steps:

1. Define the problem
2. Determine inclusion/exclusion criteria
3. Gather relevant literature
4. Record data from each study
5. Analyze results

I will now describe each step for the purpose of understanding where the data come from and to assist future attempts at replication and extension of this review.²

² The article database, reproduction data, and code will be made available on my Dataverse upon publication.
Define the Problem

For the purpose of evaluating the Berry and Berry (1990) research paradigm, I define the research problem/question simply: how do internal characteristics, external influences, and policy attributes affect the likelihood that a state will adopt a policy innovation? Thus, the conceptual definition of the dependent variable can be drawn from Walker (1969, 881): “an innovation will be defined simply as 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.” The operational definition most often used for statistical analysis of adoption patterns is a dichotomous indicator of whether a policy is adopted in a given year.

Determine Inclusion/Exclusion Criteria

Given the breadth of diffusion research, the most important demarcation between included and excluded studies is whether they were conducted on a policy innovation adopted by the American states. This confines the subsequent review to a tightly connected body of work (Graham, Shipan, and Volden 2013) using a common unit of analysis. Drawing connections between the clustered work in American politics and the more disconnected work in comparative politics is very important; however it is not the purpose of this chapter.

Having drawn a clear conceptual line, I also draw a clear methodological one in that I included only studies that modeled the adoption of a policy using EHA. Studies were included regardless of specific modeling type (e.g., logistic regression) and other
choices (e.g., modeling duration dependence), as long as the dependent variable was a
dichotomous indicator of adoption. Thus, qualitative studies or those with an alternative
dependent variable were excluded. For example, I excluded Volden (2006) due to its
dyadic approach to modeling adoption, which is an important methodological innovation,
but also a substantial departure from the typical EHA design. Descriptive studies, like
Jones-Correa’s (2000-2001) case study of the diffusion of racial restrictive covenants, are
also excluded.

**Gather Relevant Literature**

Identifying the corpus of literature that is potentially relevant to a systematic
review is not an easy task. If the search systematically excludes certain studies, the results
may be biased (Cooper 1998). One substantial consideration is whether to include both
published and unpublished research. Ideally, including unpublished work reduces the
potential for publication bias (i.e., the publication of only positive findings). Scholars,
however, have also pointed out the potential problems with including this so-called “grey
literature” (Valentine 2009, 120). They argue that publication signals a baseline level of
scientific rigor that helps weed out studies that are methodologically flawed (Keel and
Klump 2003; Weisz et al. 1995).

A common response to this argument is that there are inherent biases in the body
of published work, particularly toward publishing exciting and counter-intuitive findings,
but not null effects (Francis 2013; Gerber, Green, and Nickerson 2001; McAuley et al.
2000; Sutton 2009). In fact, there is a documented divide between meta-analysts and
journal editors, in particular, over whether to include grey literature (Cook 1993; Tetzlaff 2006). That being said, the studies by Cook et al. (1993) and McAuley et al. (2000) found that only one-third of meta-analyses included grey literature. Furthermore, evidence from the physical sciences suggests that working papers and abstracts presented at conferences are often missing information necessary to conduct research synthesis (e.g., Bhandari et al. 2002). Within political science, a past synthesis included only published research, due to claims that grey literature is often incomplete (Doucouliagos and Ulubasoğlu 2008).

Given this controversy and the difficulty in incorporating incomplete research into a systematic review and research synthesis, I chose to only search for published literature.

The literature search proceeded as follows. I began by gathering the studies cited by Berry and Berry in the appendix of their 2007 chapter in Sabatier’s *Theories of the Policy Process*. This provides a useful starting point, as the authors include a list of studies published between 1990 and 2006 that use EHA to “test a model of innovation reflecting both internal predictors and intergovernmental diffusion” (259). Building on this, I performed a Web of Science search on Berry and Berry’s 1990 article on state lotteries, given that it is one of the most cited articles by diffusion scholars in American politics (Graham, Shipan, and Volden 2013) and is likely to be cited in work that replicates their analytical approach. In total, 90 articles were identified using this search approach. Of these, 23 were excluded for not meeting the criteria established above. This results in 67 included studies with a total of 141 innovation adoption models. The articles were published in refereed journals between 1990 and 2013. It is important to note that there are, more often than not, multiple models nested within a single study. Sometimes these are different specifications for the same adoption data; other times there are
different models for different innovations. All are recorded in the database of found studies.³

**Record Data from Each Study**

Details from each study were recorded in an Access database. Given that there are multiple innovation adoption models in some studies, each entry in the database represents one model. Table 2.1 displays the measures of study characteristics gathered from each article. Sixteen aspects of each study/model were measured under four broad categories: the article, data, included geographic characteristics, and modeling choices.

**Table 2.1: Data collected from included diffusion articles**

<table>
<thead>
<tr>
<th>Article Information</th>
<th>Data</th>
<th>Geography</th>
<th>Modeling Choices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Citation Information</td>
<td>Major topic code*</td>
<td>Neighbor measure included?</td>
<td>Model type</td>
</tr>
<tr>
<td></td>
<td>Sub-topic code*</td>
<td>Type of neighbor measure</td>
<td>Effects type</td>
</tr>
<tr>
<td></td>
<td>Included state count</td>
<td>Other geographic measures?</td>
<td>Duration method</td>
</tr>
<tr>
<td></td>
<td>Excluded states</td>
<td>Description of other geographic variables</td>
<td></td>
</tr>
<tr>
<td></td>
<td>DC included?</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>First adoption year</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Last adoption year</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

³ These are the major and sub-topic codes developed by the *Policy Agendas Project* and subsequently modified to fit state politics for the *Pennsylvania Policy Database Project*, Principal Investigator Joseph P. McLaughlin, Temple University (McLaughlin 2010).

**Analyze Results**

Upon completion of data collection, a series of descriptive analyses were conducted in order to assess the current state of the policy diffusion literature and its measurement and methodological coherence. Specifically, I measured the types of

³ Link to the Dataverse location for this database will be provided upon publication.
policies included in all of the models, adoption spans included in each model, the type of neighbor adoption measurement used, statistical method used, and method for accounting for duration dependence in the chosen model. These results provide a comprehensive picture of the evolution of diffusion studies that built on Berry and Berry’s (1990) analytical approach, as well as their incorporation of subsequent advances in survival analysis methodology. Finally, I synthesize the body of evidence for five important and widely modeled predictors of policy innovation diffusion: neighbor adoptions, ideology, legislative professionalism, slack resources, and federal intervention.

**Results of the Systematic Review**

To begin, Figure 2.1 displays a count of the studies included in this analysis by publication year. ⁴ While the initial studies in 1990, 1992, and 1994 were all conducted by Berry and Berry, the research program maintained an average of approximately four new studies per year since 2000. This, of course, does not capture the policy diffusion work that utilizes an alternative analytical approach, including the recent crop of research that uses either a different statistical method (Boehmke 2009a; Volden 2006) or a different dependent variable (Nicholson-Crotty 2009). That being said, the single-policy EHA approach was widely used during this time period and continues to be used even in light of the movement towards the study of macro-level dynamics and causal mechanisms (e.g., Karch and Cravens 2014).

---

⁴ Note that the n is 67 when presenting summary results at the study-level and 141 when they are at the model-level. This is due to the fact that there are sometimes multiple models nested within a single study.
Figure 2.1: Count of included articles by publication year from 1990 to 2013

The first question to answer with this data is regarding the coverage of policy topics and time provided by the entire set of studies. A continual concern with this line of research is the convenience sampling approach to data collection that typifies many of these studies (Savage 1978; Walker 1973). Boehmke and Skinner (2012b) also recognize this problem in their large-n analysis of state innovativeness; however they point out the benefit of aggregating adoption data in order to overcome potential biases from this sampling approach. Similarly, there is benefit in examining the policy coverage of the entire body of work in order to identify areas where further data collection and analysis are necessary, as well as to prevent passing over well-trod ground in the future.
Figure 2.2 displays a count of all included single-policy models by their major topic codes from the Pennsylvania Policy Database Project (McLaughlin 2010). Given the policy responsibilities of many states, some of the coverage is surprising. For instance, there are no models that represent local government or agricultural policy. This is surprising given that states are ultimately sovereign over their local governments and they have changed the scope of their responsibilities over the past 100 years. For example, since 1917, eight states passed home rule power for their local governments through statutes and 22 others incorporated it into their constitutions through amendments. Furthermore, most states are involved in some regulation of agriculture, albeit for very different products, which are dependent on their local environment. Therefore, these two topic areas, in particular, provide important avenues for future research.

---

5 More specific sub-topic code descriptions were used to determine the major topic code for each policy. The Pennsylvania Policy Database Project was used for this coding instead of the larger Policy Agendas Project because it is adapted for the purpose of coding state policies.
Among the well-trod policy domains are administrative policies and civil rights and liberties (e.g., Taylor et al. 2012). The administrative policies category, however, is inflated by the large subset of studies that replicate and extend Berry and Berry’s original lottery model. It is to be expected that this category should receive a lot of attention, given recent trends in state policymaking. Administrative policies are likely to encompass a fair proportion of state legislation, given that these laws most often deal with the conduct of state government. Policies included in this category often either add to or subtract from the day-to-day responsibilities of the legislature, executive agencies, or the judiciary. Furthermore, given the management reforms of the past four decades (Lynn
2006), from new public management in the 1970s to the current age of austerity, this should remain an important area of policymaking for states. Thus, even though this category appears to be well attended, the large set of lottery studies obfuscates a lack of coverage of an important component of state lawmakers.

The high degree of coverage for civil rights legislation, on the other hand, is likely due to scholarly interest and the utility of using them as a foil for other diffusion studies. Many of these studies examine morality policies, like abortion (Allen, Pettus, and Haider-Markel 2004), the death penalty (Mooney and Lee 2000), and gay marriage bans (Haider-Markel 2001). These issues provide a useful line of inquiry for identifying whether the same policy diffusion predictors apply to these often simpler, yet more controversial, policies. Furthermore, the development of morality policy as a distinct locus of research (Mooney 2001b) also likely contributes to the wider coverage in this area. Finally, morality policies have been a hot topic for several decades due to scholarly debate over the culture wars in America (Fiorina, Abrams, and Pope 2010; Gibson 2004; Haider-Markel and Kaufman 2006; Layman 1999; Layman and Green 2006; Lindaman and Haider-Markel 2002), and thus may attract more scholarly interest.

Moving to the temporal coverage of these studies, Figure 2.3 displays the range of adoption dates for each model included in the dataset. The models are arranged from bottom to top by order of the first adoption year. The vast majority of the included studies capture adoptions occurring after 1960. There is very little coverage before that, and a gap of no coverage between 1940 and 1955. Fortunately, there is data available for this period from Walker's (1969) early study. His dataset included adoptions from 1812 through 1966. The disadvantage of examining earlier adoptions, however, is the lack of
measurement for important covariates. For example, Berry et al.’s (1998) citizen and elite ideology scores are commonly used to account for state liberalism in these adoption models. Unfortunately, this measure only goes back to 1960. Thus, diffusion researchers are often limited to studying innovations that spread after 1960.

Figure 2.3: Spans of first and last adoption for each included diffusion model
Having examined the topical and temporal coverage of this body of literature, I now turn to evaluating its methodological consistency. When Berry and Berry (1990) originally introduced event history modeling to the research program, they did so using a probit model. There has been some methodological advancement in terms of modeling diffusion patterns (Boehmke 2009a; Darmofal 2009; Volden 2006), but studies largely still use either a probit or logit model. This is demonstrated in Figure 2.4, which provides a simple breakdown of the included models into logit, probit, or other categories. In total, 50 percent of the models use logistic regression and 22 percent use probit.

Of the remaining 28 percent, many use a discrete time Cox proportional hazards model. In fact, this approach has become increasingly prevalent, due to the challenge of choosing the correct functional form for modeling duration dependence in logit and probit models (Beck, Katz, and Tucker 1998; Buckley and Westerland 2004; Carter and Signorino 2010). It appears that some researchers have abandoned the older approach for one that has a very flexible baseline hazard. Using a Cox model in this case is essentially equivalent to using logistic regression with dichotomous indicators for each year (Beck, Katz, and Tucker 1998; Thompson 1977). Including this flexibility in the logit approach, however, consumes an additional degree of freedom for each year measured in the study; thus the attractiveness of a discrete Cox model. The disadvantage of a Cox model, of course, is the challenge of dealing with ties (Allison 1982), which occur frequently in grouped diffusion data. It appears that no researchers have adopted either the cloglog link or Bayesian approaches suggested by Buckley and Westerland (2004) and Darmofal (2009). Instead, they are keeping to more familiar models.
There is also a great deal of variation in the approaches taken to accounting for duration dependence in these BTSCS models. Figure 2.5 displays an annual count of each model by year of publication, which is broken into six categories based on the approach to duration dependence: none, count of time, log of time, spline of time, polynomial of time, and other. Initially apparent is the fact that even in the last decade, many authors do not model, or at the very least do not report modeling, duration dependence at all (e.g., Homer and French 2009). This essentially assumes that the hazard rate is flat (Box-Steffensmeier and Jones 2004), however it is not often asserted as a clear assumption, nor tested, by the author.
Buckley and Westerland (2004) called attention to the problem with the untested assumption of a flat baseline hazard within policy diffusion research, while Beck, Katz, and Tucker (1998) raised this issue for BTSCS data more generally. Beck, Katz, and Tucker (BKT) promoted using cubic splines of time as a useful trade-off between a monotonic functional form and the time-dummies approach that mimics the flexible baseline hazard of a Cox model, though diffusion scholars rarely take that approach. Granted, this is not only the case within diffusion research, as Carter and Signorino (2010) point out. They found that, in the wake of BKT, many scholars either did not try
the spline approach, or used the same knot placement as demonstrated by BKT, even though they were using different duration data. Carter and Signorino (2010) thus recommended including a third-order polynomial of time as a simpler alternative.

It does not appear that these three methodological critiques, one centered squarely on policy diffusion (Buckley and Westerland 2004) and the other two focused on BTSCS data more broadly (Beck, Katz, and Tucker 1998; Carter and Signorino 2010), have had a strong impact on diffusion researchers' choices in modeling duration dependence. Some splines of time did appear after 1998, but they are still very rare. Only two studies (a total of 5 models) included polynomials of time (Boehmke and Witmer 2004; Grossback, Nicholson-Crotty, and Peterson 2004), and both were published prior to Carter and Signorino’s critique.

One additional thing to note regarding duration dependence is the large “Other” category represented in Figure 2.5. While this category includes studies that use a Cox proportional hazards model, it also includes another approach that was more widespread in this body of research than was expected. A relatively common approach to duration dependence in these models is to estimate the year with the highest hazard rate and then take the square root of the absolute distance from the current year to the peak year. This provides an alternative method for including a non-linear time trend (Mooney and Lee 1995) and was one method not considered in Buckley and Westerland’s (2004) comparison of duration dependence approaches. Given this, and the introduction of polynomials of time (Carter and Signorino 2010), it seems appropriate to update that comparison.
Moving from modeling approach to measurement, I examined one of the foundational predictors of policy diffusion: previous adoption by a state's neighbors. The neighbor effect is important to test in many of these models, as they are sometimes critiqued as not showing diffusion if there is no evidence of external influence. Granted, there are other measures of horizontal and vertical influence, including federal incentives (Welch and Thompson 1980) and relative ideology (Grossback, Nicholson-Crotty, and Peterson 2004). As noted above, however, regional patterns of adoption have been long been identified as important for signifying a diffusion process (e.g., McVocy 1940; Walker 1969). Thus, it is necessary to identify the extent to which adoption models account for this potential spatial relationship. First, it is important to note that not all, but still the vast majority (70 percent), of the models account for contiguous neighbor adoption. The remaining 30 percent may include another geographic indicator (e.g., a South dummy), but not one that indicates past adoption by a state's contiguous peers.

Figure 2.6 visualizes the approach taken by the 70 percent of models that include a regional adoption measure. The majority of these studies (55 percent) measure either the proportion or percentage of contiguous states that previously adopted a given innovation. This measure properly accounts for the fact that not every state has the same number of neighbors. Berry and Berry (1990) originally use a count of neighbors, though that quickly lost favor because of variation in the potential number of neighbor adoptions for each state. While the percentage of studies using a count is non-trivial (35 percent), many of these studies are actually replications and extensions of Berry and Berry's original article. That being said, this is not the case for all.
In terms of the “Other” category, some researchers do not limit their measure to contiguous adoptions. For instance, they instead, for instance, measure whether states in the Census region previously adopted. While this does not conform to previous work on the importance of contiguous neighbors, it does begin to capture, in a rough way, regional effects that do not only come from states that share a border. In fact, the diffusion work that focuses on the U.S. states has not adopted more complex spatial modeling that allows
for these extended relationships to emerge. Such approaches are more ubiquitous in the international diffusion literature and thus provide a useful avenue for better communication and learning within the broader policy diffusion research community (Graham, Shipan, and Volden 2013).

The results of this systematic review show that while the research on policy innovation diffusion in the American context covers a broad span of policy domains and has good coverage of adoptions since 1960, there are substantial gaps that can be filled using the existing paradigm. For instance, Figure 2.2 should guide researchers toward particular policies that have not been well represented or studied at all. This leads researchers away from hotter topics, like morality policies, and towards lower-profile policies like agriculture, local governance, public administration, and commerce, among others. This should be embraced for the sake of filling in these gaps in understanding.

Furthermore, the results above point to substantial variation in the extent to which diffusion researchers are embracing advances in event history modeling. While some take duration dependence seriously, others do not. This is the case for articles published both within and outside of political science journals. One promising advancement that accounts for Beck, Katz, and Tucker’s (1998) critiques, without consuming degrees of freedom via time dummies or introducing multicollinearity with polynomials of time, is the increased use of discrete time Cox proportional hazards modeling. Regardless of whether researchers use a Cox model or logit or probit, they should evaluate the assumption of a flat hazard rate when not including any measure of duration dependence in their models (Beck, Katz, and Tucker 1998; Buckley and Westerland 2004).
**Research Synthesis Results**

Having answered the questions regarding the policy and temporal scope of these studies, as well as their methodological consistency, I now turn to synthesizing the results for important diffusion predictors that are drawn from Berry and Berry’s (1990, 2007) general model of diffusion (see Equation 1). Ideally, each study should include at least some measures of spatial effects (e.g., past neighbor adoptions), internal characteristics (including political and demographic), availability of slack resources, and measures of problem severity. Furthermore, some policies experience vertical pressure for diffusion from the introduction of incentives or mandates from the federal government (Nicholson-Crotty 2009; Welch and Thompson 1980). Before examining the expectations for these variables and synthesizing the findings from the extant research, it is important to assess the extent to which these variables are captured in the studies included in this analysis.

**Inclusion of Key Covariates**

Table 2.2 displays the percentage of studies that included and excluded each of the measured categories of important diffusion covariates. It is immediately apparent that contextual measures are the most prevalent in these models. These measures speak directly to the innovation at hand and little argument is often given regarding the potential generalizability of these measures. For example, Carley and Miller’s (2012) study of the spread of renewable energy portfolio standards (RPS) included measures of electricity price and renewable energy production potential. Each of these is clearly important for a state’s propensity to adopt an RPS, however these measure are not
expected to generalize to other policy domains (e.g., civil rights policies). A full 87 percent of the models included in this analysis used contextual covariates that apply narrowly to the innovations at hand.

Table 2.2: Inclusion and exclusion of key diffusion predictors

<table>
<thead>
<tr>
<th>Predictor(s)</th>
<th>Percent Included</th>
<th>Percent Excluded</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contextual measure†</td>
<td>87 percent</td>
<td>13 percent</td>
</tr>
<tr>
<td>Slack resources†</td>
<td>77 percent</td>
<td>23 percent</td>
</tr>
<tr>
<td>Other political measure†</td>
<td>77 percent</td>
<td>23 percent</td>
</tr>
<tr>
<td>Demographic measure†</td>
<td>72 percent</td>
<td>28 percent</td>
</tr>
<tr>
<td>Previous neighbor adoption</td>
<td>70 percent</td>
<td>30 percent</td>
</tr>
<tr>
<td>Ideology (Liberalism)</td>
<td>55 percent</td>
<td>45 percent</td>
</tr>
<tr>
<td>Other geographic measure†</td>
<td>30 percent</td>
<td>70 percent</td>
</tr>
<tr>
<td>Legislative professionalism</td>
<td>14 percent</td>
<td>86 percent</td>
</tr>
<tr>
<td>Federal Intervention</td>
<td>7 percent</td>
<td>93 percent</td>
</tr>
</tbody>
</table>

†Includes at least one variable, but may include more than one

n = 141

Turning to covariates that are expected to have an impact on the diffusion process more generally, it is encouraging that over 70 percent of the included models capture at least one slack resource (77 percent), at least one political measure other than liberalism or legislative professionalism (77 percent), at least one demographic measure (72 percent) and a measure of previous adoption by the state’s neighbors (70 percent). There is, of course, heterogeneity in the measures used within the slack resource, political, and demographic categories. As noted above, fewer studies capture geographic effects besides contiguous neighbors (30 percent).

One political predictor that is consistently measured using the same dataset across policies is Squire’s (1992, 2007) legislative professionalism. While this measure helps capture legislative capacity and is available for the time span covered by most of these studies, it was included in only 14 percent of the models. Likewise, citizen or government
ideology is most often measured using Berry et al.’s (1998) liberalism scales, but they are more widely incorporated than legislative professionalism, with 55 percent of studies including some measure of within-state ideology. Finally, only 7 percent of studies include a measure of federal involvement in the dissemination of a particular policy. On one hand, this reflects the fact that direct federal intervention is not relevant for every policy and more often than not comes after a policy has already begun spreading through the states. On the other hand, federal attention has at least some influence on state policy activity (Baumgartner, Gray, and Lowery 2009), but implicit federal influence is rarely captured in these models. Now that I have established the extent to which these covariates are included, I turn my attention to synthesizing the effects identified in these models.

**Synthesis of Results**

To understand the weight of the evidence drawn from the existing body of single-policy diffusion research, I chose five particular predictors: neighbor previous adoption, liberalism, legislative professionalism, slack resources, and federal intervention. All five are generally expected to have a positive effect on the likelihood of a state adopting a policy innovation. In the case of neighbor adoption, this may be the result of either learning or competitive pressures from surrounding states (Berry and Baybeck 2005). Furthermore, contiguous states are more similar to each other in terms of their internal characteristics relative to farther states, thus they are more likely to face similar problems and be open to similar solutions to those problems (Walker 1969).
Liberal states are generally expected to be more open than conservative states to innovative policies that include new programs or government intervention (e.g., Matisoff 2008). That being said, not all innovations champion liberal causes. For example, abortion restrictions (Allen, Pettus, and Haider-Markel 2004) and same-sex marriage bans (Haider-Markel 2001) are represented in this dataset, both of which are conservative causes. In fact, a striking amount of the policies studied by diffusion researchers are traditionally conservative interests (e.g., electric deregulation).

Both legislative professionalism and slack resources (as a collective) are important measures of legislative capacity. Professionalism is also useful to include because it is more often than not measured in an identical manner across studies using Squire’s (1992) scores. Greater legislative capacity should allow for states to more quickly take up new innovations that help them solve problems. Additionally, slack resources, like a state’s tax base (often measured using per capita income) or the proportion of its budget committed to particular policy domains, speaks to the ability of a given state to take up policies that may require additional resources. That being said, there is substantial heterogeneity in the complexity and bureaucratic burden of policies, so the effect may not always be positive across all policies. For instance, it is more likely that slack resources play a role in consideration of highly technical and resource-intensive policies like renewable energy portfolio standards (Chandler 2009) than simple statutory changes, like criminalizing hate crimes (Allen, Pettus, and Haider-Markel 2004; Grattet, Jenness, and Curry 1998).

Finally, federal intervention should also have a positive effect on the likelihood that a state adopts an innovation. One way to think of this is that federal incentives and/or
attention raise the relative advantage of an innovation over the status quo experienced by an adopting state. This likely has the most profound effect on states that equally weight the status quo and a new policy. In this case, federal incentives can tip the scales. Furthermore, the federal government has a stronger effect when its signaling of preferences is clear (Allen, Pettus, and Haider-Markel 2004).

It is important to note what is not included in this analysis. Foremost are the pervasive contextual variables. It is difficult to assess their general effects given that the expectation for their impact on the likelihood of adoption is highly dependent on the given policy. A summarization of these variables would be fairly meaningless. Similarly, demographic variables are often included as controls in these models and, as such, their effects are often left un-interpreted or are only briefly mentioned. Furthermore, the direction of their effects is also highly contingent on the topic of study.

Table 2.3 displays the results of the research synthesis. The results from each study are partitioned based on whether the resultant effect was positive and statistically significant ($p < 0.05$), negative and statistically significant ($p < 0.05$), or not statistically significant ($p \geq 0.05$). The total number of coefficients for each variable is also included so that the percentages have more meaning. What is perhaps the most interesting finding is that every predictor except for legislative professionalism has significant effects in both the positive and negative directions. Neighbor adoptions and legislative professionalism are the only predictors with clearly positive effects. The significant effects for slack resources, liberalism, and federal intervention are split fairly evenly between positive and negative. This demonstrates the diversity in findings that result from the fractured study of policy diffusion.
Table 2.3: Summary of effect direction for key diffusion predictors

<table>
<thead>
<tr>
<th>Significance* and Direction</th>
<th>Neighbor Adoption</th>
<th>Liberalism</th>
<th>Legislative Professionalism</th>
<th>Slack Resource</th>
<th>Federal Intervention</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significant, Positive</td>
<td>35 percent</td>
<td>16 percent</td>
<td>15 percent</td>
<td>16 percent</td>
<td>29 percent</td>
</tr>
<tr>
<td>Significant, Negative</td>
<td>4 percent</td>
<td>11 percent</td>
<td>0 percent</td>
<td>19 percent</td>
<td>21 percent</td>
</tr>
<tr>
<td>Not Significant</td>
<td>61 percent</td>
<td>73 percent</td>
<td>85 percent</td>
<td>66 percent</td>
<td>50 percent</td>
</tr>
</tbody>
</table>

n 100  83  20  187  14
*p < 0.05

The results of this synthesis imply that even the predictors that are expected to generally apply across policy domains likely have policy-specific effects. What is perhaps even more profound is the abundance of null results across these models for covariates that are expected to generally have an impact on innovation adoption in the states. Most important to diffusion scholars is the fact that 61 percent of studies did not demonstrate significant regional patterns. The presence of some external influence, be it vertical or horizontal, is important for inferring that a diffusion process may have occurred. Thus, if regionalism is either policy- or time-specific, then scholars need to turn more attention to identifying alternative causal processes that motivate the spread of innovations. This work is being done (Berry and Baybeck 2005; Shipan and Volden 2008), however it is currently a nascent aspect of policy diffusion research, not a coordinated analytical approach, like Berry and Berry’s (Maggetti and Gilardi Forthcoming).
There are two very important caveats here that are also important for the advancement of this research program. First, while most of the single-policy diffusion models have several hundred observations due to repeated inclusion of an observation for a state until it experiences an adoption event, there are, at most, 50 events in any given analysis. This means that the five to ten covariates included in each model are explaining only a few events. Thus, there may not be enough data to precisely estimate many of these variables that generally raise the likelihood of adoption. Therefore, the null effects highlighted above cannot be interpreted as the lack of an effect. There simply may not be enough data in any particular adoption model to estimate the effect at a level of precision that is acceptable to political scientists.

The second caveat is that the variation in these supposedly general motivators of adoption may be due to temporal changes in the political environment in which they being measured. Meaning, it is possible that the predictors of diffusion presented by Berry and Berry, as well as the rest of this body of research, are not fixed over time. Recall that Figure 2.3 demonstrated that the vast majority of these studies are conducted on adoptions occurring after 1960. Furthermore, the depth of coverage grows over time. Meaning, the 1980s, 1990s, and 2000s are especially well covered, whereas the 1960s and 1970s are less so. This means that changes in these predictors due to broader changes within the states and across the federal system could drive the unexpectedly large presence of null effects for many of these predictors.
Conclusion

The purpose of this systematic review and research synthesis is to provide a baseline for conducting the larger-scale analysis of policy diffusion patterns. As this body of research shifts away from its dominant analytical paradigm towards large-n and mechanistic analyses, it is important to first take stock of what we have learned from the large body of individual quantitative case studies conducted over the last 25 years. Moving forward does not strictly speaking mean moving completely away from this approach. It does, however, mean that attention must be paid to the ground that has already been covered and that which requires additional attention. In providing this baseline, the above systematic review and research synthesis answered questions about the breadth of these studies, their prevailing methods, and the body of results.

In terms of the breadth of the studies, I find that there is a fair spread of coverage across many, but not all, of the policy domains that appear on state policy agendas. For example, I did not identify any studies of local governance or agricultural policy, while at the same time there is a lot of attention paid to hotter topics like morality policies. This suggests that future diffusion studies should pay attention to not only evaluating new and interesting predictors of adoption, but also replicating existing results over un- and under-studied domains. This is a situation where further utilization of Berry and Berry’s approach makes sense.

As for methodological approach, many diffusion scholars appear to still be most comfortable with using logit or probit, however there has been a noticeable shift towards using discrete time Cox proportional hazards modeling. This is likely in response to
criticism of researchers not taking seriously the assumption of a flat baseline hazard function for models that do not account for duration dependence (Beck, Katz, and Tucker 1998; Buckley and Westerland 2004). Cox modeling provides a flexible hazard without consuming available degrees of freedom with dichotomous indicators of time. That being said, there are still a substantial number of studies that either do not model duration dependence or choose an approach based on previous work without evaluating its appropriateness for the data at hand. This type of tailoring is necessary when modeling adoption using survival analysis, particularly when using logistic regression or probit.

Finally, the research synthesis identified the substantial variation in the inclusion of important predictors of policy diffusion and the abundance of context-dependent predictors. This, combined with the variegated measurement of similar concepts makes it difficult to determine average effects for specific predictors. That being said, the included synthesis does show that even those predictors expected to have general effects on adoption tend to also be context-dependent. Furthermore, the excess of null results suggests that many of the models may not have enough data to precisely estimate these effects.

The findings of the synthesis motivate the remainder of this dissertation, specifically addressing the question of why there is so much instability in these results. Chapter 3 overcomes the small-n problem that results from estimating effects within individual studies by pooling across adoption data for a large number of policies. This allows for the specification of a single model that tests whether the predictors are in fact generalizable across diverse policies. Then, I test the supposition that diffusion predictors may change over time as states, as well as the broader federal system, change. Chapter 4
then tests whether these predictors change throughout the diffusion lifecycle. Chapters 5 and 6 then turn to the question of identifying the causal mechanisms underlying policy diffusion. Chapter 5 still approaches this issue at the macro-level, by examining diffusion speed, whereas Chapter 6 moves to the micro-level in order to establish a foundation for understanding how elite socialization diffusion works. Thus, the remainder of this dissertation builds directly off of the findings and future directions presented above.
Chapter 3

The Decline of Neighbors and Rise of Ideology: Changes in Policy Diffusion Predictors from 1960 to 2010
Berry and Berry's (1990, 2007) model of internal and external diffusion predictors inspired a quarter century of research on the topic of policy innovation diffusion. As the preceding chapter highlights, this research gave rise to a wealth of single policy studies that broaden our understanding of additional predictors. The chapter also demonstrates the conflicting findings regarding the generality of Berry and Berry’s general diffusion model. Scholars, however, recently began assembling large datasets of policies in order to both assess the generalizability of this accumulated knowledge and push the program forward (Boehmke and Skinner 2012a; Boushey 2010; Nicholson-Crotty 2009). This approach opens new avenues for testing fundamental assumptions and hypotheses that are impossible to test within a single policy study.

One theory that was previously untestable, but has profound implications for this research program, is the notion that the forces driving the spread of policy innovations may change over time. In fact, the seminal research in this program predicted that adoptions would increase in likelihood and speed as state communication networks develop (Walker 1969, 1971). Important changes in state government over the last 50 years raise the questions of whether and to what extent the predictors in Berry and Berry’s (1990, 2007) general model of policy diffusion change over time. This chapter seeks to answer two important questions. First, is the general model generalizable across a broad array of policies and a substantial time span (1960-2010)? Second, how do these predictors change when assessed across that time? Meaning, which factors vary in importance and which have relatively stable effects?
I proceed to answer these questions by first discussing the general model of policy diffusion and how it may evolve in a changing world. Drawing testable implications from this theory, I use a pooled dataset of 119 policies to first test the generality of the key predictors of adoption across the entire dataset. Then, I test the model within each decade in order to gain some intuition as to how the predictors change over time. Finally, in light of the findings, I discuss theoretical and empirical considerations for advancing the policy diffusion research program.

**The General Diffusion Model through Time**

State governments have experienced a great deal of change in the last 100 years. For instance, many states replaced or reformed their constitutions in the post-war era, some reorganized their executive and judicial branches (Chackerian 1996; Teaford 2002), professionalized their legislatures (King 2000; Teaford 2002), changed the powers of key elites (Mooney 2013), and either instituted term limits or had them imposed by voters (Kousser 2005). The states also faced an increase in the number of active interest groups (Gray and Lowery 1993) and elite polarization (Shor, Berry, and McCarty 2010; Shor and McCarty 2011). They rode the waves of public management reform (Burns and Lee 2004; Moynihan 2006), as well as the increasing use of direct democracy (Magleby 1988; Waters 2003). Finally, professional organizations (e.g., the Council of State Governments) facilitate increasing interconnectedness among the states (Walker 1969, 1971), but so do the rise of ideologically driven organizations, like the American
Legislative Exchange Council (ALEC) and the State Innovation Exchange (SiX). These organizations serve a similar purpose (i.e., spreading ideas and norms), but with a distinctly ideological bent.

Given such institutional and behavioral changes, it stands to reason that the internal and external predictors of policy diffusion are not static over time. In fact, even when looking back at the period of 1870 to 1966, Walker (1969) found both stability and change in the social, economic, and political correlates of policy innovativeness. Furthermore, while the regional clustering of diffusion for many policies was persistent in that era, states no longer primarily compete with their neighbors and are far less limited in their ability to gather policy information from beyond their region.

Gray (1973a), among others (e.g., Menzel and Feller 1977), argued that diffusion patterns, particularly the states serving as leaders and laggards, vary based on policy and time. Thus, it is not unreasonable to expect that the predictors identified in Berry and Berry's (1990, 2007) general model also vary across time. In fact, Chapter 2 demonstrates such variation, even in key independent variables. Perhaps the most important for diffusion theory is variation in the impact of contiguous states on the likelihood of innovation adoption. In some cases, neighbors matter (Berry and Berry 1990; Carter and LaPlant 1997; Renzulli and Roscigno 2005; Satterthwaite 2002), and in other cases policies did not spread with clear regional patterns (Carter and LaPlant 1997; Karch 2006; Mooney and Lee 2000; Soule and Earl 2001). Of course, the question remains as to which predictors are most likely to have changed over time and which are more stable.
Until now, it was difficult to test temporal variation in the general model of policy diffusion. Many diffusion studies focused on a single policy or narrow set of policies in order to develop new insights into the predictors of diffusion. While these studies have taught us a great deal about additional predictors, this fractured approach has diminishing returns (Boehmke 2009a) and cannot test which findings generally matter for diffusion and which are idiosyncratic to specific policies and/or times. Moreover, it limits the ability of researchers to systematically test how innovation attributes condition the likelihood and speed of adoption.

Recent research, however, provides important advancements in both of these regards. First, researchers confirmed that innovation attributes condition the rate (Nicholson-Crotty 2009) and likelihood (Makse and Volden 2011) of innovation adoption. Second, a number of studies evaluated diffusion dynamics on larger datasets of policies that cross multiple domains (Boehmke and Skinner 2012b; Boushey 2010; Nicholson-Crotty 2009). The aggregation of adoption data provides the opportunity to update Walker's analysis of the relative stability of diffusion predictors across time. This is important for tying together the large body of individual policy studies from the last 25 years and identifying which parts of the core theory of policy diffusion require revision and further testing moving forward. Before testing the generality of the model and how it changes across time, I will describe my expectations regarding both stable and dynamic components of the model and the data used to test those expectations.
Expectations

External Influences

The tendency for policy innovations to spread within regional clusters is a long-standing tenet of the policy diffusion research program (Berry and Berry 1990; McVoc 1940; Walker 1969). Some states are generally thought of as leaders, while others tend to be laggards (Savage 1978; Walker 1969); however these positions are not fixed (Boehmke and Skinner 2012b; Gray 1973a). Early diffusion work expected information to spread in concentric circles from regional innovators to their neighbors (McVoc 1940). This process made a great deal of sense in a time when Pennsylvania legislators were more aware of new ideas coming out of New York than those being introduced in California. However, the country has gotten smaller with the development of interstate communication networks. Furthermore, states face competition not only within their region, but across the entire country. The movie industry provides a stark example of the nationalization of inter-state competition. Where California previously dominated the movie industry, many states and localities now offer tax incentives for filming within their borders (McDonald 2007, 2011). Thus, competitive pressures have weakened California's hold on this niche industry.

Increasing interconnectedness among citizens and state elites is particularly important for the diffusion of policy innovations, as it affects each causal mechanism identified by previous research (Graham, Shipan, and Volden 2013; Karch 2007b; Pacheco 2012; Shipan and Volden 2008). Legislators can learn from one another more easily than ever before, as can citizens, thus increasing the likelihood and rapidity of
policy learning and social contagion. Additionally, states now compete regionally and nationally. Furthermore, the increased informal and formal connectedness of legislators fosters the spread of not only policy information, but also norms of behavior that facilitate diffusion (Sugiyama 2008a, 2008b).

Whereas in the past it may have been more difficult for legislators in New Jersey to know what was happening in the Washington state legislature, now it can be done with the click of a mouse. In fact, the dramatic increase in the speed and volume of communications over the last 50 years creates a situation where legislators and their staff have an overwhelming amount of information available at their fingertips. Sometimes this can lead to diffusion overload through an over-crowded agenda (Nelson and Mason 2007), but it also likely means the sources of policy information have changed. No longer are legislators in New Jersey limited to learning from their counterparts in New York or Pennsylvania, they can now learn from whomever they wish. Given the above, I expect that the effect of neighbor adoptions on the overall likelihood of adopting an innovation has decayed over time. The effect of neighbors is captured in a traditional manner, by measuring the proportion of a state's contiguous neighbors that have previously adopted a given innovation.

If neighbor state cues are declining, what has taken their place? There is evidence that some policies spread among subsets of states that share a very particular characteristic, such as gendered diffusion (Bouché and Wittmer 2014). In light of the efforts of groups like ALEC and the more general growth of elite polarization in American politics (Layman, Carsey, and Horowitz 2006), it is possible that ideology is increasingly a relevant cue in policy diffusion. While the narrative about polarization
focuses primarily on the American federal government, researchers have found evidence of concomitant polarization in America's statehouses (Shor, Berry, and McCarty 2010; Shor and McCarty 2011). Furthermore, polarization and gridlock at the federal level have led partisan organizations to focus their efforts on affecting policy change within the states. Relatedly, diffusion scholars identify the relative ideology of previous adopters as a component of a state's decision to adopt an innovation (Boehmke and Skinner 2012a; Grossback, Nicholson-Crotty, and Peterson 2004; Volden 2006). Specifically, a state is more likely to adopt an innovation if past adopters are more ideologically similar. I expect this finding, however, to be stronger at the turn of the 21st Century than in earlier decades. The ideology of previous adopters relative to each state is measured using a formula previously established and tested within this research program (Grossback, Nicholson-Crotty, and Peterson 2004).

The motivating influence of the federal government on state behavior is a constant feature of the American federal system (Nicholson-Crotty 2009; Welch and Thompson 1980). In this case, it is captured in two ways. First, by using a dichotomous indicator of whether federal incentives were available for a particular policy while it was being adopted by the states (Nicholson-Crotty 2009). Second, research also demonstrates that federal attention to issues, at least temporarily, increases state attention (Baumgartner, Gray, and Lowery 2009), which could increase the likelihood of innovation adoption for that particular policy domain.

---

6 For example, ALEC was actively involved in promoting the spread of Florida's stand-your-ground law (Lichtblau 2012; NUL 2013).
Therefore, I include a measure of Congressional hearings from the *Policy Agendas Project* that is coded and matched to each policy by subtopic.\(^7\) Increased federal attention is expected to positively affect the likelihood of adopting an innovation; however that effect should remain constant across time periods.

**Internal Characteristics**

Elites are not the only part of the polarization story. While elite polarization has increased, it is less evident that there is a related rise in mass polarization (Ahler 2014; Fiorina, Abrams, and Pope 2010; Hetherington 2009; Prior 2013). However, there is evidence that citizens perceive polarization in the mass public (Ahler 2014). Thus, it is possible that the effect of citizen liberalism, as captured by Berry et al. (1998), has also increased over time, particularly in recent decades. An alternative hypothesis is that liberal states tend to be more innovative, in general, than conservative states (Boehmke and Skinner 2012b), though the evidence of this general effect is mixed (Carter and LaPlant 1997; Matisoff 2008; Mooney and Lee 2000). Therefore, I expect the effect of citizen liberalism to either remain stable or gain in importance over time. Citizen liberalism is captured using Berry et al.’s (1998) updated ideology scores for the period of 1960 to 2010. The scores are on a 0 to 100 scale that indicates increasing citizen liberalism.

---

\(^7\) Matching based on the subtopic is a finer-grained approach than matching on the broader major topic (e.g., environmental policy). This way, it measures Congressional attention to a narrower set of policies that are more similar to the policy in the dataset.
One change experienced by a subset of states is the increasing use of initiatives, referenda, and recalls since the late 1970s (Magleby 1988; Waters 2003). Since there is evidence that initiatives increase a state's innovativeness (Boehmke and Skinner 2012a, 2012b) and responsiveness (Boehmke 2005; Gerber 1996), they should generally increase the likelihood of adopting new policy innovations. However, this effect is only expected after the 1970s, when the use of direct democracy mechanisms became more common. Similar to previous approaches (Boehmke and Skinner 2012a; Boehmke and Witmer 2004), I include in the model a dichotomous indicator of initiative states based on information from the Initiative & Referendum Institute.

States are also institutionally dynamic. Since the 1960s, they have rewritten and amended their constitutions, reorganized entire branches, and experimented with waves of managerial reforms. While these changes alter an individual state's likelihood of adoption (i.e., its general level of innovativeness), the overall effect of these institutions should remain the same across time. For example, one broadly accepted measure of a state's institutional capacity is the professionalization in its legislature (Squire 1992, 2007). Greater institutional capacity should increase the likelihood of adopting policy innovations (McNeal et al. 2003). Furthermore, the general effect of professionalization should remain stable across time as the uneven professionalization of state legislatures preserves variation across the states (King 2000).

Slack resources, such as population and per capita income, help states overcome internal friction that delays innovation adoption (Walker 1969). The positive effects of these resources should remain constant over time. Both are measured using data from the United States Census. On the other hand, divided government serves as an additional
barrier to diffusion (Boehmke 2009a; Boehmke and Skinner 2012a) and should be so across the entire time period studied. It is measured using a dichotomous indicator of split party control of the state legislature and governorship.8

**Policy Attributes**

Finally, there is a great deal of policy-specific heterogeneity in terms of the propensity for passage. For instance, some policies are more technically complex than others, while others receive a higher profile in media and/or public attention. Policy complexity and salience should be relevant in all time periods. That being said, it is possible that the effect of complexity declines over time as legislatures become more professional, on average. National media salience is measured using coverage in the *New York Times* and public salience is measured using Gallup's *Most Important Problem* data.9 Policies are coded as either complex or non-complex based on current convention (Nicholson-Crotty 2009).10

**Methods and Data**

The dependent variable for this analysis is a dichotomous indicator of whether a state adopted a given policy innovation in year $t$. Given that the policy adoptions are pooled, each observation is a state-year-policy. I use logistic regression for this binary

---

8 The data are from Klarner (2003), as well as updates available on the State Politics and Policy web site. [http://academic.udayton.edu/SPPQ-TPR/klarner_datapage.html](http://academic.udayton.edu/SPPQ-TPR/klarner_datapage.html).

9 Both are drawn from the *Policy Agendas Project*.

10 Policies are complex if they fall into the “energy, environmental pollution, health care (provision, finance, and licensing), taxation, trade, and fiscal regulation” (Nicholson-Crotty 2009, 198) policy domains.
time-series-cross-sectional data (Beck, Katz, and Tucker 1998), with a polynomial of time included to account for duration dependence (Carter and Signorino 2010). Furthermore, I include random intercepts for the policies and states (Gelman and Hill 2009). There are theoretical and empirical underpinnings to this decision. First, states vary in their basic levels of innovativeness (Boehmke and Skinner 2012b; Gray 1973a; Walker 1969) and the random intercepts account for this. Relatedly, there is likely to be unobserved heterogeneity in the propensity to adopt policies based on unmeasured innovation attributes.

Boehmke and Skinner (2012b) compiled the largest publicly available dataset of policy adoptions for their study of state innovativeness. The dataset includes original data collected by the authors as well as adoption data used in previous diffusion studies. In total, it includes 137 policies that were adopted by the states between 1912 and 2009. This formed the foundation of my data, however, I also included criminal justice adoption data from Makse and Volden (2011) and fifteen policies that I collected. The final dataset for this analysis includes 119 policies that spread among the states between 1960 and 2010. Policies whose first adoption occurred before 1960 are excluded due to limitations in measuring the independent variables.

---

12 Alternative analyses were performed for the purposes of robustness checking. Specifically, the adoption models within each decade were estimated with no random effects and only policy random effects. The supplementary information includes the results from these alternative specifications.
13 Details on the policies in the Boehmke and Skinner (2012b) database can be found in the appendix to their paper. Details for the Makse and Volden (2011) data are included in the supplemental materials for their published article. Finally, details about the fifteen policies that I collected are included in Appendix A. Note that there were overlaps between the Boehmke and Skinner (2012b) and Makse and Volden (2011) datasets. In the case of overlap, I included the most complete record of adoptions.
14 Policies whose first adoption occurred before 1960 are excluded due to limitations in measuring the independent variables.
Figure 3.1 displays the proportion of policy adoptions in each period based on its major topic code. While there are policies from fourteen different domains included in the total dataset, they are not evenly distributed across the time periods. The 1960s are the least mixed, with the bulk of policy adoptions representing transportation and law policies. However, the mixture improves as the decades advance and growth in some categories reflect differing policy priorities in those decades. For example, administrative policies make up a larger proportion of adoptions in the 1970s, which coincides with the rise of public management reform in the states. This also reflects the lack of a clear sampling frame for diffusion research and the difficulty of collecting this data. Due to this difficulty, convenience sampling has been both a necessity and challenge for this research program throughout its history (Savage 1978). That being said, as the datasets grow in size they also grow in diversity, which increases the external validity of the research program's findings. I turn now to evaluating the general diffusion model across each decade in the dataset.
Figure 3.1: Policies adopted in each decade included in the analysis, by major topic
Results

Generalizability

Given the conflicting findings in Chapter 2, it is first important to assess whether the general model is in fact generalizable across policies and time. To do this, I pool all of the data before examining adoptions within decades. Figure 3.2 displays a plot of the coefficients and their confidence intervals for the diffusion predictors laid out above.\(^\text{15}\) In terms of external influences, adoptions by a state’s neighbors generally increase the likelihood that the state will adopt any given innovation. Interestingly, federal incentives do not have a general effect, but that does not mean that they are not highly important for the subset of policies that receive such attention from the federal government. Congressional attention, on the other hand, shows weak positive effects \((p < 0.10)\) on state innovation. Finally, the relative ideology of previous adopters exhibits a generally negative effect. This is expected given the coding of this variable. Essentially, this result demonstrates that a state is less likely to innovate the more distant previous adopters are in terms of ideology. Thus there is evidence that liberal states tend to follow other liberal states, likewise for conservative states.

In terms of internal characteristics, initiatives, divided government, and per capita income do not show any general effects. However, population size and citizen liberalism are positively associated with innovation adoption. Perhaps the most surprising finding is that legislative professionalism has a negative association with innovation adoption. Why might this be the case? Should larger states with a greater capacity to legislate be more

\(^\text{15}\) See Appendix B for a table of the results for this model and alternative specifications of the random effects.
likely to adopt new ideas? While requiring additional exploration, this finding is substantively significant for diffusion theory.

Two possible explanations for this negative effect come to mind. The first is that this is capturing the occurrence of copying among less-professionalized states. It may be the case that smaller, less-professionalized, states are more prone to copying and are thus able to move on new ideas more quickly than states with greater capacity. The second, and related, explanation is that more capacity does not automatically imply more action. It may, in fact, mean more diffusion overload (Nelson and Mason 2007), whereby the agenda space is far more crowded and any given new idea may not be taken up quickly. Both explanations require further systematic inquiry, as they have important theoretical and normative implications for state politics. In terms of copying, there is the question of what these states are copying. Indeed, there is evidence that ALEC model bills tend to be more successful in these legislatures (Hertel-Fernandez 2014). As for diffusion overload, the evidence of this is presently qualitative and limited to state lotteries (Nelson and Mason 2007).

Finally, innovation attributes show mixed general effects. Most interesting is the broader replication of the interactive effect of salience and complexity on innovation adoption. Nicholson-Crotty (2009) and Chapter 5 of this dissertation both demonstrate the interactive effects on speed, however this shows that the two attributes have an interactive effect on likelihood of adoption too. For easier interpretation, Figure 3.3 displays simulated predicted probabilities of an increase in salience, as measured by Gallup’s Most Important Problem polling, for complex and non-complex policies. For non-complex policies, salience increases the predicted probability of a state adopting any
given innovation. However, for complex policies, states are actually less likely to adopt as salience increases. This suggests that while states may be quick to adopt simple policies that receive a lot of public attention, they do slow down and take their time when the policies require additional expert advice. This is both encouraging and concerning from a normative perspective, as faddish copying of simple policies may not comport with the ideologically neutral good governance assumption of policy learning, slow consideration of more difficult and impactful legislation warrants more time, even in the face of greater public attention.
Figure 3.2: Coefficient plot for the completely pooled analysis, includes random effects for policy and state
Change Over Time

In order to test whether diffusion predictors remain fixed over time, I split the data by decade and modeled policy adoption using the same covariates in each decade.\textsuperscript{16} Doing so tells us two things. First, these models with pooled adoption data provide insight into which predictors generally shape diffusion patterns and, likewise, which may be idiosyncratic to the particular policy domains where they were previously identified. Second, these models show how the size and significance of these effects change over time. Table 3.1 displays the full set of results for each decade.\textsuperscript{17} In discussing the results, I start with the predictors that signal external influence (i.e., diffusion) before turning to internal and policy-level predictors.

**Figure 3.3: Plot of Predicted probability of innovation adoption for non-complex and complex policies as salience increases, as measured by Gallup's Most Important Problem Poll**

\textsuperscript{16} Alternative specifications of this model were run for robustness checking. Specifically, one alternative model includes no random intercepts and the second includes random intercepts for just policies. The results presented here are very similar to those found with random intercepts for policies, as there was little variation in the state intercepts.

\textsuperscript{17} Caution must be taken in interpreting the results from the 1960s. Whereas the later decades include observations at all stages of the diffusion process (see Rogers 2003, 281), those in the 1960s represent mainly adoptions by innovators and early adopters due to the truncation in 1960. Therefore, the results for the 1960s may be modeling the predictors of adoption for these two types of adopting states and not the overall effects of the predictors for adoption in that specific decade. This will be more explicitly addressed in Chapter 4.
Table 3.1: Models of policy adoption for each decade from 1960 through 2010

<table>
<thead>
<tr>
<th>Covariate</th>
<th>1960s</th>
<th>1970s</th>
<th>1980s</th>
<th>1990s</th>
<th>2000s</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>External Influences</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of Neighbors</td>
<td>-0.021</td>
<td>0.085</td>
<td>0.094**</td>
<td>0.086**</td>
<td>-0.032</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.054)</td>
<td>(0.041)</td>
<td>(0.037)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Relative Ideology</td>
<td>-0.013</td>
<td>-0.008</td>
<td>-0.015***</td>
<td>-0.007</td>
<td>-0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Federal Influences</td>
<td>-0.302</td>
<td>0.626</td>
<td>0.431</td>
<td>0.476</td>
<td>0.173</td>
</tr>
<tr>
<td></td>
<td>(1.680)</td>
<td>(0.603)</td>
<td>(0.482)</td>
<td>(0.417)</td>
<td>(0.533)</td>
</tr>
<tr>
<td>Congressional Hearings</td>
<td>-0.850*</td>
<td>0.181</td>
<td>0.148</td>
<td>0.065</td>
<td>-0.113</td>
</tr>
<tr>
<td></td>
<td>(0.490)</td>
<td>(0.213)</td>
<td>(0.140)</td>
<td>(0.108)</td>
<td>(0.177)</td>
</tr>
<tr>
<td><strong>Internal Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citizen Liberalism</td>
<td>-0.005</td>
<td>0.010**</td>
<td>0.004</td>
<td>-0.003</td>
<td>0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Divided Government</td>
<td>0.016</td>
<td>-0.125</td>
<td>-0.076</td>
<td>0.056</td>
<td>-0.132</td>
</tr>
<tr>
<td></td>
<td>(0.213)</td>
<td>(0.116)</td>
<td>(0.092)</td>
<td>(0.068)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Income</td>
<td>1.360*</td>
<td>0.419</td>
<td>0.499</td>
<td>1.411***</td>
<td>1.339***</td>
</tr>
<tr>
<td></td>
<td>(0.758)</td>
<td>(0.364)</td>
<td>(0.339)</td>
<td>(0.303)</td>
<td>(0.479)</td>
</tr>
<tr>
<td>log(Population)</td>
<td>-1.216</td>
<td>-0.137</td>
<td>-0.327</td>
<td>-1.180***</td>
<td>-0.985**</td>
</tr>
<tr>
<td></td>
<td>(0.747)</td>
<td>(0.363)</td>
<td>(0.343)</td>
<td>(0.316)</td>
<td>(0.498)</td>
</tr>
<tr>
<td>Legislative Professionalism</td>
<td>-0.013</td>
<td>-0.022**</td>
<td>0.001</td>
<td>-0.011**</td>
<td>-0.026***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.009)</td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.008)</td>
</tr>
<tr>
<td><strong>Policy Attributes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most Important Problem</td>
<td>0.001</td>
<td>0.037*</td>
<td>-0.038</td>
<td>0.034***</td>
<td>-0.038***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.021)</td>
<td>(0.024)</td>
<td>(0.006)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Complex Policy</td>
<td>0.251</td>
<td>0.049</td>
<td>-0.820**</td>
<td>0.962***</td>
<td>-1.321***</td>
</tr>
<tr>
<td></td>
<td>(1.960)</td>
<td>(0.524)</td>
<td>(0.412)</td>
<td>(0.331)</td>
<td>(0.408)</td>
</tr>
<tr>
<td>MIP x Complex</td>
<td>2.038</td>
<td>-0.003</td>
<td>0.041*</td>
<td>-0.091***</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>(1.475)</td>
<td>(0.030)</td>
<td>(0.025)</td>
<td>(0.012)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>New York Times</td>
<td>0.107</td>
<td>0.084**</td>
<td>0.006</td>
<td>-0.009</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.040)</td>
<td>(0.028)</td>
<td>(0.018)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Time</td>
<td>1.530***</td>
<td>0.056</td>
<td>0.232***</td>
<td>0.212***</td>
<td>0.202***</td>
</tr>
<tr>
<td></td>
<td>(0.332)</td>
<td>(0.077)</td>
<td>(0.051)</td>
<td>(0.028)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Time²</td>
<td>-0.549***</td>
<td>-0.004</td>
<td>-0.014***</td>
<td>-0.012***</td>
<td>-0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.126)</td>
<td>(0.012)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Time³</td>
<td>0.044***</td>
<td>0.0002</td>
<td>0.0003***</td>
<td>0.0002***</td>
<td>0.00005</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.001)</td>
<td>(0.0001)</td>
<td>(0.00004)</td>
<td>(0.00001)</td>
</tr>
<tr>
<td></td>
<td>(2.374)</td>
<td>(1.406)</td>
<td>(1.276)</td>
<td>(1.126)</td>
<td>(1.962)</td>
</tr>
<tr>
<td><strong>Variance Components</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State Level</td>
<td>&lt; 0.001</td>
<td>&lt; 0.001</td>
<td>0.056</td>
<td>0.042</td>
<td>0.146</td>
</tr>
<tr>
<td>Policy Level</td>
<td>4.433</td>
<td>1.196</td>
<td>1.423</td>
<td>1.698</td>
<td>1.231</td>
</tr>
<tr>
<td>Observations</td>
<td>1,949</td>
<td>10,823</td>
<td>18,389</td>
<td>21,547</td>
<td>9,264</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-372</td>
<td>-1,441</td>
<td>-2,715</td>
<td>-4,371</td>
<td>-2,316</td>
</tr>
</tbody>
</table>

* p < 0.1; ** p < 0.05; *** p < 0.01. Standard errors are in parentheses.
**External Influences**

Of the four external influences tested, only the horizontal relationships show any positive results in Table 3.1. In fact, federal incentives and Congressional attention shows remarkably little effect across each decade. This does not invalidate past results suggesting that federal incentives have a positive effect on state adoption, however it does tell us that while the presence of an incentive may raise the relative advantage of adopting an innovation, the lack of an incentive may not be a detriment to innovation, thus the positive effect does not show through the noise of the vast majority of the policies that do not receive federal support.

**Figure 3.4: Change in odds ratios and 95% confidence intervals for the effects of neighbor adoptions and relative ideology of previous adopters on innovation adoption from 1960 to 2010**

As for the peer-state effects of geographic and ideological neighbors, Figure 3.4 displays a plot of the odds ratios (and 95 percent confidence intervals) for these two variables within each decade. The positive effect of neighbor adoptions (Figure 3.4a) is statistically significant ($p < 0.05$) in the 1980s and 1990s, but disappears in the early 2000s. Regionalism has long been an important component of the policy diffusion
research program (McVocy 1940), but its limits are increasingly being recognized (Boehmke 2009a). A state's ideology relative to past adopters (Figure 3.4b), on the other hand, appears to be important in the 1980s and 2000s. In fact, the effect is larger in the 2000s than it was in the 1980s. In the 1980s, as the average ideology of previous adopters moved one standard deviation further from a state that had not adopted, its risk of adopting dropped 1.5 percent. In the 2000s, the same change resulted in a 3 percent reduction in the risk of adoption. Admittedly, these effect sizes are small, but that should meet our expectations given that this is the general effect of external adoption behavior on a state adopting any given policy innovation. The neighbor effects are similarly small in size, but are substantively important (Gelman and Weakliem 2009).

The most important finding is that while contiguity and ideology co-existed as predictors in the 1980s, a state's immediate neighbors were relevant in the 1990s, but were supplanted by its ideological “neighbors” by the 2000s. By plotting predicted probabilities, Figure 3.5 demonstrates how similar the two effects are in these two time periods. The first panel (a) shows that as the percentage of a state's neighbors approached 100 percent in the 1990s, a state's probability of adopting an innovation increased from approximately 0.06 to 0.13. In the 2000s, a state's probability of adopting increased from near zero to approximately 0.15 as the average ideology of previously adopting states moved closer to its own. While the magnitudes of these outside influences are relatively small, they do serve to generally influence the likelihood of state innovation and appear to mirror each other. These findings support Walker's (1971) hypothesis that adoption patterns change as states become increasingly interconnected, as well as the narrative of elite polarization in the United States. While only time will tell whether this shift is
permanent, this finding provides evidence that the laboratories of democracy are no longer looking to their geographically nearest neighbors for ideas, but to their ideological “neighbors” instead.

**Figure 3.5: Predicted probability of adoption and 95% confidence intervals for percent neighbors in 1990s and relative ideology in 2000s**

Internal Characteristics

Turning to the internal characteristics of the states, I further divide these into political and demographic features. Many of the political variables display limited or intermittent association with innovation adoption. Figure 3.6 displays the odds ratios for two of the most interesting political variables, citizen liberalism and legislative professionalism. Both are reinforcing of findings presented above. Citizen liberalism (Figure 3.6a) shows a positive association with innovation adoption in the 1970s and 2000s. The finding in the 2000s, in particular, reinforces the importance of ideology for policy adoption at the turn of the century. Much like the completely pooled model, legislative professionalism (Figure 3.6b) exhibits a fairly stable negative relationship with the likelihood of innovation adoption.
Figure 3.6: Change in the odds ratios and 95% confidence intervals for the effects of citizen liberalism and legislative professionalism on innovation adoption from 1960 to 2010

The initiative process produces effects that behave oddly, in that they are the most dependent on specification of the random effects. While the positive effect of being an initiative state only surpasses a relaxed standard of statistical significance in the 1990s when random intercepts are included for both policies and states (see Table 3.1), the effect is clearly significant ($p < 0.01$) in the 1990s and weakly significant ($p < 0.10$) when random effects are only included for policies. These findings provide additional, albeit weak, support for the hypothesis that direct democracy promotes greater responsiveness in state legislatures (Arceneaux 2002; Burden 2005; Gerber 1996; Lascher, Hagen, and Rochlin 1996). In this case, however, that responsiveness is not necessarily to citizen demands, but to new policy ideas.

Figure 3.7 displays two additional demographic predictors of adoption: the slack resources of population and per capita income. Both are log transformed due to the likelihood of diminishing marginal effects for a one-unit increase in each as they approach their respective upper limits. Interestingly, these resources have divergent
effects on the likelihood of innovation adoption. As expected, a bigger tax base (i.e., per capita income) increases the likelihood of adoption; however, a larger population decreases it. The fact that the negative effect of population only manifests in the 1990s and 2000s supports the hypothesis that the crowded agendas and of larger states produces diffusion overload, which reduces their ability to respond quickly to innovative policies. Money, on the other hand, still matters for enhancing a state's capacity to innovate.

**Figure 3.7: Change in odds ratios and 95% intervals for the effects of population size and per capita income on innovation adoption from 1960 to 2010**

![Graphs showing changes in odds ratios and 95% intervals](image)

**Policy Attributes**

Finally, the attributes of the adopted policies show very mixed effects on adoption over time. For instance, *New York Times* coverage was positively associated with adoption only in the 1970s. This likely reflects the decline of print news and rise of 24 hour news networks and the Internet in the ensuing years. Given that the coefficients for complexity and the proportion of votes for a particular policy domain in Gallup's *Most Important Problem* poll are constituent terms in an interaction, it is not intuitive to directly interpret them. It is clear, however, that the direction of their effects change
depending on the decade, though the interaction itself is only statistically significant in the 1990s. In that case, the relationship between policy complexity, public salience, and adoption comports with previous findings (Karch 2007a; Nicholson-Crotty 2009) in that policy complexity moderates the relationship between salience and adoption.

Figure 3.8 helps make the interaction effect findings more intuitive by plotting the predicted probability of adoption for complex and non-complex policies as salience increases, as measured by Gallup’s Most Important Problem poll. The 1990s is the only decade in which the interaction exhibits the expected effects and matches the pooled results depicted in Figure 3.3. In the 1970s, there is an increase in the probability of adopting a complex policy as salience increases, but the confidence bands are so wide that there could be no actual increase. Neither type of policy exhibits much effect in the 1980s, but in the 2000s the probability of adopting non-complex policies actually declines as public attention increases. Two things could drive these results: (1) policy-specific differences that are distributed systematically across the decades and/or (2) the low construct validity of the available measures of complexity and salience. Given the better mixture of policy types in the 1980s, 1990s, and 2000s (see Figure 3.1), the first explanation seems unlikely. Given the bluntness of these proxy measures, however, the second explanation warrants further attention in future work.

---

18 The 1960s are not plotted because no part of the interaction is statistically significant.
It is important to note that these findings do not invalidate past research regarding specific predictors of particular policies. Instead, the summation of the extant policy-specific models and these results suggest that while there are some diffusion predictors that are influential across different policy domains and time, there are others that are time- and domain-specific. To an extent, this validates both Walker (1973) and Gray (1973a, 1973b) as to whether there is stability in the process of policy diffusion in the American states. Gray was correct that innovativeness is conditional on issue and time, but Walker was correct in the notion that aspects of diffusion are stable.
Discussion

The federal structure of government in the United States results in a complex web of horizontal and vertical relationships between the levels of government. The policy diffusion research program is inherently interested in understanding this complexity and answering the motivating question of why states adopt the policies that they do. Berry and Berry (1990) unified the two major aspects of the research program with their general model of diffusion. Subsequent research has uncovered a lot of ground in terms of identifying internal and external forces that shape the likelihood of policy adoption, as well as untangling the causal mechanisms underlying the diffusion of policy innovations. However, it is only recently that scholars began using larger datasets of policy adoptions to test the general model of diffusion at the macro-level. Building on that foundation, I have demonstrated that while some of the predictors are fairly generalizable across time, others only matter in particular time periods. This begins to unify the fractured extant findings, but also raises important questions for future diffusion research.

Perhaps the most important implication of these findings is the potential decay of regional diffusion patterns and the concomitant rise of ideologically driven diffusion. Granted, only time will tell whether political polarization among elites has a lasting impact on politics and policy in the United States. That being said, these findings provide further evidence that the polarization in the federal government, which receives the bulk
of scholarly and public attention and consternation, also affects policymaking in the states. If these findings hold in further replication and extension, diffusion scholars will need to consider that a state's nearest neighbor may no longer be defined by geography but ideology.

These findings also highlight the need to better understand how organizations like ALEC have shaped state politics. ALEC only recently gained public attention as its role in spreading stand-your-ground and voter identification laws came to light. But, in fact, ALEC has been providing states with model legislation since 1978. This leaves the effects of ALEC as a large hole in our understanding of state policy making and diffusion. As additional organizations develop which target state legislators (e.g., SiX) and existing organizations turn to state houses for policy success in the face of a gridlocked Congress (e.g., increasing the minimum wage), it will be vitally important to understand the sources of innovations and pressure to adopt them. The diffusion research program is well positioned to speak to these concerns, but must continue to develop the methodological tools for understanding micro-level causal pathways as well as macro-level patterns.

Regionalism is a long-standing feature of policy diffusion research (Berry and Berry 1990; McVoy 1940; Walker 1969). If, however, the locus of the diffusion process is shifting from geography to ideology, diffusion scholars will need to increase their attention to less-researched causal mechanisms. Specifically, learning and competition have received a great deal of attention from researchers, but true emulation (also known as socialization) and social contagion (Pacheco 2012) have only recently begun to receive attention. While learning for the sake of solving a problem and competition between the
states have not gone away, there appears to be greater potential in the system for ideologically driven emulation, in particular. Thus, it is important to better understand how legislators' social networks operate, as well as how they transmit policy information and normative cues that promote the adoption of policy innovations. Recent media attention to stand your ground and voter identification laws highlights the potential for ideologically driven emulation as a causal mechanism driving diffusion.

This potential shift in scholarly focus also draws attention to the normative implications of these findings for students of politics in the United States. The image of states being laboratories of democracy is strong within political science. Ideologically neutral good governance, a legacy of the progressive movement, is closely associated with that image, given that the purpose of experimentation is to find the best policy solutions to social problems. Policies that spread due to social learning, competition, or social contagion associate well with this image because the underlying motivations of legislators are related to their roles as delegates and stewards of the public. However, diffusion that arises from motivations of appropriateness (March and Olsen 1989, 2006) may not uphold such democratic ideals. This is not to say that ideologically motivated diffusion does not involve a sincere search for the best policy solutions, however there is the opportunity for other motivations. Of course, these are empirical questions for further research. They may not be easy to untangle, but they are important for understanding legislators as they make policies that affect citizens' daily lives. More research is necessary to understand the communication patterns of elites and motivations of ideologically driven policy diffusion.
Beyond the shifting influence of region and ideology, these results demonstrate that policy attributes belong in the general model of diffusion alongside predictors that are internal and external to the states. Much like Berry and Berry's (1990) fusion of internal and external predictors, innovation attributes should be included in any study of policy diffusion at the macro-level. There are many avenues for advancing our understanding of how these attributes condition the likelihood and speed of policy adoption. Measurement should be one major area of focus. The broader theory of innovation adoption outlines five common attributes: relative advantage, observability, compatibility, complexity, and trialability (Rogers 2003). Given that these attributes are identified “in the eye of the beholder,” the most internally valid method for measuring them requires surveys of political elites (Makse and Volden 2011). This approach, however, is highly resource intensive and thus difficult to scale up in a way that allows us to examine their effect in a macro-level model. Therefore, additional effort is required to develop archetypes of these attributes that can be measured, and thus compared, across policies.

Finally, this analysis demonstrates how policy diffusion research can be useful for understanding broader patterns in American politics. To that end, diffusion scholars will only be able to pursue a better understanding of these patterns if our data continues to develop. The research program has long recognized the difficulty of obtaining a random sample of policies (Savage 1978), but it is encouraging that successive studies are no longer reinventing the collection of this data, but are instead aggregating data from existing studies, adding to it, and making it available freely for the use of others.
Adoption data is difficult to collect, but the more we have from a broader array of policy areas, the stronger the conclusions we will be able to draw from our findings.

Conclusion

The policy diffusion research program is large, vibrant, and continues to advance both theoretically and methodologically. This study builds on the most recent advancements by testing an expanded version of the general model of policy innovation adoption at the macro-level. Specifically, it examines whether important predictors identified by previous research are stable across time. I find that while a key predictor, neighbor adoptions, appears to have declined in importance, other predictors, such as ideology, concomitantly rose in importance. This is important for diffusion scholars, as well as those studying policymaking in the states and political polarization. Researchers are beginning to understand the extent to which polarization affects the states, and this study provides evidence that polarization is broadly shaping the types of policies that states enact. For diffusion scholars, this finding means that more attention must be paid to external influences like ALEC, as well as policies that spread in ideological, as opposed to geographical, patterns (e.g., stand your ground laws). Policy learning is no doubt still important, however it may be taking on an ideological color that is neither well understood empirically nor fully captured in policy diffusion theory.

More broadly, the findings here have normative importance for the good governance image of the states as laboratories of democracy. The underlying assumption of the laboratories frame is that the states are experimenting for the purpose of finding the
best policy solutions. Ideological learning, however, may violate this assumption if it fosters the spread of policies falling closer to the ideological fringe. Of course, this raises a jointly normative and empirical question of whether policies spreading in traditional diffusion patterns are in some sense ‘better’ than those that are driven by ideology.

In addition to finding changes in the horizontal relationship between states, this study finds that explicit and implicit federal coercion do not exhibit a general relationship with the likelihood of adopting a policy innovation in any time period. Furthermore, slack resources like per capita income show fairly stable effects, while there is mixed evidence for changes in the effects of innovation attributes like complexity and salience. Collectively, these results suggest that while some predictors generally affect the adoption of policy innovations, others are idiosyncratic to specific policies, policy domains, or time periods. The results help explain disparate findings across the numerous single-policy studies that serve as the foundation of the diffusion research program.

Moving forward, researchers should continue to identify how these effects differ across policy domains while also testing the broader applicability of newly identified predictors.

Finally, these results reinforce the utility of using the states to test broader trends and theories in political science. In particular, they draw further attention to the possibility that elite polarization is not only a phenomenon in Washington. It appears to be influencing how states learn from each other and which new ideas they are more likely to listen to. Thus, it is possible that the search for new ideas to solve policy problems is conditioned by ideological considerations. Instead of looking to geographically close states who likely have more similar natural resources, political cultures, and demographics, among other things, states may be looking to their ideologically-similar
peers for new ideas. By leveraging variation across the states, we can better understand how broader phenomena, like polarization, are shaping American politics and policy.
Chapter 4

Predictors of Policy Diffusion across the Stages of Adoption
The states serve as important testing grounds for innovative policies. They can test new solutions to problems and contain potential failures to a narrower population. Observers of state politics are left to wonder, however, why do some states act quickly while others lag behind? What internal and external forces drive states to adopt when they do as a policy spreads among their peers? Policy diffusion scholars find that there is a fairly stable trait of innovativeness, with some states tending to lead and others tending to lag (Boehmke and Skinner 2012b; Savage 1978; Walker 1969). Even laggard states, however, take the lead on some innovations (Carter and LaPlant 1997; Gray 1973a).

Previous research descriptively (Jacob 1988; Mansbridge 1986) and quantitatively (Allen and Clark 1981; Hays 1996) suggests that the predictors of diffusion in Equation 1 have differential effects throughout the diffusion lifecycle. Meaning, the influences of internal characteristics and external forces affect innovators, early adopters, the early majority, late majority, and laggards differently (Rogers 2003). The fractured approach to diffusion research, however, also negatively affects building and testing clear theory related to how and why the general diffusion model fluctuates as diffusion progresses.

This chapter seeks to answer these how and why questions using the same large dataset of adoptions from the previous chapter. First, I review the existing evidence for differential influences of adoption on leaders and laggards. Then, I provide a theory for why the components of the diffusion model change across all five of Rogers’ (2003) categories of adoption. After developing this theory, I provide a method for categorizing adoptions within policies that spread at very different rates. Finally, I test the effects of
internal characteristics, external influences, and policy attributes within each of the five adoption categories. I find that while nearly every included predictor derived from past research predicts adoption in at least one category, there is a lot of variation across each category. Innovator adoptions, for instance, are entirely predicted by the slack resources available to those states.

External influences exhibit the most interesting changes over time. Regionalism is most often cited as a culprit for policy diffusion, and a state's neighbors do matter for early adopters and the early majority, however the effect of neighbor adoptions disappears thereafter. It is replaced with cues from the ideology of past adopters. Specifically, in the late majority and laggard stages, states are less likely to adopt an innovation as the average ideology of past adopters moves further from its own. Thus, later adopters are not taking regional cues from peer states that are often demographically, economically, and geographically more similar, but peers that are ideologically similar. While Chapter 3 demonstrated the general effect of ideology, as well as its increased importance in recent adoptions, this chapter shows when and how that influence actually matters.

Leaders and Laggards

Since Jack Walker’s (1969) early work, diffusion scholars have paid intermittent attention to the notion that some states are generally innovative, while others have a tendency to lag behind their peers. Innovativeness is a trait-based measure of how quickly a state adopts available policy innovations and is thus a summary of how quickly states
act across a large number of specific policies. When assessing a large collection of policies, some states are typically leaders (e.g., California), while others are often laggards (e.g., Mississippi), and their position is a function of internal characteristics like the availability of slack resources and political ideology (Boehmke and Skinner 2012b; Walker 1969). There is, however, substantial within-state variation in innovativeness that is dependent on the policy and time period (Gray 1973a). Aggregating to a summary score, however, hides this variation and makes it difficult to identify how the predictors of diffusion may vary across different types of adopters.

A small set of studies suggests that states do behave differently as policy diffusion unfolds. For instance, Allen and Clark (1981) found that laggard states adopted policies with similar broad scope and stringency as leaders, while middle states sometimes adopted less comprehensive policies. The work on policy reinvention by Glick and Hays (1991) confirms that laggards may adopt more innovative policies because they are learning as the diffusion process unfolds. Relatedly, leader states may amend their policies as learning occurs. Furthermore, they find that regionalism and copying are more important for early adopting states. Mooney (2001a) provides additional support for the possibility that regionalism matters more for early adoption than later. However, Carter and Laplant (1997) do not find a strong regional pattern in their study of health care policy leaders and laggards. Although, they do find that policy liberalism is positively strongly associated with innovativeness for three health care policies. Thus, the findings are mixed, particularly in reference to external influences, and limited in scope due to the
same drawbacks of the broader research program. Many of these studies are on a single or small set of policies, which not only limits their generalizability, but also their ability to estimate adoption models across all five of the adoption categories (Rogers 2003).

Thick descriptive accounts of the diffusion process provide a better picture of how states behave as the diffusion process unfolds. Specifically, Jacob's (1988) study of no-fault divorce laws devotes a chapter to the spread of the policy between 1969 and 1985. The author argues that the low cost and low controversy of no-fault divorce allowed for rapid diffusion, however the forces driving adoption were not fixed across the states. Iowa, a leader state, experienced legislative drift after enactment. Illinois, a laggard state, faced great pressure to conform from other laggard states. Whereas, Wisconsin, a middle adopting state, grappled with an enlarged scope of conflict due to increased engagement from the feminist movement, but also with outside influence from other states. Jacobs points to the perceived legitimacy coming from fellow state adoptions as an important driver of rapid diffusion. Mansbridge's (1986) study of the Equal Rights Amendment also shows that a policy can enjoy rapid uncontested adoption early on, but then be stifled by growing controversy and resistance by laggard states.

In sum, the existing evidence suggests that different forces motivate states as the diffusion process unfolds. Meaning, leader, middle, and laggard states respond to internal and external forces differently. A focus on individual policies, however, limits the generalizability of these findings and also limits the leverage available for understanding how the impact of key predictors in policy diffusion theory changes across the diffusion life-course. Specifically, breaking up the analysis of a single policy into the stages of diffusion rapidly reduces the data available in each cell and the reliability of inferences.
drawn from the subsets. On the other hand, analyzing innovativeness measured as a state trait tells us a lot about what characteristics generally differentiate states that are more or less innovative, in a broad sense; however it also masks underlying variation in innovativeness within each policy and thus does not provide specific inferences about each category of adoption. Pooling policies and estimating an adoption model within each category overcomes these challenges and provides the leverage necessary to understand how diffusion predictors change as adoption progresses. Before describing the analytical approach of this study, it is first necessary to establish a theory for why state motivations change across the diffusion lifecycle.

**Theory of the Diffusion Lifecycle**

While important differences between leader and laggard states receive some attention within the policy diffusion research program, a strong theoretical foundation remains undeveloped regarding how adoption predictors differ as diffusion unfolds. Broader innovation diffusion theory, however, provides a useful starting point for developing and testing a theory that is relevant to policy innovations. Everett Rogers (2003) provides this framework in his foundational work on innovation diffusion. Specifically, Rogers identifies five mutually exclusive adopter categories: innovators, early adopters, early majority, late majority, and laggards. He uses the mean and standard deviation of the distribution of adoptions over time to create these categories. Figure 4.1 shows a replica of this adopter categorization. Innovators represent 2.5 percent of the distribution, early adopters 13.5 percent, the early majority 34 percent, late majority 34
percent, and finally laggards make up 16 percent of the distribution of adopters. Rogers admits that the classification is not exhaustive, in that it does not include non-adopters. In fact, the categories are “ideal type” (Rogers 2003, 282) and best represent aggregated scores of innovativeness rather than individual innovations, given that there is variation in the normality of individual adoption curves.

**Figure 4.1: Reproduction of adoption categories from Rogers (2003)**

Innovation

Innovators serve as initial test subjects that are willing, and able, to go out on a limb and try a new innovation. In fact, “venturesomeness” is a trait that describes those adopters that regularly put themselves in that position (Rogers 2003, 282). Adoption in the innovator stage should be solely influenced by the internal characteristics of those early states. These states are often geographically dispersed (Boehmke and Skinner
2012b; Walker 1969) and include the very first state or states to adopt an innovation, so they should not exhibit neighbor effects.\textsuperscript{19} There could be an effect of ideological similarity for these states if a policy’s spread is solely motivated by ideology, however it should not have a generally strong effect for innovator states across a diverse set of policies.\textsuperscript{20} These states could also be responding positively to the presence of federal incentives\textsuperscript{21} and public or media attention\textsuperscript{22} that provide exogenous shocks to state issue agendas (Boushey 2010, 2012).

The ability to be venturesome on any given issue is likely a function of the availability of the slack resources: state wealth, population size, and urbanity.\textsuperscript{23} A large population and tax base provides a deeper set of financial resources for states to try new policies and absorb the cost of failed attempts. Resource poor states, on the other hand, may only fall into the innovator category on very specific issues that are most meaningful to them. Tennessee, for example, is not commonly at the top of lists of innovators (Boehmke and Skinner 2012b; Walker 1969), however Carter and LaPlant (1997) found them to be highly innovative on six health care policies in the 1980s. In general, however, slack resources should have a positive effect during the innovation phase.

\textsuperscript{19} Measured as the percentage of neighbors that have previously adopted a given innovation.

\textsuperscript{20} This is captured using a measure of relative ideology. Relative ideology is the absolute value of the distance between a given state’s citizen ideology (Berry et al. 1998) in year $t$ and the average ideology of states that adopted the innovation prior to year $t$. Thus, it should have a negative effect on the likelihood of adoption. See Boehmke and Skinner (2012a) and Grossback et al. (2004) for more details regarding the calculation of relative ideology. Similar to Boehmke and Skinner (2012a), I modify the Grossback et al. (2004) approach by subtracting the average ideology of previous adopters from each potential adopter.

\textsuperscript{21} Adopting a previous approach, an indicator variable is used for innovations that have associated federal incentives during the time they are adopted by the states (Nicholson-Crotty 2009).

\textsuperscript{22} Federal issue attention is captured using the percentage of Congressional hearings held on a particular policy subtopic in a given year. This is drawn from the Policy Agendas Project.

\textsuperscript{23} Population size, per capita income, and the percentage of population living in an urban area are all collected from either the U.S. Statistical Abstract or the U.S. Census. Population and per capita income are logged due to the expected diminishing returns of each additional unit of each as they become very large.
Beyond slack economic resources, institutional variation across the states also constrains the ability of some to adopt innovations. For instance, states tend to be less innovative when experiencing divided government (Fiorina 1992), though this effect may depend on the issue as divided government makes some policy options more desirable than others (Berry and Berry 1990). A slack political resource that should be valuable to innovator states is a state’s legislative capacity. Legislative professionalism should thus have a positive effect on adoption in the innovator stage.

There is evidence that the availability of an initiative process also increases a state's innovativeness (Boehmke and Skinner 2012b) and responsiveness (Boehmke 2005; Gerber 1996) through a “gun behind the door” effect. Essentially, legislators in these states react to innovations faster than non-initiative states due to fear that they will be pre-empted by groups working through the initiative process. On one hand, innovator adoptions may be positively affected by the presence of initiative due to the gun behind the door. On the other hand, initiatives may play a greater role later in the diffusion process in order to force the hand of recalcitrant legislatures that are not adopting a desired innovation.

The complexity and salience of policies should show mixed effects for this diffusion category. Given that these are the earliest adopters, it is unlikely that they are less likely to adopt complex policies. They may, however, be positively affected by

---

24 Divided government is measured using a dichotomous indicator from Klarner's (2003) legislative data.
25 Initiatives are measured using a dichotomous indicator based on information from the Initiative & Referendum Institute.
26 I follow current convention in dichotomizing policies as complex and non-complex. Policies are complex if they fall into the “energy, environmental pollution, health care (provision, finance, and licensing), taxation, trade, and fiscal regulation” (Nicholson-Crotty 2009, 198) policy domains. Presently there is no
public and/or media attention to the issue areas in which they are innovating. In fact, such attention is likely important for starting the spread of innovations. In this case, innovators are likely responding to increased attention to a particular policy problem. A useful example would be the tax revolt that spread quickly in the 1970s (Sigelman, Lowery, and Smith 1983). Widespread and strong opposition to taxes contributed to adoption in some, but not all, states.

**Early Adoption**

Innovators, however, are not typically the primary influences of subsequent adoptions. Rogers describes early adopters as the local opinion leaders that other adopters look to when considering an innovation. They tend to be respected among their peers and serve the role of reducing uncertainty about the potential impacts of adopting an innovation. This harkens back to Gray’s (1973a) s-shaped cumulative adoption curves. Innovators are willing to try something new, even though it may fail, but early adopters provide a policy with legitimacy that sparks a steady spate of adoptions in the early and late majority. If adoptions are following a regional pattern (McVocy 1940; Walker 1969), then neighbor adoptions should have a positive effect in early adoption. However, given that this is the phase whereby a policy receives its legitimacy, neighbor effects may be weaker than in subsequent stages. Likewise, relative ideology should exhibit a weak other measure of complexity for these policies, such as bill length (Gerber and Teske 2000), lexical complexity, or citation complexity (Bommarito II and Katz 2010; Katz and Bommarito II 2014).

27 National media coverage is captured using the percentage of annual coverage in the *New York Times* and public opinion is measured using Gallup's *Most Important Problem* poll. Both measures are drawn from the *Policy Agendas Project*. They are matched to each policy using its major topic code, thus they capture the amount of attention paid to a general policy topic in a given year. For example, the major topic for health insurance portability (hiport) is healthcare (3) and thus the two measures capture media attention and public opinion regarding healthcare in year $t$. 
negative effect on the likelihood of adoption in this stage. Federal incentives and attention should still matter, as they raise the profile and relative advantage of adopting for all states.

Internal slack resources and political characteristics should be fairly consistent with what is found in the innovator stage. Higher per capita incomes, larger populations, and greater urbanity should be positively associated with adoption in this stage. Legislative professionalism should also exhibit a positive effect, but divided government likely inhibits adoption. Initiatives may matter more in this stage if they are in fact being used to pressure the adoption of a new idea. Finally, complexity and salience are likely both relevant for early adopters, with complexity decreasing the likelihood of adoption and salience increasing it.

**Early and Late Majority Adoption**

The early and late majority phases comprise the largest categories of innovation adoptions. Early majority adopters are deliberate in their consideration of an innovation, but are not prone to stepping out early. They debate the adoption of an innovation longer than innovators and early adopters, but are also more likely to begin the reinvention process (Glick and Hays 1991; Hays 1996). Rogers describes the late majority as more skeptical than the early majority. They may respond due to “economic necessity” or “peer pressure” (Rogers 2003, 284). Furthermore, their timidity may result from a lack of slack resources, which means they will wait until little uncertainty remains regarding the impacts of an innovation.
This means that while outside horizontal influences – i.e., neighbor adoptions and relative ideology – should matter for both, but be stronger for the late majority that is more prone to responding to peer pressure. Federal attention at this stage is less clear. Whereas early states may be prompted to innovate due attention and incentives provided by the federal government, later adopting states are being constrained by internal factors that keep them from early adoption. Thus vertical forces from the federal government may matter less than horizontal influences from peer states. Otherwise, these states would have responded more quickly vertical stimuli.

Likewise, I would expect the late majority to be influenced more greatly by economic conditions. In this case, I would expect per capita income to have a negative effect, given that early adopters are able to act quickly due to the availability of such slack resources, later adopters are likely those with fewer resources that ultimately act due to competitive pressures from other states. Furthermore, I would expect states adopting in these later stages to be less professionalized. I would also anticipate that initiatives would have a stronger effect in later adoption stages, as gun behind the door pressures build. Finally, the later the stage of adoption, the less salience and complexity should matter because these states are increasingly likely to copy, or even improve upon (Glick and Hays 1991), the policies adopted by states in earlier stages.
**Laggard Adoption**

Laggards are resistant adopters, or sometimes never-adopters. They are isolated members of a social system, suspicious of innovations, and more likely to follow the lead of other adopters with similar characteristics (Rogers 2003). This cautiousness may come from an extreme lack of resources or it could also signal disjunction between the norms and values of the laggards and the innovation being considered. So what motivates adopters at this stage? I would expect that external influences bear the greatest impact on the likelihood of adoption in this final phase. Laggards may finally give in to either competitive pressure from their region or ideological pressures from observing other like states adopt the same measure. They are unlikely, however, to be responding to federal pressure or issue salience, as they would have likely acted more quickly if those factors mattered.

Given that resource shortage is likely a factor in delaying adoption of an innovation, slack resources like population, per capita income and urbanity may in fact exhibit a negative effect on the likelihood of adoption during this phase given that these adopters are likely poorer, smaller, and less urban. Other internal political characteristics, such as state liberalism and the presence of an initiative should not matter, however legislative professionalism would be expected to exhibit a negative association with adoption if less professionalized states adopt in this last phase. Finally, while salience may not matter for these adoptions, complexity could conceivably show a positive association with adoption due to the fact that these states have waited to adopt more complex policies.
While Rogers' discussion of adopter categories hews more closely to the general trait of innovativeness, ala Walker (1969) and Boehmke and Skinner (2012b), it is important to recognize that states shift between these categories depending on the innovation under consideration. Therefore, it is important to not only evaluate the characteristics of states that typify these categories generally, but to also examine how the components of the simplified diffusion model (see Figure 1.1) have different effects across the diffusion lifecycle. That is the approach taken here. Breaking each adopted policy into the relevant categories and pooling within each category allows me to examine the common predictors of adoption for innovators, early adopters, the early majority, late majority and laggards, regardless of which states fall into those categories for a given policy. Having laid out the expectations for how the predictors in each phase of adoption, I now turn to describing the data and method used to test them, as well as my method for dividing adoptions into the five categories.

Data and Methods

Drawing from the prevailing methodology of policy diffusion research, I use discrete event history analysis to examine the likelihood of policy adoption within each adoption category. Unlike most previous studies, I do not examine each policy separately. Instead, I pool the observations in order to draw conclusions with greater external validity (Boehmke 2009a) as well as gain the statistical leverage necessary to estimate the effects of diffusion predictors within each stage of adoption. There are a total of 104 policies in
the dataset that were adopted by the states between 1960 and 2010. The adoption data are drawn from two existing datasets (Boehmke and Skinner 2012b; Makse and Volden 2011) and 15 policies collected by the author. Given that the data are pooled, the unit of observation for this study is the state-year-policy. The dependent variable is a dichotomous indicator of whether or not a state adopted a given policy innovation in year \( t \). Once a state adopts the policy, it is no longer at risk for adoption, and thus drops out of the dataset.

I use logistic regression for this binary time-series-cross-sectional model (Beck, Katz, and Tucker 1998) and include a count of time since the first adoption to account for duration dependence (Buckley and Westerland 2004). Random intercepts are also included in the model for each policy and state in order to account for remaining unobserved heterogeneity (Gelman and Hill 2009). The use of random effects also has theoretical support, in that researchers have identified variation in the base innovativeness of the states (Boehmke and Skinner 2012b; Gray 1973a; Savage 1978; Walker 1969), as well as additional innovation attributes that do not yet have reliable measures, short of surveying policymakers directly (Makse and Volden 2011).

The data are divided based on the five innovation categories in Figure 4.1. Taking into consideration the variation in adoption patterns for each specific policy, adoption years for each individual policy is divided into five categories. Specifically, each observation includes a count of the number of years since the first year of adoption. I take

---

28 More specifically, only policies whose first adoption occurred in 1960 or later are included. The Boehmke and Skinner (2012b) dataset includes policies that diffused prior to 1960, however these were excluded due to limitations in measurement of the independent variables. Furthermore, I excluded fifteen policies that only had adoption data for three years or less because these adoptions cannot be broken into five mutually exclusive categories based on time.

29 See Appendix A for a description of the adoption data collected by the author.
the total measured adoption time for each policy and multiply it by the percentages provided by Rogers (Rogers 2003, 281) and included in Figure 4.1. Innovator states fall into the first 2.5 percent of the total adoption time, early adopters the next 13.5 percent, the early majority the next 34 percent, late majority the next 34 percent, and finally the laggards fall into the last 16 percent of the total time. As this is done for each policy, the data are pooled within each category.

An example should make this more intuitive. Figure 4.2 plots the counts of state lottery adoptions in each year since the first observed adoption in New Hampshire in 1964. Lottery adoptions are measured through 1993, or for 29 years with the initial year of innovation coded as zero. The cut-points for each category of adoption are included on the x-axis. Year 1 divides innovation from early adoption, year 5 marks the end of the early innovation, year 14 the end of early majority adoption, year 24 the end of late majority adoption, and the remaining adoptions are classified as laggards. Note that the density of adoptions across time in Figure 4.2 does not look like the normal distribution from Figure 4.1. This is important because any given adoption is unlikely to have a perfectly normal distribution of adoptions over time.

Individual innovations, and even broader policy domains, sometimes exhibit adoption patterns that deviate from the standard normal (Boushey 2010). Therefore, my approach for using the cut points based on the normal distribution of innovativeness allows for variation in the number of adoptions within the given categories for each policy. For instance, if a policy spreads very quickly and widely across the states, my categorization approach would capture the fact that there are more innovator and/or early adopter states than expected from a normal adoption pattern. In the case of the lottery, it
allows for more adoptions to be classified in the late majority category than would be expected under a normal distribution. Taking this approach better captures the reality of variation in adoption patterns across specific policies.

**Figure 4.2:** Count and density of state lottery adoptions across time broken into five adopter categories: innovators, early adopters, early majority, late majority, and laggards

Figure 4.3 provides an intuition as to the distribution of the policy domains across each category. In Chapter 3, the domains were not evenly distributed across each decade (see Figure 3.1), however they are much more uniformly distributed across the adoption categories used for this analysis. Meaning, there is a better mixture of policy domains in each of the categories of adoption. That being said, law and health policies still dominate,
something that can only be corrected through further accumulative data collection moving forward. Having described the data and methods, I now turn to the results of this study.

Figure 4.3: Distribution of policy types within each category of adoption
Results

Table 4.1 displays the results for the innovation adoption model within each adopter category. The first general observation is that every covariate drawn from policy diffusion theory is a relevant predictor of adoption in at least one of the stages of diffusion, except for policy complexity and initiative states. There is, however, substantial variation in relevant predictors across the five categories.
**Table 4.1: Multi-level models of policy adoption for each stage of the diffusion process (Rogers 2003), with random effects for policy and state**

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Innovation</th>
<th>Early Adoption</th>
<th>Early Majority</th>
<th>Late Majority</th>
<th>Laggard</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>External Influences</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of Neighbors</td>
<td>0.005</td>
<td>0.01*</td>
<td>0.01***</td>
<td>-0.004</td>
<td>-0.01</td>
</tr>
<tr>
<td>Relative</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.03***</td>
<td>-0.02***</td>
<td>-0.03***</td>
</tr>
<tr>
<td>Ideology</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Federal</td>
<td>-0.17</td>
<td>0.42</td>
<td>0.47</td>
<td>0.59</td>
<td>0.63*</td>
</tr>
<tr>
<td>Incentives</td>
<td>(0.29)</td>
<td>(0.58)</td>
<td>(0.47)</td>
<td>(0.37)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Congressional</td>
<td>-0.07</td>
<td>0.63***</td>
<td>0.28*</td>
<td>0.17</td>
<td>0.26</td>
</tr>
<tr>
<td>Hearings</td>
<td>(0.21)</td>
<td>(0.20)</td>
<td>(0.17)</td>
<td>(0.14)</td>
<td>(0.23)</td>
</tr>
<tr>
<td><strong>Internal Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citizen</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01**</td>
<td>0.01**</td>
<td>-0.004</td>
</tr>
<tr>
<td>Liberalism</td>
<td>(0.01)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Divided</td>
<td>-0.06</td>
<td>-0.08</td>
<td>0.23***</td>
<td>-0.05</td>
<td>-0.19*</td>
</tr>
<tr>
<td>Government</td>
<td>(0.15)</td>
<td>(0.11)</td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>log(Per Capita)</td>
<td>-0.41***</td>
<td>-0.07</td>
<td>0.07</td>
<td>0.84***</td>
<td>0.18</td>
</tr>
<tr>
<td>Income</td>
<td>(0.14)</td>
<td>(0.27)</td>
<td>(0.23)</td>
<td>(0.24)</td>
<td>(0.28)</td>
</tr>
<tr>
<td>log(Population)</td>
<td>0.60***</td>
<td>0.22</td>
<td>0.13</td>
<td>-0.55**</td>
<td>-0.06</td>
</tr>
<tr>
<td>Legislative</td>
<td>-0.004</td>
<td>-0.001</td>
<td>-0.01</td>
<td>-0.02***</td>
<td>-0.01</td>
</tr>
<tr>
<td>Professionalism</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td><strong>Policy Attributes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Most Important Problem</em></td>
<td>-0.01</td>
<td>0.02</td>
<td>0.01</td>
<td>0.03***</td>
<td>0.002</td>
</tr>
<tr>
<td><em>Problem</em></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Complex Policy</td>
<td>-0.18</td>
<td>0.22</td>
<td>-0.36</td>
<td>0.44</td>
<td>-0.34</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.52)</td>
<td>(0.39)</td>
<td>(0.33)</td>
<td>(0.35)</td>
</tr>
<tr>
<td>MIP x Complex</td>
<td>0.01</td>
<td>-0.02</td>
<td>-0.01</td>
<td>-0.06***</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td><em>New York Times</em></td>
<td>-0.05</td>
<td>0.09**</td>
<td>0.01</td>
<td>0.003</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.04)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Time</td>
<td>-0.78***</td>
<td>0.28***</td>
<td>0.05**</td>
<td>0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.08)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-6.19***</td>
<td>-8.14***</td>
<td>-7.17***</td>
<td>-10.24***</td>
<td>-4.62***</td>
</tr>
<tr>
<td></td>
<td>(1.75)</td>
<td>(1.43)</td>
<td>(1.13)</td>
<td>(1.10)</td>
<td>(1.38)</td>
</tr>
<tr>
<td><strong>Variance Components</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State Level</td>
<td>0.09</td>
<td>0.04</td>
<td>0.06</td>
<td>0.02</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Policy Level</td>
<td>0.35</td>
<td>3.21</td>
<td>2.51</td>
<td>1.43</td>
<td>1.15</td>
</tr>
<tr>
<td>Observations</td>
<td>6,463</td>
<td>10,609</td>
<td>20,860</td>
<td>16,460</td>
<td>5,464</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-868</td>
<td>-1,494</td>
<td>-3,231</td>
<td>-3,175</td>
<td>-1,479</td>
</tr>
</tbody>
</table>

* p < 0.1; ** p < 0.05; *** p < 0.01. Standard errors are in parentheses.
First and foremost, the findings support the notion that the effect of a state's neighbors is not constant throughout the diffusion lifecycle (Mooney 2001a). This modeling approach, however, demonstrates that neighbors primarily matter for adoptions by the early majority, though there is weak evidence of a positive effect for early adopters. Innovators and late adopters alike do not necessarily seek information from their neighbors. This makes intuitive sense for innovators, as they are initiating action and serve as the source of diffusion in their region (McVoy 1940; Walker 1969). The finding is surprising, however, for later adopters. They are expected to be the most receptive to peer pressure, however it does not appear that they are responding to regional peers. Instead, these states are responding to their ideological peers. Indeed, the relative ideology of past adopters shows the expected negative effect for the early majority, late majority, and laggards. It seems that while regional effects matter earlier in the spread of an innovation, horizontal influence shifts to being ideologically driven for later adopters.

In terms of federal coercion, incentives are only positively associated with adoption in laggard states and federal issue attention (i.e., Congressional hearings) only shows a positive association with early adoptions. The finding for federal incentives runs counter to both scholarly and practical expectations. Presumably, these incentives are provided to prompt early innovation adoption; however they only show a weakly significant effect late in the process.

The finding for federal attention supports past research that identifies a positive, but quickly decaying, effect of national issue attention on state policymaking (Baumgartner, Gray, and Lowery 2009). Although, the lack of an effect for innovator states is an interesting avenue for further work. It could be because innovator states are
acting first and the federal government steps in to incentivize further adoptions or it could be that these states are truly resistant to federal coercion. Either way, this analysis shows that the states may be taking the lead on these particular issues, with federal incentives serving as a catalyst for expansion of the innovation instead of its initial acceptance.

Supporting Rogers's (2003) broader innovation theory, slack resources like per capita income, population, and urbanization are important predictors of adoption for innovator states. However, the counterintuitive finding is that states with higher per capita incomes are less likely to innovate in that early stage. This is perplexing, given that per capita income is a standard proxy measure of a state's tax base. Thus, states with smaller tax bases are more likely to adopt innovations in the first stage. This phenomenon deserves additional scholarly attention, as it conflicts with both policy diffusion and broader innovation diffusion theory.

Slack resources also matter the most for late majority adopters, however the directions of the effects of population and per capita income are switched. Wealthier states are more likely to adopt in the late majority, but so are smaller states. The negative effect for population at this stage could be evidence for innovation overload (Nelson and Mason 2007), where larger states have greater capacity for action, but are debilitated by the abundance of potential innovations and fracturing of legislative coalitions over the best solutions to problems.

Internal political predictors are also sporadic, in that they are often only relevant for one or two stages of adoption. The liberalism of a state's population has a positive effect only in early majority and late majority adoptions. Of course, this means that it has a positive effect on the bulk of innovation adoptions, given that these are the two largest
categories. The results also show that being an initiative state does not increase the likelihood of adoption at any stage. This runs counter to past evidence that initiative states generally tend to be more innovative (Boehmke and Skinner 2012a), however direct democracy mechanisms do not have a clear effect in any particular stage of adoption.

There is also interesting and unexpected variation in the effect of divided government across the different stages. In the case of the early majority, divided government associates with an increased risk of adoption, whereas for in the laggard stage divided government hampers adoption. This finding lends support to Berry and Berry’s (1990) claim that divided government may actually promote the adoption of some innovations. In their case, it facilitated the adoption of lotteries due to wariness with increasing broad-based taxes in order to generate revenue. In the face of partisan disagreement over these taxes, states with divided governments saw lotteries as a compromise option. Thus, divided government may actually bolster the adoption of innovations early on, if they are viewed as either (1) bi-partisan or (2) a compromise that is better than the status quo, but also acceptable to both parties.

Finally, innovation attributes appear to have little independent effect across the categories of adoption. There is an early response to national media coverage of a given topic (i.e., in the New York Times), while there is later attention to public opinion (i.e., Gallup's Most Important Problem). Thus, national media attention may help legitimize an innovation for early adopters, but positive public opinion matters more for the more skeptical late majority.
Discussion

This study sought to answer the question of whether the simplified model of policy diffusion is stable throughout the lifecycle of diffusion. This question was difficult to answer without data on a large number of policy innovations. Scholars have shown that certain internal characteristics shape state innovativeness (Boehmke and Skinner 2012b; Walker 1969) and leaders and laggards differ in behavior (Carter and LaPlant 1997; Glick and Hays 1991; Mooney 2001a). However, there is not enough statistical power using a small set of innovations to test differences in the effects of external influences, internal characteristics, and policy attributes during the five stages of innovation adoption. Leveraging a large dataset, this chapter was able to do so. I find that while nearly every included predictor of diffusion associates with the likelihood of innovation adoption in at least one stage. That being said, no predictor is significant across all stages. Furthermore, not all predictors exhibit the expected effects. Instead, an interesting picture emerges of who states are influenced by throughout the diffusion process.

During the innovation stage, adoption is solely associated with internal characteristics. In particular, slack resources are important, but not in completely expected ways. Whereas diffusion theory would assume that those with a large tax base are better able to innovate, I find that larger, more urban, but less wealthy (as measured by per capita income) states are more likely to adopt in this stage. In fact, I only find a
positive effect for state wealth for late majority adoptions. This reinforces the notion that larger, richer, more urban states like California and New York are not always the first to innovate (Gray 1973a).

Early adoptions are clearly different from innovator adoptions, as they are associated with national and regional forces, but not internal characteristics. It is the only stage of adoption that associates positively with national media coverage, but it also exhibits a positive relationship with Congressional issue attention. Thus, the vertical pressures experienced by the states are most prevalent in this group. That being said, they also tend to positively respond to adoptions by contiguous neighbors. Therefore, the group that is often viewed as legitimizing an innovation, and is more often copied by later adopters (Rogers 2003), is itself responding to pressures external to the adopting state.

Early majority adoptions are the only case where regional peer influence and ideological peer influence overlap. This suggests that for some innovations, these followers of the early adopters are listening to their neighbors, while for other innovations they are listening to early adopters that are closer to them ideologically. Given that neighbor adoption disappears as an important covariate in the next two phases, there appears to be only a limited window when neighbors matter. This is an important finding for diffusion scholars, as it can help explain the mixed findings of regionalism reported in Chapter 2. The presence of a regional effect in a single policy model may depend on (1) whether relative ideology is also modeled and/or (2) whether the bulk of
adoptions occur during these earlier periods where neighbors tend to matter. Slowly diffusing policies, and certainly those following ideological patterns, are unlikely to exhibit a neighbor effect, as there are fewer adoptions occurring during the phases where neighbors matter the most.

Interestingly, the adoption model is best specified for late majority adoptions. While neighbors no longer show an effect in this phase, relative ideology does, as do multiple internal characteristics, policy salience, and the salience-complexity interaction. This is the only stage, however, where the negative effect for legislative professionalism found consistently in Chapter 3 is replicated. In this case, a negative relationship is expected, given that we expect less professionalized legislatures to wait to adopt until later in the process. That being said, it is surprising that legislative capacity shows no effect during any other stage even though it has a generally negative effect on any type of adoption (see Table 3.1). It is becoming apparent that there is something very interesting and curious going on with legislative capacity when it comes to diffusion, therefore more work should focus directly on its role in fostering or preventing the spread of new ideas. Systematic examination of the impact of diffusion overload on more professionalized states is one potentially fruitful avenue of exploration.

Finally, the most skeptical states of all, the laggards, tend to be more urban, but are inhibited by the presence of divided government. Combining that result with the negative effect of relative ideology suggests that laggards are highly reactive to the ideology of previous adopters. This may be why divided government inhibits adoption by those who trail behind the rest of the states. If they are responding strongly to ideological cues, it may take unified control of government for these states to adopt innovations that
the supportive party finds favorable. Whereas divided government can be an asset for adoption by the early majority, as these states may be more open to bipartisan efforts, it may be a detriment to skeptical laggard states that may only adopt something that has strong ideological cues. Again, this is a very important area of future research given the potential for increased patterns of ideologically driven diffusion due to the increasing importance of groups like ALEC and SiX.

Beyond policy diffusion, these results paint a very interesting representational picture. In the early phase of an innovation’s spread, those states that step up first appear to be doing so solely because of internal forces. Every remaining phase is influenced by at least one external player. Early adopters, the legitimizers of new ideas, are the opposite in that they appear to be solely responding to external forces. Regional and ideological adoption patterns coexist within the early majority phase, however the late majority and laggards respond to ideological peers instead of regional ones. Though internal characteristics return in importance in the late majority phase, the states remaining at risk for adoption follow an ideological pattern of diffusion instead of a regional one. Much like Chapter 3, this does not prove that citizens are not being well represented, however it does point directly towards where to look for representational slippage due to purely ideological conformity.
Chapter 5

Measuring Policy Adoption Speed in the American States
The American federal system affords the states opportunities to experiment with new ideas while learning from the experiences of their peers. Some ideas take hold and spread quickly, while others spread more slowly, and still others never get off the ground. The policy diffusion research program is inherently interested in why and how quickly innovative policies are adopted. However, much of the extant research examines the predictors of why a policy is adopted. Speed is less often systematically examined, primarily because it requires treating the policy as the unit of analysis and large datasets of policies have only recently become available. This chapter addresses this shortcoming in order to test how adoption speed changes over time and provide a mechanism for future explication of diffusion speed.

Studying the speed of policy adoption across the states is important because it speaks to the different causal mechanisms underlying policy diffusion. Many studies frame diffusion as a process of incremental learning, however this is not the only potential causal pathway (Graham, Shipan, and Volden 2013; Shipan and Volden 2008). Incremental learning belies a process where some states innovate while others wait to evaluate their success before adapting and adopting. In other cases, however, states simply copy each other's policy wholesale, which allows it to spread more quickly than otherwise expected under an incremental process. Past research makes clear that the American political system is not only prone to incrementalism, but also to periodic punctuations where policies spread quickly (Boushey 2010, 2012; Nicholson-Crotty 2009) and in geographic patterns that are different than those anticipated by the early work on diffusion (Sigelman, Lowery, and Smith 1983). Examining the rate of policy
adoption is a promising avenue for understanding why some policies follow an incremental adoption pattern while others burst onto the policy scene more quickly.

Furthermore, studying the rate of adoption using the policy as our unit of analysis allows diffusion researchers to determine how characteristics of the policies shape their speed of adoption. It is important to understand how these features shape both the likelihood (Makse and Volden 2011) and speed of adoption, as they are often manipulable by supporters for the purpose of facilitating more rapid adoption. Thus, examining adoption speed not only provides additional insight into the causal mechanism driving diffusion, it can eventually help scholars understand how the manipulation of particular features affects the causal pathway.

While the extant work in this area provides insight into how attributes of policy innovations predict whether a policy is adopted quickly or slowly (Nicholson-Crotty 2009), further advancement requires the development of a continuous measure of the dependent variable: adoption speed. Doing so would allow researchers to determine how speed increases or decreases as a function of the policy's characteristics. To that end, I present a new continuous measure of adoption speed. Additionally, I use the measure to examine how adoption speed varies across time and policy domain. Finally, I demonstrate the utility of the continuous measure by employing it as a dependent variable in order to provide additional insight into how innovation attributes – relative advantage, compatibility, complexity, and observability – relate to adoption speed. Using the new measure and a different dataset of adoptions, I am able to replicate past results as well as identify additional policy characteristics that predict the rate of innovation adoption among the states.
Adoption Speed and Its Predictors

The normal s-shaped adoption curve identified by innovation adoption scholars (Gray 1973a; Rogers 2003) hides significant variation in the speed and patterns of diffusion across different policies. It represents a process whereby a few initial innovators adopt a new policy while the rest of the potential adopters wait to see how that policy is working before they adopt it. Of course, the policy may be adopted wholesale, but it may also be altered to suit the needs and characteristics of a given state. While the s-curve is a useful heuristic for policy diffusion, researchers have noted that adoptions over time are not always normally distributed. In fact, some policies are adopted markedly faster, while others have long tails or are never adopted by some states (Boushey 2010; Gray 1973a; Nicholson-Crotty 2009; Savage 1985; Welch and Thompson 1980). Even in Walker's (1969) seminal work, “23% of policies ... were enacted by the majority of adopters within the first five years” (Nicholson-Crotty 2009, 192). In fact, scholars have consistently demonstrated that punctuation is as much a part of the American political system as incrementalism (Baumgartner and Jones 2005; Boushey 2012). Thus, it is important to understand how and why some policies spread faster than others.

The most comprehensive study of diffusion speed is Nicholson-Crotty's (2009) analysis of 57 policies, which shows how policy characteristics like salience and complexity interact to shape whether a policy is adopted quickly or not. While this is an important advancement, the dependent variable, diffusion speed, is a dichotomous categorization. The cut point is theoretically justified using the normal adoption curve from innovation theory (Rogers 2003), however it does not capture the continuous
underlying concept of adoption rate. Therefore, the present approach only allows us to draw conclusions about the categorization of a policy as fast or slow. It does not offer a continuous measure of adoption speed and thus we cannot draw conclusions about the degree to which attributes of the innovations increase or decrease the speed of adoption. Furthermore, a continuous measure, when combined with a dataset of policies drawn from different time periods, will facilitate a study of how speeds have changed over time.

Diffusion research outside of political science identifies five general attributes of innovations that condition adoption patterns: relative advantage, compatibility, complexity, trialability, and observability (Rogers 2003). Existing studies of policy diffusion do not always use this same theoretical framework for organizing their findings, however they find evidence supporting the notion that innovation attributes condition the rate of innovation adoption. For instance, technically complex policies tend to spread slowly, as they require the extensive engagement of experts both for formulation and implementation (Boushey 2010; Clark 1985; Eshbaugh-Soha 2006; Gormley 1986; Nicholson-Crotty 2009). Highly salient policies, on the other hand, diffuse more quickly, as there is a higher demand among constituents for a policy solution, and thus a stronger electoral incentive for legislators (Boushey 2010; Eshbaugh-Soha 2006; Gormley 1986; Hays 1996; Karch 2007a; Mooney and Schuldt 2008; Nicholson-Crotty 2009) (Boushey 2010; Eshbaugh-Soha 2006; Gormley 1986; Hays 1996; Karch 2007a; Mooney and Schuldt 2008; Nicholson-Crotty 2009). Additionally, there is evidence that policy cost (Gormley 1986), flexibility in the form of post-adoption modification (Mossberger 2000),

30 Policies were categorized as rapidly adopting if at least 50 percent of adoptions occurred in the first third of the overall distribution of adoptions over time.
federal incentives (Nicholson-Crotty 2009; Welch and Thompson 1980), issue fragility (Savage 1985), and policy framing (Donovan 2001; Schneider and Ingram 1993) shape patterns of adoption. This work points clearly to the impact of innovation attributes on the likelihood and speed of adoption, however it often focuses on a single attribute at a time.

Authors that test the influence of multiple attributes support the notion that they have discrete and joint influence on the likelihood and speed of policy adoption (Makse and Volden 2011; Nicholson-Crotty 2009). However, there are limitations to the approaches taken due to data constraints. For example, Makse and Volden (2011) test all five attributes alongside internal and external predictors of diffusion in their study of criminal justice policy. The authors surveyed lawmakers in order to develop their measures of Rogers's (2003) five attributes. They did so in recognition that many attributes are best captured in the eye of the beholder. This approach provides a rich understanding of how the attributes shape the likelihood of adoption, however it has limited scalability due to the use of expert surveying. This gives the results high internal validity, but reduces the conclusions that can be drawn across policy domains. An alternative approach, uses the policy as the unit of analysis instead of the state year, and tests how archetypes (i.e., observable outcomes of unobservable concepts) of two specific attributes, salience and complexity, predict whether a policy is adopted quickly or slowly (Nicholson-Crotty 2009). This approach trades a degree of internal validity and precision for greater generalizability of the findings. I hew towards this approach for the purpose of
demonstrating the utility of the new speed measure for diffusion research. In doing so, I also develop and test additional attribute archetypes. Specifically, I focus on four of the attributes: relative advantage, compatibility, complexity, and observability.

**Relative Advantage**

Rogers (2003) defines relative advantage as the “degree to which an innovation is perceived as being better than the idea it supersedes” (229). Essentially, lawmakers make the determination of whether a new idea offers some economic, social, and/or political advantage over the status quo or competing alternatives. This suggests that policies with higher relative advantage should be adopted more quickly. While a lawmaker's perception of relative advantage can be driven by their state's economic and political context (e.g., Berry and Berry 1990), federal mandates and incentives also serve to broadly increase the relative advantage of a policy innovation (Allen, Pettus, and Haider-Markel 2004; Nicholson-Crotty 2009; Welch and Thompson 1980).

---

31 By archetype, I mean a proxy that stands in for the given attribute. An archetype refers to a typical example of the thing it represents. Thus, each of the archetypes I include is an example of the attribute.

32 The fifth innovation attribute identified by Rogers, trialability, is not included in this analysis. This is due to the challenge of reliably measuring the concept without access to the actual pieces of legislation. Trialability refers to “the degree to which an innovation may be experimented with on a limited basis” (Rogers 2003, 258). Essentially, the more flexibility an adopter has in testing out an innovation, the more likely they are to adopt it (Mossberger 2000). Provisions in a piece of legislation that increase its trialability include sunset clauses and allowances for bureaucratic discretion. At this time, it is not clear how to measure this concept with just titles and brief descriptions of laws. One would need to examine the text of adopted legislation to determine whether such elements also spread.
Compatibility

Compatibility is defined as “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (Rogers 2003, 240). Essentially, adopters use their past experience, as well as present values, to reduce uncertainty surrounding the benefits of an innovation. One way to test if compatibility relates to adoption speed is to identify any “technology clusters” (LaRose and Atkin 1992) that may have been adopted in tandem, and thus more quickly as a cluster than as discrete policies.

Complexity

Complexity has already been incorporated into the study of policy innovation adoption and refers to the perceived difficulty in using or implementing an innovation (Boushey 2010; Clark 1985; Eshbaugh-Soha 2006; Gormley 1986; Nicholson-Crotty 2009). If a policy is highly complex, it is more likely to follow the incremental learning pattern, whereas simple policies can spread more quickly. For instance, natural resource strategic planning efforts require participation of key staff in state regulatory agencies. Likewise, state licensing requirements require the expertise of people familiar with that field in order to successfully establish the program. Such policies should spread slower than average and thus complexity could be thought of as an additional resource constraint that must be considered by adopting states. On the other hand, states will more quickly consider policies requiring fewer legislative and/or bureaucratic resources for implementation. For example, statutory changes such as lemon laws spread quickly
across the states and do not require many resources to implement. They are essentially legal changes, not highly technical policies.

**Observability**

The fourth innovation attribute, observability, refers to the ability of other potential adopters to see their peers accepting a new product. This brings to mind fads, like Livestrong bracelets or the newest iPod, spreading quickly because only a quick glance is required to know if a friend is a cutting-edge adopter or not. Other, more private, innovations - like safe sex practices in the era of AIDS (Bertrand 2004; Singhal and Rogers 2003) - experience greater difficulty in spreading due to their low observability. One method for capturing a policy's observability is to assess its salience (Boushey 2010; Eshbaugh-Soha 2006; Gormley 1986; Hays 1996; Karch 2007a; Mooney and Schuldt 2008; Nicholson-Crotty 2009). National media salience, as well as public opinion, have both been shown to be positively related to the adoption of policy innovations (Nicholson-Crotty 2009; Pacheco 2012). However, evidence suggests that policy complexity reduces the impact of salience on adoption speed (Nicholson-Crotty 2009). Before measuring these concepts and testing the given expectations, I will first describe the new speed measure and test some initial hypotheses about how adoption speed changes across time and policy topic.

---

33 There is a second form of observability: observing the success of results. Makse and Volden (Makse and Volden 2011) asked state policymakers whether they were able to observe the results of a given policy. Given that the definition of results is heterogeneous across policy domains, it would be difficult to measure an archetype of this consistently across each.
Measuring and Testing Adoption Speed

To improve the external validity of diffusion studies, researchers have assembled large datasets of policies adopted by the American states (Boehmke and Skinner 2012b; Boushey 2010; Makse and Volden 2011; Nicholson-Crotty 2009). The largest publicly available dataset was collected by Boehmke and Skinner (2012b) and includes 136 policies across multiple domains whose first adoption occurred between 1912 and 2009. This chapter uses their data, as well as that collected by Makse and Volden (2011) and state anti-bullying policy adoptions collected by the author (see Appendix A). This results in a full dataset of 158 policies.34 Both the Boehmke and Skinner (2012b) and Makse and Volden (2011) datasets include adoptions that were collected by the authors themselves, as well as gathered from previously published diffusion studies.

While collecting first adoption dates is becoming easier as state governments put more materials on the Internet, this dataset does not represent a random sample of policies. The lack of a clear sampling frame and necessity of convenience sampling for diffusion studies is a persistent issue for this research program (Savage 1978). This dataset, however, confers two advantages for the present study. First, it provides a diverse set of policies that cover many of the major domains of state policymaking (e.g., education, health, and criminal policies, among others). Second, given that other researchers collected these data, they were not chosen based on the dependent variable of this particular analysis (Nicholson-Crotty 2009).

34 I use the most complete record available in the case of overlap between the Boehmke and Skinner (2012b) and Makse and Volden (2011) datasets.
Measuring Innovation Adoption Speed

I use survival analysis to measure adoption speed. Survival analysis is the prevailing methodology in policy diffusion studies that examine the likelihood of state innovation adoption, however I use it in a different way to measure the relative speed of adoption for a given policy.35 This measurement technique provides a continuous measure of speed that explicitly takes into account the right censoring of observations that never adopt a policy. This is important for developing a speed measure that is comparable across policies. Nicholson-Crotty's (2009) dichotomous measure of speed relied on choosing an endpoint for the distribution of adoptions “being after two to five years of declining or zero change in the adoption rate” (197). Using survival analysis allows for the inclusion of information about the remaining number of non-adoptions in the speed measure without the need to select a cut-off point \textit{a priori}. This is similar in approach to Boehmke and Skinner's (2012b) state innovativeness measure, however instead of measuring how quickly each state adopts available innovations in a given year, it uses a survival model to generate a measure of adoption speed for each individual policy. Thus, the unit of analysis shifts from the state-year to the policy in order to examine how policy characteristics relate to the rate of adoption.

35 Typically, survival models are used to understand the degree to which explanatory variables increase or decrease the hazard of a unit changing state. In Biostatistics, these models were originally used to assess how different health factors and lifestyle choices affect the risk of a person dying. Essentially, they produce a hazard function that is calculated by dividing the instantaneous likelihood of death by the instantaneous likelihood of survival in time \( t \). Berry and Berry (1990) applied this logic to the diffusion research program in their study of lottery adoptions. In the case of public policy, a unit's change in status (i.e., death or failure) is represented by the adoption of a given policy in a given state. Therefore, the unit of analysis is the state-year. Because these models are concerned with the amount of time a unit remains in a given status, the hazard function is calculated based upon the speed at which each unit experiences the change. Since the model is only being used to calculate a measure of adoption speed, there are no covariates included, only the time to adoption.
Instead of constraining each policy to the same specification of a baseline hazard function, I used the flexible memoryless Weibull distribution for each calculation. The Weibull distribution allows the hazard to increase or decrease monotonically overtime, or reduces to a flat exponential distribution if the hazard does not change with time. The resulting scale parameter for each policy provides a measure of adoption speed that is comparable across policies. They are comparable because each model is an intercept-only model with time to adoption as the response variable. Thus, the scale parameter (i.e., the constant) for each model is akin to an average adoption time, but one that also takes into account the right censoring of states that have not adopted the policy. This is the advantage of using a survival model for calculating the speed measure over using an average of the known adoption times.

In order to make the interpretation of the speed measures and subsequent regression model more intuitive, I subtracted each from zero and rescaled them so they range from zero (slowest) to one (fastest). This yields a continuous measure of adoption speed that is useful for further statistical analysis. I take this approach instead of using a multi-level or pooled survival model because, while those models tell us a great deal about how internal and external influences shape a state's likelihood of adopting, they do not systematically examine how adoption rates differ across policies. Hence, this important conceptual difference leads to the chosen modeling approach.

---

36 The shape parameter is not used in this study, but could be meaningful in future work for analyzing whether speed changes as a function of time. Therefore, both the scale and shape parameters are included in the replication dataset, as are the standard errors of the speed coefficients.
To make the calculation of the speed measures more intuitive, Figure 5.1 displays the cumulative adoptions of three different policies over time. The name and rescaled speed calculation are included next to each plotted line. Given the distribution of adoptions over time for each policy and variation in how widely they are adopted (i.e., the degree of right censoring), the subsequent speed measures perform as expected. For example, all 48 states adopted old age assistance programs within three years of the federal government passing the Social Security Act of 1935 (SSA).\textsuperscript{37} On the other hand, states were far slower to adopt early voting and have remained reticent to do so. Two states adopted early voting in 1970 (Hawaii and Idaho), but no more followed suit until the 1990s. Furthermore, only sixteen states had adopted early voting at the time that the data were collected. As a result, these policies represent the fastest and one of the slowest in the dataset, respectively.

\textsuperscript{37} Alaska and Hawaii were not states at that time.
State adoption of the Interstate Compact on Juveniles, on the other hand, represents a middle-of-the-road policy, in terms of speed. It displays an incremental adoption pattern in that a lag occurred between the first few adoptions in 1950 and 1951 and the steady stream that followed between 1955 and 1966. These three policies highlight how this measure is useful for arraying policies by their adoption speed. It conforms with what is known about how policies deviate from the normal incremental learning pattern (Boushey 2010; Gray 1973a) and is thus useful for identifying departures from incremental learning that may instead follow an alternative causal process (Boushey 2010; Nicholson-Crotty 2009; Shipan and Volden 2008).
Preliminary Analysis Using the Speed Measures

Initial exploration of the speed measures confirms a long-posed theory that policy innovations spread more rapidly throughout the second half of the Twentieth Century (Walker 1969, 1971). Specifically, Walker predicted that interstate professional organizations for bureaucrats and legislators would increase cross-state communication, as well as the pressure to conform, and thus also increase the rapidity of innovation adoption. Figure 5.2 displays a scatterplot of the adoption speed measures across time. They are plotted based on the year of the first adoption. Also plotted is a vertical line marking the year 1965, after which point speed appears to be consistently increasing. This figure confirms Walker's prediction, which appears quite prescient given his article was published in 1969. The figure also shows a slight bump in speed during the New Deal and World War II. Furthermore, this suggests that learning is either declining as a motivating mechanism of diffusion or occurring more quickly over time. Further empirical testing is required to confirm the cause of this trend in adoption speed.
Figure 5.2: Scatterplot of adoption speeds across time with a LOESS line demonstrating the increase in adoption speed after 1965

Given the identification of each policy with a particular domain, I can also examine the differences in speed across domains. Figure 5.3 shows the mean and 95 percent confidence intervals for the fourteen policy domains included in the dataset.\(^\text{38}\) It also shows a solid horizontal line at the average speed (0.45) and a dashed line at the midpoint between 0 and 1 (0.5). Including both demonstrates the slight skew in the dataset towards policies that diffused more slowly. Also included is the number of observations for each policy domain. Given the variation in the number of included observations for each policy domain.

---

\(^{38}\) Each policy in the dataset was coded using major topics from the Pennsylvania Policy Database Project, Principal Investigator Joseph P. McLaughlin, Temple University (McLaughlin 2010). Gay marriage, for example, is coded as “Civil Rights and Liberties” (code 2) and anti-bullying policy is coded as “Education” (code 6). This coding scheme was adapted for state policies from the larger Policy Agendas Project. The coding manual is located at [http://www.temple.edu/papolicy/resources/documents/March2010Codebook.pdf](http://www.temple.edu/papolicy/resources/documents/March2010Codebook.pdf).
policies, there is associated variance in the precision of the estimated mean speed for each category. That being said, this figure provides an initial intuition regarding whether certain types of policies tend to spread more or less quickly than the average for the dataset. Administrative policies are the only ones that, as a group, clearly spread slower than average and social welfare policies tend to spread more quickly. The precision of these estimated means will improve as researchers continue to gather information on more policies.

Figure 5.3: Plot of mean speeds and 95% confidence intervals for fifteen policy domains (assigned based on the Policy Agendas Project coding scheme)
Validating the measure

Having laid out the logic of the new measure of adoption speed and explored some initial findings, it is now necessary to demonstrate its utility as a dependent variable. To do this, I examine how different attributes of each policy systematically relate to its speed of adoption. Beyond demonstration, this approach serves to validate the measure by replicating past findings regarding the effect of innovation attributes on adoption speed and extending that work by testing additional attributes. Drawing from the theory presented above, I test the association between four innovation attributes – relative advantage, compatibility, observability and complexity – and policy innovation adoption speed. While most diffusion studies focus on the likelihood adoption by using the state-year as their unit of analysis, this approach allows for a comparative analysis of adoption speed by using the policies as the unit of analysis.

Measuring the Attributes

Relative advantage is measured using a dichotomous indicator of whether or not there were federal incentives associated with that policy during the time in which it was adopted by the states. This means that the status quo is not receiving a financial incentive to innovate, while the alternative is to innovate and receive some compensation from the federal government. Policies with associated federal incentives, all else equal, should be adopted more quickly than those without. This, of course, is an incomplete characterization of relative advantage. Of the four attributes in this analysis, relative
advantage perhaps relies the most on the perception of individual political actors. That being said, federal incentives are included given that their purpose is to increase the relative advantage of adopting a policy for all of the states. Meaning, the incentives are intended to raise a policy's stature relative to the status quo.

For compatibility, I use two specific criteria in identifying policy clusters in the dataset. First, the policies must be topically related and second, their first adoption should occur in the same year or very close to the same year. Topical relation refers to whether the policies are categorized using the same major topic code. In the present case, I use a strict standard of temporal relation. Specifically, I only identify a group of policies as a cluster if their initial adoption year is the same.\footnote{Moving forward, this will be a useful area of additional inquiry and evaluation. Policies do not necessarily have to begin diffusing in the same year to spur each other on. However, beyond using a strict definition, it is less clear where to draw that line.} This increases the likelihood that the policies were either packaged together by the original adopter, or could potentially be packaged together by subsequent adopters. Using these criteria, I identified one clear policy cluster in the dataset. It includes four health insurance regulations --- guaranteed issue of health insurance, guaranteed renewal of health insurance, health insurance portability, and health insurance preexisting condition limits --- that are closely related in terms of the issue they are addressing (i.e., health insurance) and all started diffusing in the same year (1990). Given these two criteria, they may have been adopted, or at the very least considered, in tandem and thus spread faster than average, like a technology cluster.
I follow the current convention for classifying policies as complex, which relies on researcher evaluation and assignment of each policy to a particular domain (Nicholson-Crotty 2009; Ringquist, Worsham, and Eisner 2003). Policies are complex if they fall into the “energy, environmental pollution, health care (provision, finance, and licensing), taxation, trade, and fiscal regulation” policy domains (Nicholson-Crotty 2009, 198). Thus, policies are either complex or they are not. There are 25 complex policies in the final dataset. Consistent with current evidence, I expect that technically complex policies are adopted more slowly than simple ones.

I include two measures representing observability: national media salience and public opinion. National media salience is measured using the proportion of New York Times coverage for a given policy's major topic area. Public opinion is captured via Gallup's Most Important Problem (MIP) poll. The Gallup Poll provides a useful proxy for observability of an issue among the public, as it captures the public's view of the relative importance of each policy topic. National media and a higher ranking of importance among the public should increase the speed at which states consider and adopt policy innovations.

Note that these are finer-grained definitions of policies than the major topics from the Policy Agendas Project.

An alternative method for measuring complexity could be bill length (Gerber and Teske 2000), however, as Nicholson-Crotty (2009) points out, this is difficult to measure given the long time period included and bill texts are not readily accessible for every issue from every state. Furthermore, he asserts that the use of this coarse measure is at the very least conservative, as it increases the potential for a Type II error instead of a Type I error.

Nicholson-Crotty (2009) searched the New York Times Index for stories that directly related to each innovation in his data. While this provides a more direct measure of a given policy's individual salience, it proves difficult to replicate. The approach used in this analysis provides three advantages. First, articles in the index are randomly sampled from all Times coverage in a given year. Second, the measure is normalized over the total coverage in a given year, as opposed to an un-standardized measure that is difficult to compare. Third, it improves replicability, as the data are publicly available from the Policy Agendas Project.

This is also drawn from the Policy Agendas Project.
Finally, I include interactions between each salience measure and complexity in order to test their conditional relationship with speed. I expect salience to still show a positive effect on adoption speed, but for that effect to be smaller when a policy is complex. In summary, Table 5.1 shows the covariates representing each of the four included innovation attributes and the expected direction of the relationship between that covariate and adoption speed. In general, policies with high relative advantage, compatibility, and observability (i.e., high salience) should be adopted more quickly, while complex policies are expected to spread slowly.

Table 5.1: Innovation attributes, their measures, and expected effects on adoption speed

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Covariate</th>
<th>Expected Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative Advantage</td>
<td>Federal Incentive</td>
<td>+</td>
</tr>
<tr>
<td>Compatibility</td>
<td>Health Insurance Cluster</td>
<td>+</td>
</tr>
<tr>
<td>Complexity</td>
<td>Complexity</td>
<td>-</td>
</tr>
<tr>
<td>Observability</td>
<td>NY Times Coverage (NYT)</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Most Important Problem (MIP)</td>
<td>+</td>
</tr>
<tr>
<td>Complexity x Observability</td>
<td>Complexity x NYT or MIP</td>
<td>-</td>
</tr>
</tbody>
</table>

See Appendix B for variable descriptions and descriptive statistics
Results of the Adoption Speed Model

Figure 5.4 provides a graphical representation of the OLS coefficients from the model of diffusion speed (see Appendix D for full output). The model confirms some of the expectations drawn above from innovation adoption theory. Importantly, it shows the conditional influence of public salience (i.e., Gallup's *Most Important Problem*) and policy complexity on adoption speed. This interaction was an important finding of previous research in this area (Nicholson-Crotty 2009) and it is replicated here with a different dataset of policies and the new measure of the dependent variable. Media salience (i.e., coverage in the *New York Times*), on the other hand, shows no effect on adoption speed. This suggests that states do not move faster in taking up an issue that receives more national traditional media coverage, however they do respond more quickly to public recognition of problems.

---

44 Only the results for the interaction between complexity and MIP are reported in Figure 5.4. Neither the constituent terms nor the interaction showed significant effects when *New York Times* coverage was used instead of MIP. The results of this model are included as Model 2 in Appendix B.

45 Recognizing that the large number of law policies included in the dataset may be driving the results, I also examined the influence of those observations on this model and its sensitivity to their removal. See Appendix E for this analysis.
An important advancement is possible, however, given the continuous measure of the dependent variable. Whereas, Nicholson-Crotty (2009) was able to examine the probability of adoption for discrete categories of policies, the continuous measure allows me to see how these factors relate to the predicted speed of adoption. Figure 5.5 demonstrates how complexity conditions the relationship between public salience and
adoption speed. It shows speed values predicted across the range of Most Important Problem values found in the dataset. The left-hand panel shows the predicted value when complexity is set at zero (i.e., a non-complex policy) and the right-hand panel shows the values when complexity is set at one (i.e., a complex policy). All other values are held at their means for continuous measures and modes for discrete. Figure 5.5 shows that as public salience increases, so does the predicted adoption speed. This positive effect, however, is only present for non-complex policies. There is no public salience effect present when policies are complex.
Figure 5.5: Plot of the moderating effect of policy complexity on the positive effect of salience (MIP) on the predicted speed of adoption

This finding is important for three reasons, two of which are methodological and one theoretical. First, as mentioned, it corroborates past findings with new data and a new approach. Second, the predicted values plot demonstrates the utility of using a continuous measure of adoption speed. Instead of examining the predicted probability of adoption for policies sorted into discrete categories, researchers can now directly examine how predicted adoption speeds change across covariates of interest. From a theoretical
standpoint, this finding provides additional evidence that the states exhibit a trade-off in responsiveness and caution when adopting policy innovations. The interaction shows that states are quicker to act when citizens perceive a policy topic as an important concern, however legislators exhibit caution when that policy is complex. Therefore, while some policies may spread in a faddish nature, meaning with rapid uptake due to high popularity, more complex policies are not approached in a similar manner. Instead, they are given additional time for experimentation and gathering information about the potential consequences of a policy (Karch 2007a).

In addition to replicating the interaction of complexity and salience, the model suggests that, when using a more relaxed level of significance ($p < 0.10$), federal incentives have a small positive effect on the rate of adoption. This finding concurs with prior research highlighting the positive influence of the federal government on the adoption of policy innovations (Karch 2006, 2012; Nicholson-Crotty 2009; Welch and Thompson 1980), however it is a weak effect. Finally, the health insurance policy cluster experienced more rapid adoption than the average policy in the dataset. This demonstrates that, as a group, policies that are closely related and arrive on the agenda space at the same time may be bundled together and thus increase the speed that they are taken up, relative to innovations that stand alone. While only one set of policies in this dataset clearly fits the “technology cluster” definition, this finding highlights how broader innovation diffusion theory (Rogers 2003) can still inform our own theory about the spread of policy innovations. Additional data collection and analysis are required to determine whether all policy clusters behave in this way, or whether there is variation in the extent to which related policies are bundled together by the states.
Conclusion

Diffusion scholars are increasingly turning their attention to examining adoption patterns across policy domains in order to test the generalizability of the findings from the last 25 years of research. One approach to understanding adoption dynamics across policy domains is to examine how characteristics of the policies themselves relate to the rate at which they spread. This paper makes two important contributions to this line of inquiry. First, it provides a method for a continuous measure of adoption speed. The continuous measure provides confirmation of Walker's theory that diffusion rates would increase as more avenues for the transference of policy and political information across state lines became available. Furthermore, the measure allows for initial analysis of which policy domains are adopted faster or slower than average. Finally, using the measure as a dependent variable not only replicated important past results – including the conditional effect of complexity and salience on adoption speed and the positive influence of federal incentives on the rate of adoption – but it also allows for the prediction of speeds across values of interesting covariates. This will be useful as additional innovation attribute archetypes are identified and measured.

Second, this paper contributes to the process of identifying innovation attribute archetypes by examining how the clustering of four health care policies related to faster than average adoption rates. As noted, additional data collection and testing are required to gain a better understanding of variation in the success of policy clusters, but this paper provides a method for defining and testing them. Further identification of useful innovation attribute archetypes is important because they allow researchers to examine
their effect on policy adoption without having to survey decision makers on each and
every policy included. While this sacrifices some of the internal validity of survey-based
measures, it yields results that have higher external validity across diverse policy
domains.

Fortunately, Rogers's (2003) general theory of innovation diffusion offers many
avenues for further research in this area. For instance, the effect of innovation naming
remains understudied in the broader innovation literature, but applies quite well to public
policy (e.g., Lederman 2010). Catchy titling can help increase the compatibility of
legislation, and could thus be used as a measure of this attribute. Additionally, measures
of previous related policy adoptions can help us understand the degree to which
compatibility helps policies spread, as well as factors that limit the effect of
compatibility. Likewise, complexity and trialability are two attributes that require further
advancement in measurement. Currently, the complexity measure is blunt, in that it only
takes into account a broad categorization of policy type. Relatedly, trialability is
particularly difficult to measure without knowing the details of the policies being
adopted. Thus, improvements in both of these areas will likely require machine coding of
legislation for the purposes of creating accurate indices of both concepts.

Finally, an avenue for further development of the observability measures could
come from measuring or estimating (e.g., Lax and Phillips 2009a, 2009b) sub-national
public opinion on an array of policies. The national measures of media coverage and
public opinion used in this analysis are valid for understanding how observability may
broadly impact diffusion, but it still masks important variation in salience within the
states and across issues. For instance, state-level measures of public opinion for each
policy would provide the opportunity to understand the variance in opinion across the states. It is possible that policies with little variance in opinion across the nation are adopted more quickly than policies that exhibit a lot of heterogeneity. Essentially, a policy that most can agree on is likely to be adopted more quickly and broadly than one where there are highly divergent opinions. In fact, evidence suggests that adoption of consensus and contentious policies are affected differently by public opinion and elite ideology (Mooney and Schuld 2008). Measuring opinion sub-nationally would allow us to examine variation in observability within the states.

Beyond studying the effect of attributes independently, this area of research demonstrates the need to include attributes as part of the general model of policy diffusion (Berry and Berry 1990, 2007). To that end, future tests of this model using pooled datasets should include attributes alongside internal and external predictors that have been previously identified by diffusion scholars (e.g., Makse and Volden 2011). Doing so will test how all of these factors relate to each other. That is to say, innovation attributes likely interact with both internal and external predictors in important ways. For instance, policy complexity may moderate the influence of legislative professionalism on diffusion. Specifically, legislative professionalism likely has a stronger effect for complex policies than for simple ones. Likewise, state-level characteristics could also condition the effect of policy attributes. For example, trialability could be far more influential in states with high bureaucratic professionalism, than in states with less professional bureaucracies. These brief examples highlight the necessity of incorporating
attributes into our tests of the general model of policy diffusion. All of these potential avenues for future research can serve to expand our theoretical and empirical understanding of policy diffusion in the American states.
Chapter 6

The Causal Mechanisms Underlying Policy Innovation Diffusion: Understanding Socialization Diffusion
Having established changes in the broader dynamics of policy innovation diffusion and explored one means for identifying different causal mechanisms – adoption speed – this chapter is very different from Chapters 2 through 5 in method and focus. Whereas the preceding chapters examine the macro-level dynamics of policy diffusion, this chapter narrows in on the causal micro-processes that motivate those larger patterns of adoption. The purpose is to begin to explain why there is instability in the general model of diffusion. I argue that sorting out these causal mechanisms is necessary for understanding why results vary greatly across time and policy area. The research on diffusion’s causal mechanisms suggests that there may not be one single broad model of diffusion, but several mechanisms that vary in their specific predictors.

In turning to these causal pathways, it is necessary to first formally develop a theoretical framework for the previously identified mechanisms of diffusion (i.e., learning, competition, coercion, social contagion, and elite socialization) and push forward on developing the most under-explored mechanism: socialization/emulation. To these ends, I develop a theoretical framework for organizing the known mechanisms and provide a foundation for explicating the micro-process of elite socialization through a laboratory experiment. The goal is to provide the foundation for an experimental paradigm that allows diffusion researchers better understand the individual-level spread of innovations through elite social networks, particularly ideological networks. This is not only the least developed mechanism, but also one that is increasingly likely in a polarized political system where ideologically driven diffusion is coordinated by national groups like ALEX and SiX.
Scholars largely focus on examining a single causal pathway for diffusion at a time, and have thus not developed a common theoretical framework for sorting the mechanisms. Some have tried to differentiate between a subset (e.g., Berry and Baybeck 2005) or nearly all of the mechanisms (Shipan and Volden 2008), but conceptual slippage remains a problem due to the lack of a common framework (Maggetti and Gilardi Forthcoming). Furthermore, while learning, competition, and coercion have received the bulk of the theoretical and empirical attention of diffusion researchers, there is a shallower understanding of how the social interactions of elites and the mass public shape the spread of policy ideas and motivate their adoption. This is important not only because of the under-developed nature of these mechanisms, but also because they closely fit the macro-level findings of the previous four chapters. For instance, Chapters 2 and 3 demonstrated that diffusion does not always occur in regional patterns due to the influence of contiguous neighbors. In fact, there is evidence that policies are increasingly spreading among subsets of states that share particular characteristics, such as ideology. Furthermore, the development of ideologically-motivated policy organizations, like ALEC and SiX, raises the question of how legislators’ social networks help facilitate the spread of innovations to states with similar characteristics that may not be contiguous neighbors.

The strong and consistently negative relationship between legislative capacity and innovation adoption suggests that states, particularly those with less-professionalized legislatures, are copying each other. Given the success of ALEC in these legislatures (Hertel-Fernandez 2014) and the organization’s approach of diffusing their policy priorities through a network of state legislators, it is important to understand how social
influence shapes the private acceptance of new ideas (Sherif et al. 1954/1961) and public compliance (Asch 1956) with the demands of one’s peers. I turn now to establishing a theoretical framework for the currently known mechanisms of policy diffusion before then providing the foundation for experimentally testing the role of social influence and conformity pressure on the acceptance of new information and ideas.

**Mechanisms of Diffusion**

For the purposes of developing a common theoretical framework for identifying the causal mechanisms underlying policy diffusion, I draw five specific mechanisms from the extant literature: learning, competition, coercion, social contagion, and elite socialization. The concept map in Figure 6.1 attempts to organize the pieces of policy diffusion theory into a single structure. This does not capture the complexity of each piece, but provides a reductive organizational mechanism for keeping track of the different pressures that condition the likelihood and speed of innovation adoption. It not only recognizes the five causal pathways described below, but also internal characteristics of the states and anti-diffusion efforts from outside the state, whereby neighboring states or interests within those states actively work to prevent the spread of a policy (Nelson and Mason 2007). Furthermore, it incorporates the notion of diffusion overload, which occurs when too many options merge with discordant support from in-state interests, resulting in legislative paralysis on a given innovation (Nelson and Mason 2007). Having provided this organizing structure, I now turn to fleshing out the five diffusion mechanisms.
Figure 6.1: Concept map of state policy innovation mechanisms
Learning

Learning is one of the most commonly identified explanations for the diffusion process (e.g., Holyoke et al. 2009; Mooney 2001a). Walker (1969) defined this process in his seminal work and Gray (1973a) provided a useful heuristic for learning with the s-shaped cumulative distribution of adoptions over time. The s-curve demonstrates how learning is largely an incremental process that starts when a small subset of innovative states punctuate the normal equilibrium by testing a new policy (Boushey 2010, 2012). The key to learning is that state legislators are looking for ideas to solve a problem. Given their cognitive and time constraints, political elites use heuristic shortcuts when gathering political and policy information from other states (Karch 2007a). They often have some level of prior information about a policy, so they are essentially updating their priors with new information from selected peers (Meseguer 2005, 2006a, 2006b). While neighboring states are a natural place to start looking for this information (Mooney 2001a), learning is not constrained to a particular geographic area (Karch 2007a).

As time passes, middle and late adopters observe the successes and failures of the policy (Butler et al. 2014; Volden 2006), as well as unwanted political reactions. Learning allows subsequent adopters to either directly emulate the policy (Karch 2007b) or alter it to avoid additional political or policy failure (Glick and Hays 1991; Hays 1996). Of course, learning does not always lead to policy adoption. There can be negative backlash (Mooney 2001a; Nelson and Mason 2007) or avoidance of failed policies (Butler et al. 2014). Fundamentally, learning best captures the ideologically neutral good governance assumption underlying the notion that states are “laboratories of democracy.”
Although the transfer of information can be selective, particularly on ideological grounds (Gilardi 2010; Grossback, Nicholson-Crotty, and Peterson 2004), the federal system affords the opportunity for innovative states to try out a new policy and for hesitant states to follow along after the policy proves practically and/or politically effective.

**Competition**

Policy learning for the sake of solving a problem, however, is not the only reason that states innovate. The American federal system also encourages states to compete for resources including tax revenue, federal incentives, and residents (Baybeck, Berry, and Siegel 2011; Dye 1990; Tiebout 1956). This puts the states in both offensive and defensive positions with respect to each other (Baybeck, Berry, and Siegel 2011). In an offensive position, a state behaves strategically to preempt actions in other states that would place it at a disadvantage. On the other hand, when in a defensive position, states react to finding themselves at a disadvantage. Either way states prospectively or retrospectively react to their peers by adopting innovative policies that confer on them some economic advantage. This reactive behavior manifests in two distinct ways. States either work to entice economically positive elements (e.g., businesses, gamblers, tax payers) to enter or they incentivize the departure of resource draining elements (e.g., welfare recipients). Either way, legislators respond to the *assumption* that these elements
are mobile and willing to move (Tiebout 1956). While evidence does not generally support migration due to welfare benefits (Allard and Danzinger 2000; Berry, Fording, and Hanson 2003; Levine and Zimmerman 1999), legislators may still act in response to this popular narrative.

Competition sometimes leads to a “race to the bottom,” whereby states try to out-reduce each other in areas like welfare benefits, environmental protections, or tax rates (Allard 2004; Bailey and Rom 2004; Berry and Baybeck 2005; Boehmke and Witmer 2004; Peterson and Rom 1989; Rom, Peterson, and Scheve 1998; Schram 1998; Subramanian 2004; Woods 2006). Alternatively, it can also lead to an “arms race” mentality where states raise incentives to either outpace or match those being offered in other states. Movie production incentives offered by over half of the states and many municipalities provide one example of this phenomenon (McDonald 2007, 2011).

**Coercion**

The federal government also plays a coercive role, at times, in promoting particular policy innovations (Welch and Thompson 1980). Furthermore, states use coercive techniques to foster innovation adoption among local governments (Shipan and Volden 2008). Coercion takes the form of direct incentives or sanctions attached to a particular policy. A classic example is the crossover sanction between public health initiatives (e.g., the drinking age) and federal highway funding (Richardson and Houston 2008). In this case, the federal government threatens to reduce a state's highway funding
by 15 percent if it does not set its drinking age to at least 21 years of age. Such incentives serve to broadly increase the relative advantage of an innovation over the current status quo in the states.

Some question whether coercion should be considered a mechanism of diffusion, particularly at the international-level. The argument is that “diffusion implies that there are no central actors coordinating the spread of a policy” (Maggetti and Gilardi Forthcoming). Within the context of the layered American federal system, however, the influence of the federal government on state innovation remains important for diffusion scholars (Boushey 2010, 2012). First, research demonstrates that federal incentives increase the rate and likelihood of innovation adoption (Nicholson-Crotty 2009; Welch and Thompson 1980). Second, and more importantly, federal incentives do not provide uniform coordination of state policy adoption, aside from direct mandates of state action. A useful example of this is the mandated expansion of Medicaid coverage under the Affordable Care Act. The U.S. Supreme Court ruled the mandate unconstitutional, but the federal government still offered to fund any voluntary state expansions at 100 percent for the first three years and at least 90 percent thereafter. This enticed some conservative state governors to participate in the expansion even though their attorneys general sued to overturn it in the courts. The remaining states that refused expansion demonstrate that

---

46 This refers to the National Minimum Drinking Age Act of 1984 (23 U.S.C. § 158).
47 National Federation of Independent Business (NFIB) v. Sebelius (567 U.S. ____ (2012)).
while federal coercion provides an enticement to innovate, the effect is heterogeneous across units. This suggests that, at least in the American context, coercion should be considered a separate mechanism of diffusion and not simply dismissed as if it has a uniform coordination effect on all adopters.

**Social Contagion**

Social contagion is a relatively new development that recognizes the importance of public opinion in a state’s decision to innovate (Pacheco 2012). The theory suggests that opinion change among citizens in one state can spur similar change in surrounding states. In this case, influence spreads through citizen travel, individual social networks, and media coverage in markets that cross state lines. Not all citizens are equally influenced by neighbor state policy (Berry and Baybeck 2005; Sigelman, Lowery, and Smith 1983), but the effect can spread much like a virus – from host to host – until aggregate opinion changes and policymakers take notice (Boushey 2010; Cristakis and Fowler 2009).

**Elite Socialization**

Finally, the least addressed pathway, both theoretically and empirically, is that of elite socialization. This mechanism recognizes that state and local decision makers are also members of social networks (Mintrom and Vergari 1998). These networks develop their own norms and provide rapid communications that shape the spread of innovations (Frank, Zhao, and Borman 2004; McNeal et al. 2003; Mooney 2001a). Research on
citizen social networks suggests that they effectively transmit political information (Huckfeldt, Plutzer, and Sprague 1993; Huckfeldt and Sprague 1995; Sinclair 2012). Additionally, there is evidence in diffusion research that interstate professional organizations foster learning among public officials (Clark and Little 2002). Therefore, it is reasonable to expect that legislators' social networks may not only convey policy and political information, but also the social pressure and norms that accompany such relationships. In fact, Walker (1969) noted that “the constituent units of any federal system are under considerable pressure to conform with national and regional standards or accepted administrative procedures” (891). This is even more so the case in light of the social pressure applied to members of organizations like ALEC and SiX.

The response to conformity pressure is the factor that distinguishes between a true learning process and socialization diffusion. In the case of socialization, state legislators innovate due to pressures to conform to the norms of their network instead of due to the search for the best solution to an acute problem (i.e., policy learning). The distinguishing characteristic between elite socialization and social contagion among the mass public is not the type of person, but the existence of institutions and norms that constrain the behavior of elites, particularly within the legislature. For both elites and the mass public, individuals share information regarding innovations as well as normative information about the appropriate action to take. In the case of elites, however, this sharing is more structured and the scope of information constrained by the characteristics of the organization in which they operate.
Overlap

Before developing a unified theoretical structure for these mechanisms, it is important to recognize that each alone rarely typifies the entire diffusion process for a given policy. Meaning, multiple mechanisms may operate during the spread of a single innovation. For instance, some policies spread via learning first, with laggard states adopting in order to keep up with their peers (Allard 2004; Boehmke and Witmer 2004). There was evidence supporting this in Chapter 4. In other cases, competition among agencies with privatized services can spur diffusion initially, with policy learning occurring in laggard states (Bouché and Volden 2011; Gray 1994). Or, states may compete with each other at first, but slow movers may be forced to emulate others in order to avoid being the last to adopt a policy that becomes broadly popular (Gray 1994). Furthermore, regionalism may mean more at the start of diffusion than later in the process (Mooney 2001a), when positive feedback loops take hold (Boushey 2010). Finally, one mechanism may directly leverage another. For instance, coercion can overlap with competition, as programs like Race to the Top create incentives for states to compete for federal funds within the constraints of the competition guidelines. In fact, learning itself may have a competitive component (Ward and John 2013). The key point is that multiple mechanisms often shape diffusion patterns across time. This makes disentangling them difficult, and suggests the need for drawing clear distinctions between them. That is the purpose of the typology provided here.
A Typology of Diffusion Mechanisms

To begin disentangling the five identified diffusion mechanisms, we first need to define the sorting dimensions that are useful for drawing boundaries between them. In this case, I propose two dimensions: the level of analysis (micro or macro) and the direction of force of new ideas (push or pull) from the perspective of a state's legislators.48

First Dimension: Level of Analysis

The level of analysis refers to whether the mechanism is operating across multiple states (i.e., the macro-level) or across individuals within the states (i.e., the micro-level). For instance, coercion and competition pressures occur at the macro-level because they are top-down or horizontal and felt by all of the states. For example, when the federal government institutes incentives for adopting a policy innovation, those incentives are available to all of the states. This means that the pressure to adopt is applied equally from above. While any given state's reaction to this stimulus is conditional on its internal political, social, and economic environment, the pressure is constant across the states. Likewise, given the fact that states are no longer simply competing with their neighbors, competition pressures often apply across all or nearly all of the states. Returning to the film tax credit example, there is no expectation that North Carolina would adopt such a credit if it were not competing with a peer state – California – that is outside its immediate neighborhood.

48 Special thanks to Chris Zorn for inspiring these two criteria.
In contrast, the other three mechanisms – learning, social contagion, and elite socialization – occur at the micro-level through connections among individuals and thus affect state policy from the bottom up. For instance, legislators seeking to solve a problem search for effective and politically beneficial policies from legislators in other states that share their preferences. They may do this through staff research, but also through discussions at professional organizations (Balla 2001). Likewise, elite socialization occurs through the same social networks, but normative information is being transmitted alongside policy information. This is the fundamental distinction between the two mechanisms. Learning involves a search for policy information, initiated by the legislator or their staff for the purpose of solving a problem, whereas socialization involves external social pressure and the transference of norms of appropriateness alongside policy information. Finally, social contagion occurs at the micro-level within citizen social networks. In this way, policy change results from a grass-roots communication of information and preferences.

**Second Dimension: Push or Pull of Ideas**

The second dimension centers on whether innovations are pushed upon adopters or whether the adopters pull the innovations into their state. For example, federal incentives serve to push ideas upon the states from the top down, whereas, socialization and social contagion serve to push ideas into states from the bottom up. Competition encourages legislators to pull new ideas into their state in so far as they wish to keep up
with their peers. Finally, learning is more of a bottom-up approach to pulling new ideas into a state in order to solve problems.

A useful example of elite socialization is strict voter identification legislation that spread among conservative states from 2005-2012. Tightening voter identification requirements became an important initiative when multiple state governments changed hands from split or Democratic governments to Republican control in the late 2000s and early 2010s (Biggers and Hamner 2011; Hicks et al. 2014), even though there is little evidence that voter fraud is a problem in the United States (Levitt 2007; Minnite and Callahan 2003; Overton 2013). ALEC’s involvement in this policy is widely cited among the media and scholars (e.g., Mayer 2012; Minnite 2013; Weiser and Norden 2011), and there is increasing scholarly clarity on ALEC’s success in achieving its aims (Hertel-Fernandez 2014). Ideological social networking organizations, such as ALEC, not only transmit policy ideas, but also normative information that drives legislator attention to particular ideas. This fosters innovation from the bottom-up as legislators bring the policy and normative information back to their home states. Likewise, citizens are able to push ideas into other states simply through sharing information within their social networks that cross state lines.

On the other hand, learning and competition are primarily driven by legislators seeking to pull new ideas into their states. They turn to learning to find the best available solution for a particular problem. In terms of competition, states often either mimic or outperform their peers in order to maintain a level playing field or gain a competitive advantage. Either way, states pull these ideas from their peers.
Table 6.1 provides a visual representation of the two dimensions and how they sort the five mechanisms of diffusion. The mechanisms are arranged based on the direction of force the states experience (i.e., either push or pull) and whether the mechanism operates primarily at the micro- or macro-level. Additionally, a few policies are included as examples of each mechanism. The micro-push categorization is the only box that presently contains two causal mechanisms. This demonstrates that the categorization is flexible enough that as additional mechanisms are identified, they can be sorted in a meaningful way that distinguishes them from the other mechanisms. I turn now to further developing the elite socialization mechanism and laying the groundwork for experiments that will explicate the behavioral micro-process that motivates it.

**Table 6.1: Categorization of diffusion mechanisms by level of analysis and direction of idea movement**

<table>
<thead>
<tr>
<th>Level of Analysis</th>
<th>Macro</th>
<th>Micro</th>
</tr>
</thead>
<tbody>
<tr>
<td>Push</td>
<td>Coercion</td>
<td>Elite Socialization (Voter ID)</td>
</tr>
<tr>
<td></td>
<td><em>(Drinking age of 21)</em></td>
<td></td>
</tr>
<tr>
<td>Direction</td>
<td></td>
<td>Social Contagion (Public smoking bans)</td>
</tr>
<tr>
<td>Pull</td>
<td>Competition (Lotteries)</td>
<td>Learning (Electric deregulation)</td>
</tr>
</tbody>
</table>
Laying the Foundation for Understanding Elite Socialization

Information and persuasion are perhaps the most important drivers of opinion and behavioral changes in politics, but what has been given far less attention is the role of social pressure. This omission is important because humans have a demonstrated proclivity to conform to their peers when faced with social pressure. Be it in the boardroom or on Facebook, Asch and Sherif’s classic studies hold true today. Individuals conform based on a desire to be “liked” by others, which Asch (1951, 1955, 1956) called compliance (i.e., going along with the majority even if you do not accept their beliefs because you want to be accepted), or a desire to be right, which Sherif et al. (1954/1961) termed private acceptance (i.e., believing that the opinions of others may be more correct or informed than their own). Information-based social influence and normative social influence (i.e., conformity pressure) both play important, albeit distinct, roles in the theories of compliance and private acceptance (see Deutsch and Gerard 1955). In both cases, humans exhibit conformity behavior; however only in private acceptance do they actually update their beliefs due to the social delivery of new information.

Extensions of Asch and Sherif’s path-breaking work have been widely applied across a number of behavioral domains (Berns et al. 2005; Bond and Smith 1996; Deuker et al. 2013; Milgram 1974; Mori and Arai 2010; Walker and Andrade 1996; Yu and Sun 2013), to include topics of interest to political science. For example, significant attention has been focused on the import of conformity on voter turnout and participatory behaviors (Coleman 2004), including the effects of social pressure on the electoral behavior of ordinary citizens (Gerber, Green, and Larimer 2008; Kenny 1992; Klofstad
2007; Knoke 1990; Lake and Huckfeldt 1998; Leighley 1990; McClurg 2003; Sinclair 2012). This body of work points to both the subtle and overt power of social influence on electoral behavior, yet little is known about the import of social conformity for politically charged topics in context-laden circumstances, particularly those that challenge one’s values and opinions.

Testing conformity pressure in the political domain may explicate whether the pressure to align with an otherwise unified group is different when dealing with politically charged topics versus context-free topics such as the size of a line or the movement of a ball of light (see Asch 1955; Sherif 1936). Opinions on politically charged topics, though influenced by social forces (Zuckerman 2005), are complex, value-laden, aligned with cultural norms, and not easily changed (Achen 1975; Alwin, Cohen, and Newcomb 1991; Converse 1964; Jennings and Markus 1984). It remains unknown if the effects of social conformity pressures on political topics, including those tackled by legislative bodies, are conditioned by the personal nature of the locus of pressure.

Social conformity is likely one important motivator of elite political behavior, particularly among those at the state and local level that operate in smaller social environments. In fact, it is unlikely that state legislators or local school board members make decisions in a social vacuum. They are members of social networks that are just as likely to provide them with normative information as they provide policy information. Considering the fact that the decisions of smaller legislative bodies affect the daily lives of citizens more often than those made at the national level, it is important to understand how local and state elites are making decisions and how their peers influence them.
Relying upon observational research, it has proven difficult to untangle if or how social pressure independently affects behaviors given the variegated casual mechanisms, and whether changes in opinion that result from social interaction are due to compliance or private acceptance. This is vitally important for untangling social learning from social conformity, i.e., untangling the learning and elite socialization mechanisms of diffusion. Social conformity is a difficult concept to measure without live interaction. While much has been gained through observational research, even when causal models are specified, the causal relationships are assumed and the specific causal influence of social conformity often remains unknown. Experiments, like those conducted for voter turnout (Gerber and Green 2000; Gerber, Green, and Larimer 2008), provide one means to gain insight into how and why opinion change occurs.

Experimental and observational work, however, proves more challenging with elites. In terms of experiments, it is difficult to get busy lawmakers, even state lawmakers, to participate. As for observational work, this can often require building personal relationships with elites in order to gain access (e.g., Fenno 1978) or waiting until they have retired (Hibbing 1982). An alternative approach to directly studying elites is to perform a series of experiments that flesh out the expected causal mechanism driving elite behavior in order to (1) better understand the mechanism and (2) develop externally observable behaviors that typify the underlying causal mechanism. Laboratory experiments are an important source of new knowledge in the social sciences, especially for studying human behavior (Falk and Heckman 2009), however they are not as often
used in political science. Ultimately, experimental testing of social conformity will help us understand the micro-process of conformity and identify observable indicators of such behavior that will allow researchers to observe elite behavior, or even interview elites, and draw more reliable inferences from their actions and descriptions of policymaking.

The potential for conformity among political elites has important theoretical and normative implications. Broadly, testing conformity pressure in the political domain allows me to examine whether the pressure to align with an otherwise unified group is different when dealing with political opinions versus simple topics like the similarity of a set of lines (Asch 1951, 1955, 1956). Opinions are complex and often not easily changed, thus they offer a useful test of whether the effects of social conformity pressure are conditioned by the personal nature of the locus of pressure. Before laying out the experimental foundation for examining the effects of information and social conformity on individual behavior, I will discuss the extant evidence of the effects of conformity pressure on mass and elite political behavior.

**Evidence of Conformity Pressure in the Mass Public and Beyond**

Analyses of social networks form the backbone of much of the recent research on social influence and political behavior within political science (e.g., Achen 1975). Sinclair (2012) demonstrates that citizen networks convey a bounded set of political information as well as information regarding appropriate norms of political behavior.
Individuals may turn to highly informed peers (Downs 1957; Huckfeldt 2001) or aggregate information from trusted friends and family (Huckfeldt, Johnson, and Sprague 2004) in order to reduce the cost of gathering the information required to engage in political behavior (e.g., voting).

However, political information is not the only type of information transmitted through personal networks. Social pressure helps the network induce compliance with desired social norms (Cialdini and Goldstein 2004; Cialdini and Trost 1998; Scheff 2000). In this case, members of the network provide information regarding the group’s expectations for appropriate engagement in politics. Individuals that are concerned about whether or not the group will continue to accept them therefore conform out of a desire to be liked. Norms are often self-enforcing, with merely the perceived threat of potential sanctions being enough to regulate behavior and induce self-sanctioning (Ellickson 2001; Horne 2001).

The debate over the practicality and reality of deliberative democracy further highlights the importance of understanding the role of political conformity in public and elite discourse. Scholars and theorists argue that political decisions are improved and legitimized under a deliberative process (Cooke 2000; Fearon 1998; Gastil 1993; Habermas 1994, 1996; Rawls 1997, 1999), even though deliberation does not necessarily result in consensus (Cooke 1997). The crux of democratic deliberation is that participants are engaging in a rational discussion of a given political topic, which provides the opportunity for each to learn from the others and thus update their preferences (i.e., out of a desire to be right). It results in a collectively rational enterprise that allows groups to
overcome the bounded rationality of individuals that would otherwise yield suboptimal outcomes. This requires participants to fully engage and freely share the information that they have with the group. Deliberative democracy scholars often hold up citizen juries as evidence that such deliberation improves collective decision-making (Smith and Wales 2000).

Hibbing and Theiss-Morse (2002), however, raise important questions about the desirability of this ideal among the public. Using intensive focus groups, they find that citizens, more often than not, wish to disengage from discussion when they face opposition to their opinions. Instead, they appear averse to participation in politics and instead desire a “stealth democracy,” whereby democratic procedures exist, but are not always visible. In this view, deliberative environments do not ensure the optimal outcome, and can even result in suboptimal outcomes. In fact, the authors point directly to the issue of intra-group conformity (i.e., the desire to be liked) as a culprit for this phenomenon. For example, the coercive influence of social pressure during deliberation is often identified in jury deliberations (Abramson 1994; Kalven and Zeisel 1970) and other small group settings (Verba 1961).

Beyond politics, there is clear experimental evidence of the propensity to conform out of a desire to either be liked or to be right (Cialdini and Goldstein 2004; Crutchfield 1955; Insko et al. 1983; Insko, Sediak, and Lipsitz 1982; Insko et al. 1985; Strickland and Crowne 1962). Using a simple focus group format and pictures of lines, Asch (1951, 1955) demonstrated that individuals would seek the favor of a group of peers by conforming to an opinion that does not match reality. To do this, Asch asked eight members of a group to evaluate two sets of lines. The lines were either clearly identical
or clearly different and group members were asked to identify whether there was a
difference. Unknown to the participant, the seven other group members were
confederates that were trained to act in concert. At a given point in the study, the seven
confederates began choosing the wrong answer to the question of whether the lines were
equal. Consequently, the participant faced social pressure from a unified group every
time they selected their answer. Asch varied the behavior of the group, including the
number of members and number of dissenting confederates. Participants often exhibited
stress and many eventually conformed to the group consensus, even though the group
was objectively wrong.

Using a more complex format – a youth summer camp with real campers – Sherif
et al. (1954/1961) showed that humans also conform to group norms because consensus
suggests that they may have converged on a right answer. In this case, the boys in the
camp quickly coalesced into competing factions and initial outliers in the groups
conformed out of a desire to win competitions (i.e., be right). While the groundbreaking
Robbers Cave experiments revealed a great deal about group behavior well beyond
conformity, I focus specifically on this particular aspect of the findings, which have stood
the test of time in numerous replications and extensions across a wide variety of social
domains (Bohm and Rockenbach 2013; Bonner and Baumann 2008; Bonner, Sillito, and
Baumann 2007; Gaertner et al. 2000; Rabbie et al. 1974; Smith and Postmes 2009;
Tyerman and Spencer 1983).

Kenneth Hardy (1957) extended the Asch and Sherif results to political science
using a similar small-group format with six confederates and one participant focusing on
divorce attitudes. Confederates offered not only their opinions, but also reasons for their
opinions, which provided a methodological innovation by introducing more information than just the confederates’ votes. Hardy’s work provided an important starting point for identifying the micro-process of conformity in the political realm, but it remains limited. He only utilized men in his study and did not allow for repeated rounds of discussion to assess how long participants hold up to conformity pressure.

Anecdotal Evidence of Conformity Pressure and Elite Behavior

Existing research hints at the importance of socialization on legislative behavior. Through interviews with members of Congress, Kingdon (1989) found that fellow legislators provide important cues for voting behavior, but the focus was largely on reducing the cost of gathering information, not the role of social pressure. Additionally, there is evidence that legislators have emotional incentives for their behavior that go beyond personal ambition, including both camaraderie and the desire to be right (Searing 1994). At the state-level, there is anecdotal evidence that such pressure matters both organizationally and personally. Walker (1971) recognized that legislators desire a reputation among their peers both within their states and nationally. Likewise, he noted that “pressures are increasing on even the most isolated and backward states to fall into line with national standards or adopt programs that have gained popularity within developing national professional communities” (1971, 385). It is unlikely that such pressures have subsided since the 1970’s. In fact, the growth of organizations like ALEC likely increased cross-state social pressure, as do the increased engagement of professional organizations for state officials (Balla 2001; Clark and Little 2002).
Furthermore, there is evidence that state and local decision makers are members of social networks (Mintrom and Vergari 1998), which develop their own norms and provide rapid communications that shape the spread of an innovation (Frank, Zhao, and Borman 2004; McNeal et al. 2003; Mooney 2001a).

Individual legislators have also pointed to the importance of interpersonal relationships and socializing in lawmaking. For instance, former Oklahoma state representative Betty Boyd noted that after-hours social events are where legislators do their “off-the-cuff talking and a lot gets done there amazingly enough” (Finchum 2007, 15). Furthermore, former Washington state senator Lorraine Wojahn noted multiple instances of legislators changing their minds, often at a late hour and after countervailing pressures by colleagues, when discussing her time in the senate. Often, such persuasion happened off the Senate floor. In fact, in reference to floor debate, Senator Wojahn pointed out how “the longer they talked, the madder I would get. They talk a bill to death” (Kilgannon 2010, 307).
In one particularly telling story, former Oklahoma state representative Helen Arnold highlights the effect of social pressure. She tells the story of the debate over passing the Equal Rights Amendment (ERA) in the Oklahoma House. Arnold was a Democrat who supported the ERA and she is discussing two other representatives, C.H. Spearman (D) and James Inhofe (R):

Well, it was still there but everybody had changed their position. The first debate we went over there, I remember the League went over and testified for the ERA, and Spearman – have you heard of him? He was from Edmond, and he was just adamantly against the ERA. After we testified, he changed his mind. But at the same time, Jim Inhofe was for the ERA and when they got ready for the first vote, he changed his mind. There was no rhyme or reason. It was just sort of like somebody got to them. I mean, some person they knew said, ‘Oh, this is a bad idea. Forget it.’ Or, ‘This is a good idea. You ought to change your mind.’ (Finchum 2008, 17).

The source of pressure is not apparent, but it is clear that both representatives changed their position before final voting. In fact, Representative Spearman changed first because of newly acquired information (a desire to be right), and then may have changed the second time because of social pressure (a desire to be liked or respected). Granted, the source is unclear, but Representative Arnold clearly believes it was other people that “got to” the representatives.

One final piece of anecdotal evidence comes from ALEC. ALEC’s model of influence is to develop model legislation and then promote the introduction of that legislation by its state legislator members. Thus, they are relying on their own social network, as well as the social network of those members, to promote diffusion of their model bills. John Nichols is a reporter for The Nation magazine that has reported
extensively on ALEC (e.g., Nichols 2011). In a 2014 interview, Nichols said the following:

“And across the country -- heard a tremendous number of complaints, often from liberal legislators and Democrats, but also from some conservatives, who say, look, it used to be that we could come here and have a real dialogue. We could have a real debate about issues and somebody on the left, somebody on the right. But now there's a rigidity to it. There's these model pieces of legislations. There's sort of a pressure to fit into a playbook. And I think it's incredibly damaging. I do not think it's just about Democrat and Republican or left and right. I think it is about creating a circumstance where citizens have less say with their legislature – legislators at times than do corporations that are very distant and very delinked from the state” (Rehm 2014).

This, coupled with recent evidence that ALEC is especially successful in having its model legislation adopted in states with less professionalized legislatures (Hertel-Fernandez 2014), underscores the importance of understanding the role of social influence on elite behavior.

**Variation in Conformity Behavior and Expectations for the Experiment**

While my primary interest is in identifying the average effects of information and conformity pressure on opinion change, I nevertheless recognize that there is variation in humans’ responses to social pressure, depending on observed and unobserved individual characteristics. Thus the average treatment effect recovered can mask substantively important heterogeneity (Imai and Ratkovic 2013; Imai and Strauss 2011). For instance, not all of Asch’s or Hardy’s subjects complied with group opinion and there was a great deal of variation in how willing Sherif et al.’s summer camp participants coalesced into cohesive and functioning groups. In order to address this possibility I also include

\[49\] Bold added for emphasis.
measures of three factors that have been previously identified as covarying with the
average propensity to conform: personality traits, self-esteem, and ideology.

The most consistent evidence points towards those who change their opinions as
being generally more agreeable, neurotic, and having lower self-esteem (Herringer 1998).
Generating hypotheses regarding the import of other personality and ideological
dispositions on opinion change for political, moral and identity-laden topics is more
complicated. Extant research indicates support for both stability and change for these
traits and differs in the source of that change, i.e., whether it is informational or social.
For example, on the one hand conservatives may be more likely to conform to the group
overtly, given extant studies showing conservatives think less negatively toward
conformity and comply more often to group pressure and norms (Cavazza and Mucchi-
Faina 2008; Mann 1959; Sistrunk and Halcomb 1969). In addition, conservatives are also
higher on the Conscientiousness personality trait, and this trait both reflects and is related
to more conformist behavior (DeYoung, Peterson, and Higgins 2002; Digman 1990;
Roccas et al. 2002).

On the other hand, conservatism, by definition, advocates the status quo and is
related to authoritarianism, resistance to change, and greater refusal to privately accept
new information, specifically if that information contradicts one’s values (Ehrlich and
Lee 1969; Lavine, Lodge, and Freitas 2005), leading to a greater likelihood of internal
stability. In a similar manner, those high in openness, while more likely to take in new
information, and thus possibly more likely to privately accept it, are also less prone to
restrictive conformity, and thus possibly less likely to conform publically (Dollinger, Leong, and Ulicni 1996). I treat these propositions as secondary hypotheses, and explore their import in a limited manner given restrictions in the data.

**Study Design**

Given the difficulty in recruiting elites to participate in experimental research, and the fact that social conformity experiments, writ large, have not been well extended into the political domain, it is necessary to begin examining the causal micro-process underlying conformity behavior in another population. In fact, the very first step is designing an successful experiment in which the treatment of social pressure results in a conformity response. That is what is accomplished here. I present a design and initial results for testing the causal micro-process underlying social conformity behavior in the political domain. I will conclude with future avenues for this particular strain of research.

In order to explicate the independent and joint effects of compliance and private acceptance, I designed an experiment that places participants in a deliberative environment where they face unified opposition to their expressed opinion on a political topic that is relevant to their local community. Instead of a single round of discussion, however, the group discusses the topic for approximately 30-45 minutes, allowing us to assess participant behavior and opinion change throughout the discussion. Furthermore, I assess participants’ privately-held opinions, absent the group, again at the end of the treatment in order to determine whether those who expressed a change in opinion during
the discussion only did so verbally in order to comply with the group and gain acceptance or if they privately accepted the group’s opinion and truly updated their own values.

In designing the experiment, I leveraged a unique time in Penn State’s history, the aftermath of the Jerry Sandusky child abuse scandal and the firing of longtime Head Coach Joe Paterno. The firing provided an ideal topic of discussion that exhibited high salience on campus, was politically charged, and connected to the participants’ identities as Penn State students. The question posed to my participants was whether or not they felt that Coach Paterno should have been fired by the University’s Board of Trustees in November 2011. Previous research demonstrates that undergraduates may not have as clearly defined political attitudes as adults and thus may be more susceptible to conformity pressure from peers (Sears 1986). This informed my choice of the discussion topic, as it is not only highly salient on the Penn State campus, but typically invokes strong and diametrically opposed opinions in the undergraduate population and the general Penn State community. I begin by providing some background on this issue.

**Firing of Penn State Football Head Coach Joe Paterno**

The first week of November 2011 was a whirlwind for students at Penn State. Police arrested former defensive coach Jerry Sandusky on charges of child sexual abuse following the release of a grand jury report by the Pennsylvania Office of the Attorney General. In the midst of a national media firestorm and with evidence mounting that the University President, Athletic Director and Head football Coach had been aware of Sandusky’s activities, Penn State President Graham Spanier resigned and the Board of
Trustees relieved Paterno of his duties on November 9. They also placed the Athletic Director, Tim Curley, and Vice President, Gary Schultz, on administrative leave after being indicted for perjury regarding their testimony about their knowledge of Sandusky’s sexual assaults of young boys. Immediately after the firings and suspensions, students poured into campus and downtown State College, causing some damage and flipping a news van (Viera 2011). Various student protests persisted for weeks. The following summer brought Sandusky’s conviction, but controversy has not subsided, especially in Pennsylvania. The firing continues to be a topic of conversation, as lawsuits against the university and the trials of Spanier, Curley, and Shultz continue to progress and as Paterno’s family and supporters seek to restore his legacy.

While the real-life context of our design adds its external validity, the discussion topic’s high salience and likelihood of evoking a strong opinion also improves the internal validity of the experiment. Paterno was more than an employee; he was a symbol of Penn State and thus tied to students’ identities as members of the community. Given the emotion surrounding this issue, it is not unlike morality policies that evoke strong responses from individuals (Mooney 2001b), thereby providing a hard test of conformity pressure on value-laden opinions. There is no better example of this than the ongoing pursuit of justice by the children subjected to abuse by Catholic priests and the mounting evidence of systematic concealment and enablement of such abuse by the Catholic Church. In this regards, the similarities between Penn State and the Church persist on
nearly every level, including the scandals threatening an important aspect of its members’ identities. In this way, the experience of students following the child abuse scandal at Penn State generalizes to politically relevant circumstances where organizational power and personal identities are challenged.

In addition to being a highly salient topic of discussion, the Paterno firing is a politically charged, if not explicitly political, issue. It weighed heavily on the 2012 Board of Trustees elections, when many candidates campaigned on their support for Paterno. Furthermore, Pennsylvania Governor Tom Corbett is a de facto member of the Board and originally launched the Sandusky investigation while serving as the state Attorney General. As a board member, Corbett advocated for Paterno’s firing and faced both praise and criticism across the Commonwealth. As a result of the scandal, Pennsylvania passed legislation that clarifies responsibilities for reporting child abuse and heightens penalties for failures to report. The abuse also received national recognition. When asked for his reaction to the firing, President Obama called on Americans to search their souls and to take responsibility for protecting children (CBS 2011). Thus, the topic has personal importance, is identity laden, and politically relevant at the local, state, and national-levels. Thus, it provides a hard test of conformity pressure. Having described the topic used for the discussion groups, I will now turn to explaining the experimental design.
Participant Recruitment

The experiment was advertised as a study on political discussion in upper- and lower-level political science courses, as well as through campus fliers and a university research website. As an incentive, participants were entered into a raffle for one of eight $25 gift cards to Amazon. The first participants completed the study in May 2013 and data collection closed in December 2013. A total of 58 students participated in either the treatment or control groups. Compared to observational studies, this may appear a small number, but it comports with current research norms that require high participant involvement and a substantial amount of their time (Keppel and Wickens 2004; Tversky and Kahneman 1971) and is consistent with the sample sizes for the foundational work in this area (Asch 1955; Bond and Smith 1996). The pre- and post-test, discussion session and debriefing required at least 1.5 hours of each participant’s time. Researchers spent, on average, at least four hours per participant recruiting, coordinating, and scheduling discussion groups, running discussion sessions, and coding behavioral data. The study generally targeted current undergraduates, but three graduate students and one recent graduate also participated. Upon expressing interest in the study, participants were randomly assigned to either the treatment (n=34) or control (n=24) group using a coin flip.

50 There were no major developments in the Sandusky scandal during the data collection phase, thus I believe that no outside events threaten the internal validity of the study. The firing of the four university officials, Coach Paterno’s death, Jerry Sandusky’s conviction, issuance of the Freeh Report, and the National Collegiate Athletic Association’s sanctions all occurred prior to the start of data collection.

51 See Appendix I for additional information.
Pre-test survey

The treatment and control groups were administered a pre-test survey using Qualtrics. For the treatment group, the survey was completed prior to attending a discussion session. In addition to basic demographic characteristics, I collected a number of psychological and behavioral traits for every participant. Ideology was measured by a modern version of the Wilson and Patterson (1968) Liberalism-Conservatism scale - an attitudinal measurement of ideology widely used to prevent measurement error that arises from the difficulty in accurately collapsing a complex view of politics into a single dimension. This measure of ideology is well validated (e.g., Bouchard et al. 2003) and serves as the basis for modern definitions of ideology across disciplines (Everett 2013; Milas, Mlačić, and Mikloušić 2013). The measure relies on respondents simply agreeing or disagreeing with a broad range of political and social topics, from evolution to taxes. In this case, I used 48 different topics, which generate an additive scale of conservatism ranging from 0 (very low) to 48 (very high).

In addition to measuring my participants’ political ideology, I assessed their self-esteem through ten statements (e.g., “I feel that I am a person of worth, at least on equal plane with others”) and asked the respondent to indicate the extent to which they agree with each (Rosenberg 1965). Personality was measured with McCrae and John’s (1992) 44-question Big 5 dimensions of personality: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism.

---

52 In fact, the two measures are highly, but not perfectly, correlated ($r = 0.73, p < 0.001$).
Finally, all participants were asked their opinion on five policies that affect undergraduates at Penn State: alcohol possession on campus; government oversight of academic performance; the firing of Paterno; prevention of State Patty’s Day celebrations; and use of the student activities fee. Participants recorded their opinion using a five-point Likert scale from “strongly agree” to “strongly disagree.” I included five different topics on the survey so that treatment group participants would be unsure as to which topic they would be discussing.

**Discussion Group**

In addition to the online survey, participants in the treatment group were scheduled individually for a discussion session. Each discussion group was comprised of a single participant and two, three, or four trained confederates. Five confederates, three females and two males, were used across the length of the study. Among them were four political science Ph.D. candidates of varying experience and one recent graduate who majored in political science. The confederates looked young and dressed informally, like undergraduate students. In terms of training, the confederates were not strictly scripted so that the discussion would not appear forced or scripted. Instead, myself and the other confederates took part in pre-experiment tests as mock participants so that they could argue both sides of the Paterno firing and develop consistent points used for the duration of the study (see Appendix G and Appendix H). Figure 1 shows a typical discussion session. Discussion sessions were held in a small room with all of the group members sitting around a table. There was no fixed seating arrangement.

53 For more information on the use of deception in this study, see Appendix J.
At the beginning of each discussion session, I reminded the group that the general purpose of the experiment is to understand political decision-making and how individuals form political opinions. They were told that a topic was randomly selected for each discussion group from the five included in the pre-test survey, with their topic being the firing of Paterno. Prior to the start of open discussion, group members were provided a sheet of excerpts from the Freeh Report (2012) regarding Paterno's involvement in the Sandusky scandal at Penn State (see Appendix F). They were told that the information was drawn from independent investigations and was meant to refresh their memories, given that two years had passed since the firing.
After providing time to read the information sheet, the group was polled verbally regarding whether or not they believed Paterno should have been fired (yes or no). Though the order appeared random, the participant was always asked to answer first. This allowed the confederates to subsequently express the opposite opinion throughout the discussion. Though very little time passed between completion of the pre-test surveys and participation in the discussion groups, I did not rely on the opinions expressed in the pre-test surveys as the basis of the confederates’ opinion. I wanted to be sure they were responding to the precise opinion held by the participant at the start of the discussion session. This way I could track the effect of conformity pressure on their opinion throughout the session.

The group was then provided 30 minutes for open discussion; however, discussion was allowed to go beyond 30 minutes in order allow participants to finish any thoughts and reflect a more natural interaction. During this discussion, the four confederates consistently argued the opposition position to greater or lesser degrees, including responding to and interacting with the participant and even agreeing with the participant on certain points. At the conclusion of the discussion time, group members were told that researchers wished to understand their true opinion at that moment and that I would be aggregating the individual opinions from the groups in order to gain a sense of overall student opinion on each of the five topics. Thus, they were instructed to complete an anonymous ballot with their final opinion. The anonymous ballot allowed me to measure whether their opinion had actually changed during the discussion, conforming to other people’s behavior due to private acceptance that what they are saying is right, or were only publically complying to other people’s behavior, without necessarily believing
in what they are doing or saying. Furthermore, each discussion session was video recorded for the purposes of coding both verbal and non-verbal indications that they changed their opinion. The combination of anonymous balloting and video recording for verbal cues is an important aspect of the study design that allows us to pull apart whether participants conformed out of a desire to be right, liked, or a combination of the two. Finally, I debriefed each participant to gather information about their personal feelings on being in the minority during the discussion.

**Control Group**

I utilized a control group in order to identify the independent effect of social pressure on opinion change. Their behavior established a baseline expectation for the amount of opinion change I could expect with just the introduction of new information and no interpersonal interaction. This baseline then allows me to compare the two groups, social influence treatment and control, in order to tease apart the independent and joint effects of social conformity pressure and information on opinion change.

To this end, the control group took the same pre-test survey as the treatment group. However, at the end of their survey, control group participants were asked to read additional information on a topic that was randomly selected from the five opinion questions. Based on their opinion regarding the firing of Paterno, I presented them with the same sheet of information provided to the treated as well as a summary of counter-arguments used by the confederates during the discussion group sessions (see Appendix F, Appendix G, and Appendix H). After reading these screens, control group participants...
were asked whether they believe Paterno should have been fired (yes or no) and the strength of that opinion. If they changed their opinion at this juncture, they did so only because of the introduction of new information, as there is an absence of social pressure. Thus, my design allows me to parse out the effect of the discussion group and the social pressure emerging from an unanimity of opinion opposite to the participants.

Results

The core finding of this study revolves around the question to what extent will people conform to an opposing opinion on a topic that is salient, politically charged, and informs some aspect of their identity? Furthermore, can I evoke deviation rates similar to the foundational studies that relied on less complex aspects of one’s psychology (Asch 1951)? And most important, what type of change is occurring? For those participants who changed their opinions, was it due to new information (i.e., private acceptance), social pressure (i.e., public compliance), or some combination of the two? To answer these questions, I first examined the degree of opinion change in both the treatment and control groups. Figure 6.3 displays the percentage of each group that did and did not change their opinion. Within the control group, which received the same information as the discussion group, but had no social interaction, only 8 percent of the participants changed

---

54 For the control group, I compared their initial opinion from the pre-test survey with the opinion they provided after reading the information sheet and counter-arguments.

55 See Appendix L for a further breakdown of these changes.
their opinion. The significance of the information-based change I observed is consistent with extant research (Druckman 2005; Gilens 2001). In addition, though a large proportion of the control group did not change their opinion, many did moderate it (i.e., strengthened or weakened) based on the receipt of new information alone.

**Figure 6.3: Discrete change of opinion in control and treatment groups**

Turning to the treatment group, 38 percent of my treated participants changed their opinion between the initial vote (after receiving information and prior to the discussion) and the final secret ballot. Even with the more complex, identity-, and value-laden topic, my findings comport remarkably close to the deviation rates of Asch (1955)
and those that follow (for a meta-analysis see Bond and Smith 1996). If all other things are considered equal, the 30 percent increase in opinion change is dependent on the treatment of participating in the group discussion ($\chi^2 = 5.094, p < 0.05$). Meaning, social pressure and/or the personal delivery of information, as opposed to simple exposure to new information, has a profound influence on either true opinion change through private acceptance or conformity through public compliance.

My research design also allows me to parse out the specific sources of change within the treatment group. Recall I accounted for both true opinion change (i.e., the anonymous ballot at the end of discussion) and verbal opinion change (i.e., declared opinion change during group discussion captured in video and coded by independent raters) for those in the treatment condition. Therefore, I divide those in the treatment group into four subgroups in order to better understand why they changed their opinion. Table 6.1 shows the percentage of treated participants that did not change their opinion overtly or covertly (no change) or changed it out of a desire to be liked (change overtly, but not covertly), a desire to be right (change covertly, but not overtly), or a combination of the two (change covertly and overtly). In sum, 47 percent of participants did not change their opinion in the final balloting and did not appear to change it during the discussion. However, ten percent of treated participants changed their opinion due to public compliance through their expressed verbal statements, out of a desire to be liked by the group, but did not actually change it in the final balloting.
Table 6.2: Percentage of treatment group participants that changed their opinion due to a desire to be liked, right, both, or did not change

<table>
<thead>
<tr>
<th></th>
<th>Desire to be liked (change overtly, but not covertly)</th>
<th>Desire to be right (change covertly only)</th>
<th>Both (change overtly and covertly)</th>
<th>No change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10 percent</td>
<td>10 percent</td>
<td>33 percent</td>
<td>47 percent</td>
</tr>
</tbody>
</table>

Furthermore, ten percent of the treatment group changed their final opinion, but did not appear to do so during the discussion session. Thus, their change was due solely to private acceptance. One of these participants went so far as to tell me that he agreed with the group but adamantly refused to agree openly. These participants were swayed by the introduction of new information out of a strong desire to be right, but did not want to look like they were changing their opinion. Finally, 33 percent of the treated participants changed their opinion in the final ballot and also verbally and visually signaled that change during the discussion. They were influenced by some combination of these two desires. Thus, my first set of analyses confirms that information plays an important role in opinion change, but social pressure also has a substantive effect. For even a topic so important to one’s identity, participants changed their previously held opinions.

**Psychological Differences**

Having established the main findings of the study and the relative import of the two causal mechanisms for why participants changed their opinion, I now turn to examining how underlying traits, including ideology, personality, age and sex, differ between those that changed their opinion and those that did not. First, I assess differences between pro- and anti-firing participants. Second, I examine the relationship between
direction of opinion change and trait differences between participants that changed their opinion and those that held firm. Due the nature of the experiment and specific focus on the question of causality, these tests are secondary to the main findings in the paper. For the following analyses, the sample sizes are small in some cases and the findings only speculative.

Across both the treatment and control groups, the pre-test survey showed almost two-to-one support for Paterno keeping his job (i.e., against the firing). As mentioned earlier, “JoePa” was not only a symbol of Penn State, but also an icon to its students, and to some degree seen as a reflection of them. Table 6.3 displays the average demographic and psychological measures for those for and against the firing, based on the pre-test survey. Interestingly, the only statistically significant difference between the groups is their political ideology. The group opposed to Paterno’s firing is, on average, more conservative in their attitude positions than those that called for his firing. It is important to note that these are college students, and thus the overall distribution of ideology exhibits a liberal skew. However, Figure 6.4 demonstrates that the pro-firing group is not only less conservative, on average, but is also more ideologically narrow, whereas those that did not support the firing are more conservative, but also drawn from a wider ideological span. This finding suggests that ideology is a substantial factor for individuals that supported the firing. Whereas support for Paterno may have a less pronounced ideological dimension, those supporting his firing may focus more narrowly on the issue of child abuse and the responsibility of those in leadership to protect vulnerable citizens.
Given that ideology is the only difference I could identify among participants’ initial opinion, I next examined whether there were differences between participants who changed their opinion and those that did not.

**Figure 6.4: Distribution of conservatism for pro- and anti-firing groups of participants**

![Kernel Densities of Conservatism for Pro- and Anti-Firing Groups](image-url)
Table 6.3: Comparison of participants who indicated support or opposition for the firing of Paterno in their pre-test survey, including t-tests

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pro-Firing Mean</th>
<th>Anti-Firing Mean</th>
<th>Difference [95% Conf. Int.]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>22.85 (4.71)</td>
<td>22.10 (2.02)</td>
<td>0.75 [-2.16, 3.66]</td>
</tr>
<tr>
<td>Male†</td>
<td>0.54 (0.53)</td>
<td>0.55 (0.51)</td>
<td>-0.01 [-0.34, 0.32]</td>
</tr>
<tr>
<td>School Year</td>
<td>3.46 (1.27)</td>
<td>3.45 (1.34)</td>
<td>0.01 [-0.87, 0.90]</td>
</tr>
<tr>
<td>Conservatism</td>
<td>10.54 (6.68)</td>
<td>16.42 (9.06)</td>
<td>-5.88** [-10.92, -0.85]</td>
</tr>
<tr>
<td>Self-Esteem</td>
<td>31.38 (6.05)</td>
<td>28.61 (6.46)</td>
<td>2.77 [-1.44, 6.98]</td>
</tr>
<tr>
<td>Extraversion</td>
<td>18.85 (6.40)</td>
<td>20.94 (5.62)</td>
<td>-2.09 [-6.35, 2.17]</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>26.62 (5.81)</td>
<td>24.90 (5.62)</td>
<td>1.72 [-2.17, 5.60]</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>26.00 (4.18)</td>
<td>25.71 (3.76)</td>
<td>0.29 [-2.51, 3.09]</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>12.77 (6.48)</td>
<td>12.13 (6.27)</td>
<td>0.64 [-3.76, 5.04]</td>
</tr>
<tr>
<td>Openness</td>
<td>28.08 (2.63)</td>
<td>26.97 (3.83)</td>
<td>1.11 [-0.93, 3.15]</td>
</tr>
<tr>
<td>Observations</td>
<td>13</td>
<td>31</td>
<td></td>
</tr>
</tbody>
</table>

** entries indicate significant t-tests, \( p < 0.05 \), * if using a \( p < 0.10 \) benchmark

†Difference in proportions test used for Male

Table 6.4 presents the means for the key demographic and psychological characteristics of participants that changed their opinion and those that did not. I find evidence both supporting and refuting the hypotheses presented above. There are significant differences (\( p < 0.05 \)) between these groups in conservatism, conscientiousness, and neuroticism, suggesting that these three traits are primarily driving the overall mean shift demonstrated above. Participants that changed their opinion are, on average, less conservative and less conscientious than those that stood their ground. However, they are more neurotic, which conforms to the general expectations regarding
neuroticism. Additionally, using a more relaxed benchmark for significance \((p < 0.10)\), which may be appropriate given the sample size, there is evidence suggesting that opinion changers, on average, also have lower self-esteem. These results demonstrate that individual differences exist across individuals that change their opinion and those that do not. Additional research with larger numbers of participants will be required to confirm these findings. They are, however, in line with expectations derived from past research and point to useful areas of future inquiry.

**Table 6.4: Comparison of participants in both treatment and control conditions who changed their opinion, including t-tests**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Change Mean (St. Dev.)</th>
<th>No Change Mean (St. Dev.)</th>
<th>Difference [95% Conf. Int.]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>21.80 (2.14)</td>
<td>22.69 (3.39)</td>
<td>-0.89 [-2.43, 0.65]</td>
</tr>
<tr>
<td>Male†</td>
<td>0.40 (0.51)</td>
<td>0.53 (0.50)</td>
<td>-0.13 [-0.42, 0.15]</td>
</tr>
<tr>
<td>School Year</td>
<td>3.27 (1.75)</td>
<td>3.60 (1.33)</td>
<td>-0.33 [-1.37, 0.70]</td>
</tr>
<tr>
<td>Conservatism</td>
<td>9.80 (5.28)</td>
<td>16.00 (8.93)</td>
<td>-6.20** [-10.09, -2.31]</td>
</tr>
<tr>
<td>Self-Esteem</td>
<td>27.33 (5.38)</td>
<td>29.63 (6.64)</td>
<td>-2.30 [-5.81, 1.22]</td>
</tr>
<tr>
<td>Extraversion</td>
<td>19.87 (3.96)</td>
<td>21.28 (6.22)</td>
<td>-1.41* [-4.24, 1.41]</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>27.07 (4.10)</td>
<td>25.70 (5.60)</td>
<td>1.37 [-1.39, 4.13]</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>24.07 (3.47)</td>
<td>26.33 (3.87)</td>
<td>-2.26** [-4.46, -0.06]</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>15.73 (6.60)</td>
<td>11.77 (5.49)</td>
<td>3.96** [0.02, 7.91]</td>
</tr>
<tr>
<td>Openness</td>
<td>28.13 (3.25)</td>
<td>26.93 (3.63)</td>
<td>1.20 [-0.86, 3.26]</td>
</tr>
<tr>
<td>Observations</td>
<td>15</td>
<td>43</td>
<td></td>
</tr>
</tbody>
</table>

** entries indicate significant t-tests, \(p < 0.05\), * if using \(p < 0.10\) benchmark
†Difference in proportions test used for Male
Behavioral Differences

Moving beyond dispositional differences, I am also interested in differences in non-verbal behaviors, which often provide information individuals seek to suppress and hide. Asch (1955; 1951), Sherif et al. (1954/1961), and Hardy (1957), all noted the agitated state that their conformity experiments often induced in participants. This experiment confirmed such behavior in a political context, thus reinforcing the notion that participants were experiencing pressure when discussing this issue with their peers. Faces reddened, voices rose, and some students withdrew entirely. Some participants shook their knees under the tables, while others withdrew into closed-off postures. Milgram (1974) noted the tendency of some participants to laugh during very stressful moments in his obedience experiments. In this case, multiple participants made jokes to break tension during the discussion. For example, one participant said, “What? Well now I feel awkward,” after everyone expressed their initial opinions. I video recorded this behavior, and explore in it greater detail below.

Participants were asked during the debriefing how they felt about being the only dissenting voice. Forty-seven percent of the treatment group participants freely offered that they felt pressure or felt intimidated. Twenty-nine percent also freely said that they felt like they had to dig in and defend their position during the discussion. This included six people that ultimately changed their minds. One said, “I’m not getting any support in this room. Alright I’ll defend my own position.” Another said, “I feel extra pressure to explain myself.” For some, their defensiveness continued into the debriefing. In particular, some students that did not change their opinion continued defending
themselves when talking one-on-one with the experimenter. They were unable to fully answer the questions about their feelings during the discussion and, instead, focused on reiterating their talking points. This demonstrates that some participants are put on the defensive when faced with a unified opposition. Of those that expressed feeling defensive, some dug in deeply and did not budge at all, while others opened up to the influence of their peers as the discussion progressed.

Given the behavioral findings in Asch, Milgram, and others, I expected participants that changed their opinion to exhibit systematic differences in behavior compared to those that did not. Table 6.5 compares the behavioral measures for the dichotomy of opinion change or no opinion change. Opinion changers tended to be less engaged in the discussion. They responded less often, raised their voice less when speaking, made less eye contact when listening, and exhibited less negative body language. While this could signal disengagement from the group, these could also be signs that opinion changers are doing the cognitively intensive work of processing new information and updating their prior knowledge. It does provide evidence that opinion changers experienced social pressure similar to participants in Asch, Sherif, and Hardy’s experiments. These physical signs are more difficult to hide than free responses during a debriefing.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Change Mean Mean</th>
<th>No Change Mean Mean</th>
<th>Difference Mean</th>
<th>[95% Conf. Int.]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(Stan. Dev.)</td>
<td>(Stan. Dev.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Responses</td>
<td>0.14 (0.13)</td>
<td>0.32 (0.30)</td>
<td>-0.18**</td>
<td>[-0.34, -0.01]</td>
</tr>
<tr>
<td>Questions</td>
<td>0.22 (0.23)</td>
<td>0.34 (0.30)</td>
<td>-0.12</td>
<td></td>
</tr>
<tr>
<td>Pejoratives</td>
<td>0.06 (0.17)</td>
<td>0.15 (0.26)</td>
<td>-0.09</td>
<td></td>
</tr>
<tr>
<td>Jokes</td>
<td>0.15 (0.26)</td>
<td>0.21 (0.27)</td>
<td>-0.06</td>
<td></td>
</tr>
<tr>
<td>Raised Voice</td>
<td>0.01 (0.04)</td>
<td>0.17 (0.30)</td>
<td>-0.16**</td>
<td>[-0.31, -0.01]</td>
</tr>
<tr>
<td>Positive Body</td>
<td>0.56 (0.30)</td>
<td>0.57 (0.32)</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td>Language</td>
<td>0.13 (0.10)</td>
<td>0.25 (0.23)</td>
<td>-0.12*</td>
<td></td>
</tr>
<tr>
<td>Negative Body</td>
<td>0.47 (0.28)</td>
<td>0.66 (0.21)</td>
<td>-0.19*</td>
<td>[-0.38, 0.01]</td>
</tr>
<tr>
<td>Language</td>
<td>0.46 (0.20)</td>
<td>0.60 (0.26)</td>
<td>-0.14</td>
<td></td>
</tr>
<tr>
<td>Hand Gestures†</td>
<td>0.85 (0.38)</td>
<td>0.88 (0.33)</td>
<td>-0.03</td>
<td>[-0.29, 0.21]</td>
</tr>
<tr>
<td>Anger†</td>
<td>0.00 (0.00)</td>
<td>0.12 (0.33)</td>
<td>-0.12</td>
<td>[-0.27, 0.04]</td>
</tr>
<tr>
<td>Observations</td>
<td>13</td>
<td>17</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

** entries indicate significant t-tests, $p < 0.05$, * if using a $p < 0.10$ benchmark
†Difference in proportions test used for Hand Gestures and Anger

I now turn to breaking the change group down into those that changed overtly out of a desire to the liked, covertly out of a desire to be right, or both. The nature of discussion experiments that require an hour or more of a subject’s time, however, typically have low numbers, making it difficult to make firm conclusions about some differences between these groups. As the treatment group is further divided, I lose the power to identify some statistical differences. However, there is interesting suggestive
evidence and I can still see whether a group falls above or below the baseline group (i.e., those that did not change their opinion) for a given behavior. In Table 5, each of the subgroups that changed their opinion is compared to the group that did not.

Table 6.6: Difference in means for behavioral variables in each category of opinion change using no opinion change as the baseline

<table>
<thead>
<tr>
<th>Variable</th>
<th>Liked, only Difference</th>
<th>Right, only Difference</th>
<th>Both Difference</th>
<th>No Change Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[95% Conf. Int.]</td>
<td>[95% Conf. Int.]</td>
<td>[95% Conf. Int.]</td>
<td>(St. Dev.)</td>
</tr>
<tr>
<td>Responses</td>
<td>0.16</td>
<td>-0.10</td>
<td>-0.16</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>[-0.73, 1.06]</td>
<td>[-0.31, 0.10]</td>
<td>[-0.34, 0.03]</td>
<td>(0.29)</td>
</tr>
<tr>
<td>Questions</td>
<td>0.18</td>
<td>-0.05</td>
<td>-0.10*</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>[-0.84, 1.20]</td>
<td>[-0.34, 0.24]</td>
<td>[-0.33, 0.13]</td>
<td>(0.27)</td>
</tr>
<tr>
<td>Pejoratives</td>
<td>-0.13</td>
<td>0.03</td>
<td>-0.16*</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>[-0.31, 0.07]</td>
<td>[-0.71, 0.78]</td>
<td>[-0.32, 0.01]</td>
<td>(0.28)</td>
</tr>
<tr>
<td>Jokes</td>
<td>0.02</td>
<td>0.09</td>
<td>-0.10</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>[-0.53, 0.57]</td>
<td>[-1.10, 1.28]</td>
<td>[-0.29, 0.09]</td>
<td>(0.28)</td>
</tr>
<tr>
<td>Raised Voice</td>
<td>0.15</td>
<td>-0.11</td>
<td>-0.15*</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>[-0.53, 0.85]</td>
<td>[-0.30, 0.09]</td>
<td>[-0.31, 0.03]</td>
<td>(0.30)</td>
</tr>
<tr>
<td>Positive Body</td>
<td>0.35**</td>
<td>0.06</td>
<td>0.06</td>
<td>0.50</td>
</tr>
<tr>
<td>Language</td>
<td>[0.07, 0.64]</td>
<td>[-0.77, 0.87]</td>
<td>[-0.21, 0.32]</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Negative Body</td>
<td>0.01</td>
<td>-0.02</td>
<td>-0.14**</td>
<td>0.25</td>
</tr>
<tr>
<td>Language</td>
<td>[-0.55, 0.51]</td>
<td>[-0.31, 0.25]</td>
<td>[-0.29, -0.01]</td>
<td>(0.23)</td>
</tr>
<tr>
<td>Eye Contact:</td>
<td>0.13</td>
<td>-0.01</td>
<td>-0.20*</td>
<td>0.63</td>
</tr>
<tr>
<td>Listening</td>
<td>[-0.04, 0.30]</td>
<td>[-0.19, 0.16]</td>
<td>[-0.45, 0.04]</td>
<td>(0.23)</td>
</tr>
<tr>
<td>Eye Contact:</td>
<td>0.25</td>
<td>0.00</td>
<td>-0.13</td>
<td>0.56</td>
</tr>
<tr>
<td>Responding</td>
<td>[-0.21, 0.73]</td>
<td>[-0.38, 0.38]</td>
<td>[-0.31, 0.07]</td>
<td>(0.25)</td>
</tr>
<tr>
<td>Hand Gestures†</td>
<td>0.14</td>
<td>0.14</td>
<td>-0.06</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>[-0.27, 0.32]</td>
<td>[-0.27, 0.32]</td>
<td>[-0.32, 0.29]</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Anger†</td>
<td>0.26</td>
<td>-0.07</td>
<td>-0.07</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>[-0.67, 1.00]</td>
<td>[-0.53, 0.18]</td>
<td>[-1.00, 0.20]</td>
<td>(0.27)</td>
</tr>
</tbody>
</table>

Observations: 3  3  10  14

** Significantly different if using a p < 0.05; * if p < 0.10 benchmark
† Difference in proportions test used for Hand Gestures and Anger
Participants that changed their verbally expressed opinion out of a desire to be liked displayed more positive body language, on average, than those that did not change. They also have the highest average for responses, asking questions, raising their voice, and eye contact. Despite the low N in each subgroup cell, my results tell us something very interesting about these individuals. It is possible that active and outspoken people are the least susceptible to changing their opinion, but may verbally moderate it in order to gain allies. This would have particularly profound implications for political elites that have to balance the demands of diverse constituents while maintaining a public presence in order to retain office. It can also help explain why legislators have a public image of flexibility in their opinions, but fairly stable voting patterns. Confirming this result will require a larger scale approach to the experiment, as the first two groups of participants are likely to always be the smallest within the larger population.

Moving to the next category, there were no significant differences between participants responding solely to a desire to be right and those that did not change their opinion. This is somewhat intuitive, given that this group did not want to appear like they conformed to the group, even though they did positively respond to the information presented. They do, however, appear to respond less, ask less questions, exhibit less positive body language, and eye contact than the participants that changed their opinion out of a desire to be liked. Once again, these are based on small n’s, so it is difficult to estimate the differences precisely. If this holds in larger samples, however, it provides an interesting picture of individuals in a social environment that are actually updating their prior knowledge based on the introduction of new information.
Amongst the participants responding to some combination of these two forces, they showed less negative body language than the group that did change. However, using a more relaxed standard of significance ($p < 0.10$), they also asked fewer questions, used fewer pejoratives, raised their voice less, and made less eye contact, on average. Thus, they appeared more disengaged, but were also more likely than not experiencing a true updating of their information and preferences.

**Discussion**

While researchers have examined the roles of social influence (public compliance) and new information (private acceptance) on opinion change, the two are less often examined concurrently and the explicit causal arrows are more often assumed than tested through an experiment. Furthermore, social conformity is a complex concept to measure through surveys or interviews alone. Live interaction provides an optimal means to understand social pressures. My experiment was designed specifically to further unpack the causal mechanisms underlying opinion change and test whether a person’s values and identity are subject to social pressure. Furthermore, the selection of the topic of study, the firing of an important symbol of Penn State, also allowed us to explicate the extent to which information and social pressure challenge a person’s deeply held values and identity. I find that while information has a key role in changing people’s opinions on a highly salient topic that is attached to a group identity, the social delivery of that information plays a large and independent role. Most individuals that changed their opinion did so out of some combination of the two forces, but there were people who
only changed their opinion overtly in order to gain social acceptance as well as those who
did not want to give the appearance of changing their mind, but still wanted to be right.

These findings have important implications for research on political behavior. They reinforce the understanding that citizens and elites cannot be simply viewed as rational utility maximizers independent of group dynamics. Yet, at the same time, rational behavior remains a critical component of opinion change. Furthermore, there are important individual differences such as ideology, conscientiousness, and neuroticism that appear to have a role in conformity. Exposure to politics and political discussion are fundamentally social, and therefore behavior is conditioned on the information one receives, and the social influence of the person or group providing that information interacting with one’s disposition. All should be considered when examining any interpersonal political environment. Be it a deliberative setting like a jury or a town hall meeting or informal gatherings of citizens, or political elites for that matter, changes in behavior are not always due to rational updating, and even when they are, that updating may be pushed by the social forces that we experience in our interactions with other humans in variegated ways dependent upon the characteristics of the individual (for example, see Grimmer, Messing, and Westwood n.d.). This was the case for simple and objective stimuli, like Asch’s lines, and it is also the case in this context-laden experiment that focuses on the complexities of personal identity and opinion. That is, the conformity of political values relies on the same psychological mechanisms underlying general conformity in other social situations.

Beyond theoretical and empirical importance for the study of political behavior, these findings also hold normative importance for democratic society. The normative
implications are perhaps best exemplified by the organizational and personal turmoil that followed the revelation of child abuse by priests in the Catholic Church. Politics forms another important aspect of the personal identities of elites and citizens. People include their political party, positions on particular issues (e.g., environmentalism), and membership in political, religious, social and academic organizations, among other things, as key aspects of their identities. My experiment helps us better understand how individuals behave when part of that identity is challenged.

That being said, this experiment only unpacks part of the causal mechanism. Like the early work on social conformity, it serves as a foundation for future studies to extend upon and further explicate the causal mechanism. For example, an extension on this design, such as varying the type and number of confederates, could help us better understand the nature and amount of pressure necessary to induce conformity across a variety of individual characteristics. Additionally, while I identify individuals whose behavior was prompted by either social pressure or information, the largest group responded to a combination of the two. Further parsing out the interaction between information and pressure and the complexity of human dynamics will require an even more complex research design on a larger scale. The numerous extensions of Asch’s original experiment demonstrate the wealth of potential extensions of this design that can help unpack this black box. Doing so requires an incremental approach that will be time and resource intensive. This study provides the foundation for those next steps.
Chapter 7

Conclusion
This dissertation began with the classical idea of the American states as laboratories of democracy. The policy diffusion research program is deep and rich and helps us better understand how new ideas develop and spread among the laboratories. While this research program is indeed vast (Graham, Shipan, and Volden 2013), it tends to be fractured. This dissertation sought to systematically examine the resulting body of evidence while advancing the macro-level testing of the general theory of diffusion and micro-level analysis of the causal mechanisms underlying diffusion. Specifically, it addressed three primary questions: Is the general model generalizable? Is it stable? Why does the model change over time? These are important questions to address, as much of the previous work on diffusion largely assumes that the model is fixed, with heterogeneity in the effect of specific predictors being policy-specific only. Chapter 2 provides a foundation for answering these questions by systematically examining the methodological approaches and major findings of previous diffusion studies. It clearly shows conflicting findings for nearly all of the most commonly tested predictors of innovation adoption. Even the cornerstone measure of neighbor adoptions shows mixed effects.

Chapters 3, 4, and 5 provide a multifaceted answer to the first two motivating questions of generality and stability. Initially, Chapter 3 shows that many predictors of innovation adoption do generalize across a broad set of policies and substantial span of time. For example, neighbor adoptions generally increase the likelihood that a state will adopt any new innovation, whereas the increasing ideological distance from previous adopters reduces the likelihood of adoption. The chapter goes on to show, however, that the predictors are more or less potent over time. The most important finding is that
neighbors appear to matter less in more recent adoptions, whereas ideology matters more. This temporal instability, combined with instability in the predictors across policies, helps explain the disparate findings summarized in Chapter 1. Furthermore, the general model proves better specified in later decades – the 1990s and 2000s – than earlier. Thus the model developed by Berry and Berry may best explain adoptions in a narrow span of time instead of statically across all time.

Recognizing that there is likely not only variation in diffusion predictors across time, but also during the spread of an adoption, Chapter 4 addresses how they fluctuate throughout the diffusion lifecycle. Internal demographic characteristics appear to be the only factors associated with innovator adoption, which comports with the expectation that these states act alone early on. Early adopters and the early majority are susceptible to neighborhood pressures from adoptions by contiguous states; however that effect is replaced by ideological pressure for the late majority and laggards. Less professionalized states are more likely to adopt in the late majority, which suggests that they are benefiting from other laboratories that have greater legislative resources at their disposal. Thus predictors drawn from the general model are not relevant in all stages of adoption as an innovation is spreading. Some states act more quickly than others and thus respond to different motivating factors when innovating.

Chapter 5 builds on the previous two chapters by recognizing that not only do some states act more quickly than others, but there is variation in how quickly policies spread. This moves beyond the probability of adoption by examining how the rapidity of adoption changes over time and is, at least partly, conditional on attributes of the innovation that is spreading. As Walker (1969, 1971) predicted, the pace of innovation
adoption increased consistently since the 1960s. Policy attributes like salience, complexity, and relative advantage relate to the speed of adoption, however better measures of these concepts are required in order to improve the construct validity of this test. The primary contribution of this chapter is methodological (i.e., a new continuous measure of adoption speed), but it provides an under-explored avenue for modeling the factors contributing to increased adoption speed.

While the above are important for advancing our understanding of diffusion theory, particularly laying theoretical and empirical groundwork for understanding how the process changes over time, it is incomplete without a discussion of the micro-level causal mechanisms that motivate the macro-level model and its instability. Chapter 6 addresses this by laying out a formal theoretical structure for classifying and differentiating the variegated causal mechanisms that underlie the broader dynamics tested in the remainder of the dissertation. It then provides a foundation for systematically testing the extent to which conformity pressure and elite socialization shape legislators’ propensity to take up new ideas and information.

This mechanism is particularly relevant as attention is increasingly turning to the influence of ALEC, and the yet un-realized influence of SiX, on state innovation (Hertel-Fernandez 2014). In fact, this may be the most important causal mechanism to flesh out in the future, as it is in conflict with the progressive good-governance assumption of the notion that states are laboratories of democracy. Furthermore, it holds promise for helping us understand why ideological conformity is increasingly relevant as regional cohesion weakens. Ideological following, as well as evidence of state copying, identified
in this dissertation fit expectations that arise from the engagement of these organizations in state policymaking, as well as broader elite polarization.

By no means does Chapter 6 provide a complete answer to the question of why diffusion patterns differ today, nor does it fully test the elite socialization mechanism. It does, however, provide a working foundation for incrementally testing the joint and independent effects of information and social conformity pressure on political behavior. This is vital for separating the learning and socialization mechanisms. As the design is systematically altered and expanded beyond an undergraduate population, it has the potential to yield a better understanding of how the micro-process of social conformity operates among the broader population and can then be used to draw expectations about how it functions among political elites. Given the difficulty in obtaining an elite sample for a laboratory experiment, this is a fruitful avenue for the merger of quantitative and qualitative work. The experiment identifies the causal micro-process of social conformity in political behavior and can be used to draw expectations for the observation of elite behavior in decision-making settings.

**Limitations**

As with any research, it is necessary to recognize the limitations and potential criticisms of the work contained within this dissertation. More detailed discussions are included in each chapter; however it is useful to summarize them before discussing the broader implications and future directions of this research. One substantial limitation that affects this work, as well as all other work on policy diffusion, is the convenience
sampling required to conduct diffusion studies. Diffusion scholars have long recognized this problem (Boushey 2010; Nicholson-Crotty 2009; Perry and Kraemer 1978; Savage 1978); however, a proper sampling frame from which to draw innovations remains elusive. In fact, simply collecting data on the very first adoption of a policy in each state is not easy. On one hand, this problem is becoming less intractable as all states now have legislation posted online. On the other hand, only laws from the last few years are commonly available. Fortunately, I was able to leverage a large dataset of policies from diverse domains for the analysis presented in this dissertation. While not providing complete coverage of all areas of state legislative activity, accumulating adoption data reduces some of the bias that may result from only studying one type of policy (Boehmke and Skinner 2012b).

Another issue that affects not only this dissertation, but also the broader policy diffusion research agenda, is the lack of a proper counterfactual. Regardless of how difficult it is logistically to collect initial adoption data, it is exceedingly difficult to gather data on innovations that did not spread. This is related to the lack of a sampling frame, but instead of just potentially inducing bias in the results, it limits our ability to clearly answer the fundamental motivating question of why policies diffuse. We can explain why some policies that already diffused did so, and why they did so quickly or slowly, but we cannot confidently say why some policies diffuse and others do not. Furthermore, this limits our ability to do reliable out-of-sample predictions of the potential spread of new innovations as they emerge. Being able to do so would push diffusion theory much further, given that we would not have to only update it post-hoc.
Researchers could refine the theory in a way that keeps it current with emerging political and social trends in the United States (e.g., the rise of polarization in state houses).

Another limitation of this dissertation, particularly Chapters 3, 4, and 5, are related to causal identification. It is difficult to argue that every possible confound is included in each model. In fact, the under-development of policy attribute measures guarantees that this is not the case. That does not mean that we cannot learn something from these models and use them to refine our theory and point to new areas of inquiry. What it does mean is that the results must be viewed as associational. Thus they need to be repeated in other samples of policies. Once again, however, there is some advantage in this project from using an aggregated dataset of many policies. As the available data grow through cooperative efforts in both quantity and scope, it not only lessens potential areas of systematic bias, but also moves us closer to population data. Again, the first two limitations still stand, and without addressing those we cannot confidently say how close we are to measuring the population of innovations, but we are at the very least pushing closer.

While causal identification is not the primary concern with Chapter 6, it is important to reiterate what that chapter does and what it does not claim to do. It provides an experimental paradigm for explicating the causal process underlying conformity behavior in the political realm. At present, however, it is not a full test of elite socialization. While strong internal validity is a distinct advantage of the experiment, there is a necessary trade-off in external validity. This not uncommon in experimental research that does not seek to make predictions about a larger population, but is instead focused on explicating micro-level causal mechanisms. It is important to make clear that
one experiment alone cannot fully test the socialization mechanism, or any of the other mechanisms of diffusion, for that matter. This requires careful and iterative design alterations in successive experiments. This is particularly the case given that the diffusion research program is most interested in elite behavior. We do not have experimental control over the legislative processes within the states, so scholars must focus on the more universal elements of human behavior that manifest in the legislative process. These can be tested experimentally in order to test and refine the theory of policy innovation diffusion.

The issue of causality yields one other substantial limitation of this research. Policy diffusion—at least in the American context— is fundamentally about the genesis and spread of new ideas in a federal system. Innovation diffusion, more broadly, is a process of sharing between individuals (Rogers 2003). This is no less the case in politics. States do not share ideas, individual elites in those states do. Regardless of whether they are learning to solve a problem, trying to gain a competitive advantage over their peers in other states, observing a stark shift in public opinion, or serving as a conduit for the top-down dissemination of ideas from ideological organizations, these processes happen at the individual level. Alas, due to the difficulty in studying innovation at this level, diffusion scholars most often do so at the state level by dichotomizing adoption and explaining it with internal, external, and policy predictors. As shown in this dissertation, that approach does teach us something about the macro-level patterns of adoption and how they change, but it also masks meaningful variation across policies and time that help us understand the more general causal mechanisms underlying policy diffusion.
Implications for Policy Diffusion Research

Much of the recent work on policy diffusion, including this dissertation, represents an important shift in the research program. Namely, scholars are shifting away from single-policy models towards the macro-level analysis of diffusion dynamics (Boehmke and Skinner 2012b; Boushey 2010; Nicholson-Crotty 2009) and a direct focus on testing the various causal mechanisms that drive policy diffusion (Berry and Baybeck 2005; Pacheco 2012; Shipan and Volden 2008). This dissertation advances those efforts on several fronts, as argued above. The questions remain as to how to view the past work on policy diffusion in light of this dissertation and how it should be conducted in the future.

The broader story of this dissertation is that diffusion is not a static process. Meaning, that while the results presented in Figure 3.2 demonstrate that the Berry and Berry model is generalizable across diverse policy domains, the remainder of this dissertation shows that there is a great deal of instability in the model across policy (Chapter 2), time (Chapters 3 and 5), and the diffusion lifecycle (Chapter 4). This raises the question as to whether there is truly a general model of diffusion beyond the extremely reductive model presented in Figure 1.1, or if it is highly context dependent. This project does not directly answer that question, but I argue that its answer lies in developing and testing a theoretical structure that ties together the causal mechanisms of diffusion. Continued aggregation of adoption data and expansion into additional policy domains and decades will help researchers better understand how diffusion patterns change over time. Answering the question of why they change requires further
development of the underlying causal mechanisms presented in Chapter 6. A theoretical structure based solely on the Berry and Berry model may provide some predictive power for certain policies at certain times, but it is at such a high level of aggregation that it is also likely to miss the mark.

What does this mean for single-policy studies? Are they bereft of benefit? The above would suggest not, as they can help us better understand the causal mechanisms potentially at work for individual innovations and draw comparisons between policies that follow like patterns. Single policy studies remain useful for identifying new predictors that may be relevant to all or a subset of policy adoptions. The key difference moving forward is that these new covariates need to be tested more than once and their effects compared across domains. Evidence from a single policy study is not enough to establish the generality of a predictor. In fact, the results in this dissertation also need to be replicated with different policies in order to test the veracity of the findings. As replication work becomes increasingly valued in political science, particularly in its journals, diffusion scholars must commit more time to testing new additions to theory across a broader range of policies. In fact, the public availability of a large dataset of adoptions makes this even more possible.

56 For example, the new open access journal Research & Politics actively calls for such work. [http://www.uk.sagepub.com/researchandpolitics/](http://www.uk.sagepub.com/researchandpolitics/)
Broader Implications

Beyond advancing the diffusion research program, the results from this dissertation have broader implications for understanding American politics. There is great concern within political science, but also among the public and elites, about the effects of political polarization on politics in the United States. While scholars have only recently begun to direct more attention to polarization in the states (e.g., Shor and McCarty 2011), practical politics are already moving in that direction. The creation of SiX is a useful indicator of the shift in attention from policymaking in Washington to state governments (Khan 2014). In one sense, it does not matter if polarization is having a concomitant effect on state legislating, because gridlock in Washington has already prompted interest groups and donors to focus their attention on the states (Ballhaus 2014; Sherfinski 2014; Waddell 2014). That being said, policy diffusion is well positioned to explicate the effects of broader changes in American politics on the policy outcomes that affect the everyday lives of Americans.

This dissertation shows that diffusion is occurring more quickly than in the past, is increasingly following ideological, instead of regional, patterns, and suggests that states with less legislative capacity are able to act quickly on innovations, which suggests the presence of policy copying. Furthermore, the experiment demonstrates that the human proclivity to publically and/or privately conform is not restricted to simplistic environments. It also manifests in a high-context and identity-laden environment.
Important work remains to explicate the causal mechanism driving the changes identified in the diffusion process; however they suggest that the specific components of the diffusion model presented in Figure 1.1 are changing in fundamental ways.

As diffusion becomes more rapid in an information-rich and ideologically polarized legislative environment, it stands to reason that groups like ALEC and SiX could capture a great deal of policymaking by the states through providing quick access to model legislation that serves partisan interests. This raises broader questions about representation in the United States. Given that corporate donors are highly influential in these policy factories, it raises the question of whether legislators are representing the interests of their constituents or the interests of these organizations and their contributors. Joe Nichols put it this way when interviewed about ALEC on the *Diane Rehm Show*:

> “But at the end of the day, ALEC remains an organization that takes goals and proposals of multi-national corporations and frames them out in the form of legislation that is then spread out across the states by legislators, again, who seem to be erring more away from their communities, not toward their communities” (Rehm 2014).

Where these interest overlap, there is no clear question of representational slippage, but in cases where the interests of the public and these policy factories diverge, this is an important concern for American politics. The progressive good governance assumption of the “laboratories of democracy” can in fact be undermined if these patterns continue or strengthen.
Future Directions

Given the broader implications of these results and the limitations described above, there are many potential avenues for future work that build on the results and analytical approaches presented in this dissertation. I will focus on three that specifically relate to my future work in this area. The first project seeks to unlock the potential of text analysis for examining how information spreads through the federal system. The second study focuses on the influence of ALEC on state lawmaking. Finally, I propose a few specific extensions on the experiment in Chapter 6.

Bill text and text analysis present potentially powerful, but untapped, resources for understanding policy diffusion. Presently, the neighbor effect, which dominates the literature, is assumed to capture some kind of regional learning (Berry and Berry 1990; Berry and Baybeck 2005). At the very least, it tells us that a state is more likely to adopt *something* when a neighbor adopts *something* else like it. However, measuring adoptions as a dichotomous indicator discards a great deal of information about the heterogeneity in the underlying bill text (Boehmke 2009a). For instance, the lottery in Pennsylvania looks very different than the lottery in New York. Understanding the extent to which bill text is copied and modified throughout the diffusion process can help us better understand how external influences and internal characteristics interact throughout the diffusion process. Therefore, I propose utilizing bill text available from state legislative websites in order to examine how text is shared among the states. This is a potentially fruitful use of dyadic analysis (Volden 2006), as bill similarity could be used as the outcome of interest in order
to test how internal characteristics and spatial relationships relate to the sharing of text. This can help further untangle policy emulation from convergence (Boehmke 2009b).

Furthermore, bill text is a powerful avenue for understanding the extent of ALEC’s influence on state lawmaking in the last 40 years. ALEC only recently began to make its model legislation available on its website; however the organization left a useful paper trail since at least 1977 (ALEC 1977). Prior to transmitting model legislation electronically, ALEC published books containing all of their current model policies. Identifying all of the books is not an easy task, but certainly not impossible. Furthermore, digital scanning technology can easily make the printed text machine-readable. An extended data collection effort would be required to gather all related state bills, however once they are collected, text analysis could be used to determine the similarity of each state’s proposed and/or adopted legislation with ALEC model bills. Doing so would provide more definitive evidence of the organization’s effect. Additionally, the similarity measures could again be used as a dependent variable in order to test whether state institutions (e.g., legislative professionalism) and/or peer-state influences (e.g., relative ideology) promote or inhibit the uptake of model legislation.

Finally, more work needs to be done to experimentally test the mechanisms of diffusion. This is necessary because while researchers can identify some observable markers of these mechanisms (e.g., Berry and Baybeck 2005), it is difficult to do so without understanding exactly how the mechanisms operate. This is particularly the case with the inter-personal mechanisms (i.e., social contagion and elite socialization). In the case of the socialization mechanism, I propose a multi-method approach to testing whether elite conformity matters for innovation adoption. First, further iterations of the
experiment are necessary in order to better understand social conformity and politics. For example, the next iteration should involve another issue and a group of students from another school. Ideally, I would be able to test another high-context and identity-laden issue. For example, students at the University of Virginia could discuss the school’s response to sexual assaults on campus. Then, moving outside of the academic setting, and expanding into a broader population of adults, a similarly designed experiment could be conducted regarding the Catholic Church’s handling of child abuse accusations. These are only a few examples of small changes that could be made to the experiment in order to increase the external validity of the body of results. As the experiment is refined, it should then address issues that are weaker in terms of context and identity (e.g., tax policy).

Those extensions of the study are useful for further explicating conformity behavior; however additional advancements are necessary to approximate the small-group decision-making environment that typifies local governments and state legislative committees. For this purpose, the experimental protocol could ask the group to make a decision instead of only registering an opinion. One approach would be to draw participants from an existing legislative body (e.g., a university student council), ask them to develop a new piece of legislation to solve a campus problem, and introduce information that clearly signals a source from a peer body. For example, if one used the University Park Undergraduate Association or the Graduate and Professional Student Association at Penn State, the group could be given policy information from Ohio State’s Undergraduate Student Government. This would more directly test learning, but careful observation and coding of recorded discussions could be used to separate out when they
are learning from a positive result and when they are simply copying because another institution legitimized the action. Herein lies the utility of a mixed methods approach. Once the conformity mechanism is better understood in the general population, behavioral observations can be used to then observe a natural environment, like a local town council, or a controlled setting like that proposed above. Both would further increase the external validity of the results, while building on the robust internal validity of the previous studies.
Appendix A

Description of adoption data collected by the author

Table A.1: Policy name, year of first and last adoption, total count of adoptions, description, and source for additional adoptions collected by the author

<table>
<thead>
<tr>
<th>Policy</th>
<th>First Year</th>
<th>Last Year</th>
<th>Total Adoptions</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>apology</td>
<td>1986</td>
<td>2013</td>
<td>37</td>
<td>Physician apology protection</td>
<td>Ho and Liu (2011)</td>
</tr>
<tr>
<td>autism</td>
<td>1999</td>
<td>2012</td>
<td>32</td>
<td>Requires insurance to provide autism coverage</td>
<td>NCSL</td>
</tr>
<tr>
<td>breastdensity</td>
<td>2009</td>
<td>2013</td>
<td>13</td>
<td>Requires patient notification of high breast density</td>
<td>Are You Dense? Advocacy</td>
</tr>
<tr>
<td>breastfeed</td>
<td>1993</td>
<td>2009</td>
<td>48</td>
<td>Protects public breastfeeding</td>
<td>NCSL</td>
</tr>
<tr>
<td>bullying</td>
<td>1999</td>
<td>2012</td>
<td>49</td>
<td>Anti-bullying statute</td>
<td>Stuart-Cassell, Bell, and Springer (2011); Bully Police</td>
</tr>
<tr>
<td>commercialcasino</td>
<td>1931</td>
<td>2009</td>
<td>23</td>
<td>Legalization of commercial casinos</td>
<td>American Gaming Association</td>
</tr>
<tr>
<td>continsurance</td>
<td>1996</td>
<td>2010</td>
<td>28</td>
<td>Mandates insurance coverage of contraception</td>
<td>NCSL</td>
</tr>
<tr>
<td>ewaste</td>
<td>2003</td>
<td>2011</td>
<td>25</td>
<td>E-waste disposal</td>
<td>Campaign for Recycling</td>
</tr>
<tr>
<td>filmtaxcredit</td>
<td>1992</td>
<td>2009</td>
<td>44</td>
<td>Movie production tax incentives</td>
<td>Tax Foundation</td>
</tr>
<tr>
<td>goodsam911</td>
<td>2007</td>
<td>2013</td>
<td>14</td>
<td>Good Samaritan reporting of overdose</td>
<td>The Network for Public Health Law</td>
</tr>
<tr>
<td>infertility</td>
<td>1987</td>
<td>2002</td>
<td>23</td>
<td>Requires insurance to provide fertility services</td>
<td>NCSL</td>
</tr>
<tr>
<td>standground</td>
<td>1994</td>
<td>2011</td>
<td>23</td>
<td>Expansion of Stand-Your-Ground protections</td>
<td>National Urban League</td>
</tr>
<tr>
<td>ultrasound</td>
<td>1996</td>
<td>2012</td>
<td>24</td>
<td>Requires ultrasound before abortion</td>
<td>National Right to Life</td>
</tr>
<tr>
<td>voterid</td>
<td>1950</td>
<td>2012</td>
<td>32</td>
<td>Request or require photo identification to vote</td>
<td>Biggers and Hamner (2011)</td>
</tr>
</tbody>
</table>

† National Council of State Legislators (NCSL)
## Appendix B

**Full output for pooled multi-level model of policy adoption and alternative specifications from Chapter 3**

**Figure 7.1: Full output for pooled adoption model and alternative specifications**

<table>
<thead>
<tr>
<th>Covariate</th>
<th>No Random Effects</th>
<th>State Random Effects</th>
<th>Policy Random Effects</th>
<th>Both</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>External Influences</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of Neighbors</td>
<td>1.276***</td>
<td>1.234***</td>
<td>0.728***</td>
<td>0.591***</td>
</tr>
<tr>
<td>(0.183)</td>
<td>(0.183)</td>
<td>(0.203)</td>
<td>(0.203)</td>
<td></td>
</tr>
<tr>
<td>Relative Ideology</td>
<td>-0.118***</td>
<td>-0.129***</td>
<td>-0.086***</td>
<td>-0.126***</td>
</tr>
<tr>
<td>(0.020)</td>
<td>(0.021)</td>
<td>(0.022)</td>
<td>(0.025)</td>
<td></td>
</tr>
<tr>
<td>Federal Incentives</td>
<td>0.273***</td>
<td>0.277***</td>
<td>0.416</td>
<td>0.426</td>
</tr>
<tr>
<td>(0.051)</td>
<td>(0.051)</td>
<td>(0.285)</td>
<td>(0.312)</td>
<td></td>
</tr>
<tr>
<td>Congressional Hearings</td>
<td>0.248***</td>
<td>0.250***</td>
<td>0.129</td>
<td>0.119*</td>
</tr>
<tr>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.066)</td>
<td>(0.067)</td>
<td></td>
</tr>
<tr>
<td><strong>Internal Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citizen Liberalism</td>
<td>0.661***</td>
<td>0.793***</td>
<td>0.682***</td>
<td>0.787***</td>
</tr>
<tr>
<td>(0.141)</td>
<td>(0.179)</td>
<td>(0.146)</td>
<td>(0.201)</td>
<td></td>
</tr>
<tr>
<td>Divided</td>
<td>-0.010</td>
<td>-0.024</td>
<td>0.006</td>
<td>-0.027</td>
</tr>
<tr>
<td>Government</td>
<td>0.037</td>
<td>(0.039)</td>
<td>(0.038)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>log(Per Capita Income)</td>
<td>0.312***</td>
<td>0.305***</td>
<td>0.073</td>
<td>-0.196</td>
</tr>
<tr>
<td>(0.035)</td>
<td>(0.036)</td>
<td>(0.108)</td>
<td>(0.143)</td>
<td></td>
</tr>
<tr>
<td>log(Population)</td>
<td>-0.083*</td>
<td>-0.062</td>
<td>0.204*</td>
<td>0.484***</td>
</tr>
<tr>
<td>(0.047)</td>
<td>(0.057)</td>
<td>(0.111)</td>
<td>(0.151)</td>
<td></td>
</tr>
<tr>
<td>Legislative</td>
<td>-1.155***</td>
<td>-1.280***</td>
<td>-1.161***</td>
<td>-1.125***</td>
</tr>
<tr>
<td>Professionalism</td>
<td>(0.219)</td>
<td>(0.288)</td>
<td>(0.231)</td>
<td>(0.338)</td>
</tr>
<tr>
<td><strong>Policy Attributes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most Important Problem</td>
<td>1.146***</td>
<td>1.151***</td>
<td>0.428</td>
<td>9.972***</td>
</tr>
<tr>
<td>(0.250)</td>
<td>(0.251)</td>
<td>(0.356)</td>
<td>(0.364)</td>
<td></td>
</tr>
<tr>
<td>Complex Policy</td>
<td>-0.258***</td>
<td>-0.258***</td>
<td>-0.152</td>
<td>-0.127</td>
</tr>
<tr>
<td>(0.056)</td>
<td>(0.056)</td>
<td>(0.234)</td>
<td>(0.254)</td>
<td></td>
</tr>
<tr>
<td>MIP x Complex</td>
<td>-1.490***</td>
<td>-1.480***</td>
<td>-2.336***</td>
<td>-2.621***</td>
</tr>
<tr>
<td>(0.364)</td>
<td>(0.366)</td>
<td>(0.650)</td>
<td>(0.656)</td>
<td></td>
</tr>
<tr>
<td>New York Times</td>
<td>-0.127</td>
<td>-0.122</td>
<td>-0.852</td>
<td>-1.215</td>
</tr>
<tr>
<td>(0.526)</td>
<td>(0.527)</td>
<td>(1.171)</td>
<td>(1.216)</td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>-0.012***</td>
<td>-0.011***</td>
<td>0.065***</td>
<td>0.188***</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.007)</td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>Time²</td>
<td></td>
<td></td>
<td>-0.007***</td>
<td></td>
</tr>
<tr>
<td>(0.0004)</td>
<td></td>
<td></td>
<td>(0.0001)</td>
<td></td>
</tr>
<tr>
<td>Time³</td>
<td></td>
<td></td>
<td>0.0001***</td>
<td></td>
</tr>
<tr>
<td>(0.00001)</td>
<td></td>
<td></td>
<td>(0.00001)</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-7.122***</td>
<td>-7.333***</td>
<td>-7.565***</td>
<td>-7.316***</td>
</tr>
<tr>
<td>(0.379)</td>
<td>(0.516)</td>
<td>(0.486)</td>
<td>(0.723)</td>
<td></td>
</tr>
<tr>
<td><strong>Variance Components</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State Level</td>
<td>0.02</td>
<td></td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td>Policy Level</td>
<td>1.17</td>
<td></td>
<td>1.40</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>61,972</td>
<td>61,972</td>
<td>61,972</td>
<td>61,972</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-12,547</td>
<td>-12,538</td>
<td>-11,672</td>
<td>-11,650</td>
</tr>
</tbody>
</table>

* p < 0.1; ** p < 0.05; *** p < 0.01. Standard errors are in parentheses.
Appendix C

Summary statistics for Chapter 5

Table C.1 Descriptions and summary statistics for innovation adoption speed analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adoption Speed</td>
<td>Calculated by author, ranges from 0 (slowest) to 1 (fastest)</td>
<td>0.45</td>
<td>0.17</td>
</tr>
<tr>
<td>Federal Incentive</td>
<td>Dummy = 1 if policy has federal incentive</td>
<td>0.17</td>
<td>0.38</td>
</tr>
<tr>
<td>Health Insurance Cluster</td>
<td>Dummy = 1 if policy is in the health insurance cluster</td>
<td>0.03</td>
<td>0.18</td>
</tr>
<tr>
<td>Complexity</td>
<td>Dummy =1 if policy is classified as energy, environmental pollution, healthcare (provision, finance, and licensing), taxation, trade, and fiscal regulation</td>
<td>0.22</td>
<td>0.41</td>
</tr>
<tr>
<td>NY Times Coverage</td>
<td>Proportion of front page coverage of policy area</td>
<td>0.09</td>
<td>0.08</td>
</tr>
<tr>
<td>Most Important Problem</td>
<td>Proportion of respondents ranking the policy area highest</td>
<td>0.08</td>
<td>0.11</td>
</tr>
</tbody>
</table>

See text for additional information on these variables.
Appendix D

Full results of adoption speed OLS models

**Table D.1 Full results for innovation adoption speed analysis**

<table>
<thead>
<tr>
<th>Covariate</th>
<th>MIP Interaction Model</th>
<th>NYT Interaction Model</th>
<th>No Law Policies Model^†</th>
</tr>
</thead>
<tbody>
<tr>
<td>Federal Incentive</td>
<td>0.074*</td>
<td>0.079*</td>
<td>0.108*</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.041)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Health Insurance</td>
<td>0.319**</td>
<td>0.303**</td>
<td>0.326**</td>
</tr>
<tr>
<td></td>
<td>(0.088)</td>
<td>(0.090)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>Cluster</td>
<td>-0.211</td>
<td>-0.032</td>
<td>-0.679**</td>
</tr>
<tr>
<td></td>
<td>(0.229)</td>
<td>(0.218)</td>
<td>(0.361)</td>
</tr>
<tr>
<td>New York Times Coverage</td>
<td>-0.211</td>
<td>-0.032</td>
<td>-0.679**</td>
</tr>
<tr>
<td></td>
<td>(0.229)</td>
<td>(0.218)</td>
<td>(0.361)</td>
</tr>
<tr>
<td>Most Important Problem</td>
<td>0.677**</td>
<td>0.291**</td>
<td>0.077</td>
</tr>
<tr>
<td></td>
<td>(0.233)</td>
<td>(0.161)</td>
<td>(0.869)</td>
</tr>
<tr>
<td>Complexity</td>
<td>-0.016</td>
<td>-0.073</td>
<td>-0.054</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.078)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>MIP x Complexity</td>
<td>-0.632**</td>
<td>-0.006</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.296)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NYT x Complexity</td>
<td></td>
<td>0.204</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.626)</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.423**</td>
<td>0.430**</td>
<td>0.471**</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.028)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>N</td>
<td>116</td>
<td>116</td>
<td>69</td>
</tr>
<tr>
<td>R²</td>
<td>0.190</td>
<td>0.157</td>
<td>0.244</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.146</td>
<td>0.110</td>
<td>0.171</td>
</tr>
<tr>
<td>Root Mean Squared Error</td>
<td>0.159</td>
<td>0.162</td>
<td>0.173</td>
</tr>
</tbody>
</table>

* p < 0.10; ** p < 0.05 (one-tailed). Standard errors in parenthesis.

^†This model is included as a robustness check to determine whether the findings change with the removal of the disproportionately large number of criminal justice policies.
Appendix E

Influence of law policies in Chapter 5

When the adoption speed model in Chapter 5 is estimated in the absence of the large set of law policies (see Model 3 in Appendix D), the coefficients for federal incentives and the health insurance policy cluster remain positive and statistically significant, but MIP does not. Instead, *New York Times* coverage has a significant negative relationship with adoption speed. However, there is reason to believe that this is due to the removal of 47 observations and not factors idiosyncratic to this policy domain.

Analysis of the COVRATIOs for each observation in the original analysis show that the law policies increase the precision of the coefficient estimates in the original model (see Figure E.1), but DFBETAS values show that they do not systematically influence the MIP coefficient differently than the other observations (see Figure E.2). As scholars continue to gather additional policy adoptions and grow their datasets, they should be attentive to collecting data on domains that are not well represented by the currently available data.
Figure E.1 Plot of COVRATIOS with law policies highlighted red
Figure E.2 Plot of DFBETASs for Most Important Problem with law policies highlighted red
Appendix F

Information sheet provided to both treatment and control groups

Below are summaries and excerpts from an investigation into the Jerry Sandusky matter at Penn State. The information addresses Head Coach Joe Paterno’s knowledge and behavior.

- Police first investigated Sandusky in 1998 for allegedly showering with an 11-year old in the Lasch Building on campus. In May of that year, Athletic Director Curly informed Vice President Shultz and President Spanier that he had “touched base with” Paterno about the incident. Days later, Curley emails Shultz: “Anything new in this department? Coach is anxious to know where it stands.”
- Witnesses interviewed in the investigation reported that Coach Paterno knew “everything that was going on” when it came to the football program and had the authority to control access to the football facilities.
- There is no evidence that Penn State officials, including Coach Paterno, actively interfered with the investigation, but they were kept informed during it. The local district attorney decided not to pursue charges against Sandusky at the conclusion of the investigation. No action was taken to limit Sandusky’s access to university facilities.
- A proposal written in 1999 by Sandusky to continue using the football facilities included a handwritten note from Paterno reading, “Is this for personal use or 2nd Mile kids. No to 2nd Mile. Liability problems.”
- In February 2001, graduate assistant Mike McQueary reported to Coach Paterno that he saw Sandusky behaving suspiciously in the Lasch showers with a young boy. Paterno told him “you did what you had to do. It’s my job now to figure out what we want to do.”
- Paterno reported the incident to Curley and Shultz the following day. Paterno indicated that he delayed because he did not “want to interfere with their weekends.”
- Additional e-mail correspondence between Curley and Shultz indicates that they consulted with Coach Paterno regarding the Sandusky situation in 2001. Subsequent to these discussions, leadership determined that Sandusky should be asked to not bring minors to campus facilities any longer. The incident was not reported to the Board of Trustees.
- The relationship between the University, Sandusky, and the Second Mile charity continued until a grand jury investigation was held in 2011 after the Pennsylvania Attorney General’s Office investigated allegations of Sandusky’s behavior. Paterno, Shultz, Curley, and Spanier are all subpoenaed to testify before the grand jury.
- Paterno consistently testified that he had no knowledge of the 1998 investigation into Sandusky. He said that 2001 was the first incident that he was made aware of.
- In a Washington Post report, Paterno was asked why he had not pursued the 2001 incident further. Paterno responded, “I didn’t know exactly how to handle it and I was afraid to do something that might jeopardize what the University procedure was. So I backed away and turned it over to some other people, people I thought would have a little more expertise than I did. It didn’t work out that way. In hindsight, I wish I had done more.”
Appendix G

Confederate talking points: Pro-firing

Yes, Coach Paterno should have been fired:

- In serious cases (e.g., allegations of rape), someone can be held accountable for not reporting the issue to the police
- Paterno had this authority and responsibility as the head of the football program
- There's enough information to suggest he knew enough about the Sandusky situation that he should have taken the allegations of child abuse more seriously and should have done more to ensure the allegations were being handled by those above him
- It is clear from the independent investigations that he knew of both the 1998 investigation and the 2001 incident in the Lasch Building
- Seems irresponsible that Paterno would privilege the weekends of Curly and Schultz more than the seriousness of the allegations that were brought before him
- There is no evidence that he followed up on the allegations against Sandusky after passing the information higher
- He did not know or follow University procedure, and that is a reasonable grounds for firing him
- He made a mistake and, therefore, should have been held accountable
- Employees are often fired for far less serious reasons (e.g., being late to work)
- He is not held to the standards of a court of law; given the evidence, it is within the right of the Board of Trustees to fire him
- Collegiate coaching is a competitive job and there are plenty of other coaches who could have made a better decision
- In light of heavy public scrutiny, the Board need to take swift action
Appendix H

Confederate talking points: Anti-firing

No, Coach Paterno should not have been fired:

• It is easy to sit here with all of the information in front of us more than a decade later and say "Yes, Paterno should have done more," but Paterno was given bit and pieces of information over a long period of time that may have been difficult for him to connect the dots as the situation with Sandusky was unfolding
• Not all the evidence was known; Sandusky had not even been convicted at the time
• The university bureaucracy itself was broken, and it is not fair that Paterno should take the blame for acting appropriately within a system that tells its employees to report issues to higher authorities and do nothing else
• He did what was required; he reported the incident to his superiors
• He responded appropriately each time given the information available to him
• Should be able to trust that the people above you will handle the allegations once they are made aware of them
• In cases of “due obedience,” soldiers are not held accountable for actions/decisions made by their superiors
• Given that the district attorney found no reason to pursue the 1998 investigation of Sandusky, Paterno may have dismissed any reasons to feel Sandusky was behaving inappropriately
• Paterno did tell Sandusky not to bring Second Mile youth onto campus facilities and cannot possibly spend his time making sure Sandusky was not in the showers with them
• It is unfair to fire Paterno for something that was really Sandusky's fault
• The firing of Paterno distracted from Sandusky and from the process of addressing the issue of child abuse
• It is unclear that someone different would have "done more" than what Paterno did
• He was going to retire anyway; so he should have been allowed to step down
• There are many more preferable outcomes to the scandal than the firing of Paterno
• Finger-pointing and name-calling are not a good way to heal from the scandal and move forward as a community
• He was obviously a good man; he made numerous contributions to the community and school which should not be overshadowed by a single bad decision
• We should have given him the opportunity to use his iconic status to make a difference (take a stand against child abuse, lead an investigation into the shortcomings of university procedure, ask him what conditions would have to be different to get him to have called the police, etc.)
Appendix I

Randomization

Not all treatment group participants were completely randomly assigned. The first 16 participants were placed into the treatment group in order to test the protocol, train the confederates, and gather information necessary for creating an effective control group survey. This was necessary so that confederates could naturally settle into a consistent set of arguments that they were comfortable with. Furthermore, it was useful to incorporate the arguments made by early students into both the confederates’ talking points and the control group survey. Given that the confederates remained consistent in their discussion points and style after initial practice with the experimenter, there was no substantial difference in treatment conditions for these participants and thus they are included in the analysis. The remaining 38 participants were randomly assigned using a coin flip.

Given that 16 of the 34 treatment group participants were not assigned randomly, we wanted to test for any significant differences in demographics and dispositions for the two sub-groups. Table I.1 presents these results and there are two significant differences. First, the non-randomized subgroup includes more males than the randomized subgroup. Second, the non-randomized subgroup is, on average, less neurotic than the randomized group.
Table I.1 Comparison of demographic and dispositional traits for non-randomized and randomized subgroups with the treatment group

<table>
<thead>
<tr>
<th>Variable</th>
<th>Non-randomized Mean (St. Dev.)</th>
<th>Randomized Mean (St. Dev.)</th>
<th>Difference [95% Conf. Int.]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>23.50 (5.15)</td>
<td>21.94 (1.43)</td>
<td>1.56 [-1.25, 4.36]</td>
</tr>
<tr>
<td>Male†</td>
<td>0.69 (0.48)</td>
<td>0.28 (0.46)</td>
<td>0.41** [0.10, 0.72]</td>
</tr>
<tr>
<td>School Year</td>
<td>3.62 (1.89)</td>
<td>3.44 (1.20)</td>
<td>0.18 [-0.96, 1.32]</td>
</tr>
<tr>
<td>Conservatism</td>
<td>14.44 (7.37)</td>
<td>11.44 (11.00)</td>
<td>3.00 [-3.50, 9.49]</td>
</tr>
<tr>
<td>Self-Esteem</td>
<td>29.62 (6.46)</td>
<td>26.83 (7.20)</td>
<td>2.79 [-1.98, 7.56]</td>
</tr>
<tr>
<td>Extraversion</td>
<td>20.56 (5.60)</td>
<td>18.72 (4.27)</td>
<td>1.84 [-1.69, 5.37]</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>26.94 (4.77)</td>
<td>25.78 (5.17)</td>
<td>1.16 [-2.31, 4.63]</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>26.44 (3.95)</td>
<td>26.28 (4.46)</td>
<td>0.16 [-2.78, 3.10]</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>10.69 (5.56)</td>
<td>15.28 (5.90)</td>
<td>-4.59** [-8.60, -0.59]</td>
</tr>
<tr>
<td>Openness</td>
<td>28.50 (4.00)</td>
<td>27.44 (2.97)</td>
<td>1.06 [-1.5, 3.56]</td>
</tr>
<tr>
<td>Pro-firing†</td>
<td>0.19 (0.40)</td>
<td>0.28 (0.46)</td>
<td>-0.09 [-0.51, 0.26]</td>
</tr>
<tr>
<td>Observations</td>
<td>16</td>
<td>18</td>
<td></td>
</tr>
</tbody>
</table>

** entries indicate significant t-tests, $p < 0.05$, * if using a $p < 0.10$ benchmark
†Difference in proportions test used for Male and Pro-Firing
Appendix J

Use of deception in the study design

My interest in social conformity necessitated the use of deception in the study design. This approach is useful for political science experiments (McDermott 2013) and is necessary when informing the participants of the true purpose of the study would alter their behavior. In fact, I believe that participants would behave differently if they know that they would be discussing a political issue with a group of peers that uniformly did not share their opinion. I wanted as honest a response as possible from the participants; therefore I used the same deception format as the extant literature (e.g., Asch 1951; Hardy 1957).

Of course, there is always concern that participants will discern the deception involved, particularly if they are familiar with psychological research or have participated in similar studies in the past. Fortunately, it appears that the deception used in this study was not identified. Participants were informed of the deception used in the research design during their debriefing in order to gather anecdotal evidence of its success. I received no indication from my participants during the debriefings that they were able to clearly discern the true purpose of the study and thus potentially manipulate its results. Indeed, only four participants indicated in their debriefing that they suspected some type of deception, but none were able to pinpoint the purpose of the study and the specific deception being used.
Given the feedback from the debriefings, I am confident that the deception worked according to the design. One participant’s comments encapsulate the types of comments we typically received after informing the participants about the deception used in the discussion session:

“Oh my god. So they were all in on it? I feel so joe schmoed right now. They were really good at that. I feel like those were their actual positions because they were really passionate about it.”

Many participants expressed appreciation for participating in the study even after learning about the deception. They generally found it to be a healthy and calm discussion. Furthermore, even after learning of the deception, participants told us that they learned a lot and had more thinking to do on the topic in light of that new information.

There were initially four confederates in each discussion group. Unfortunately, due to the length of the study, two confederates could not complete the entire study. For this reason, one additional confederate was recruited and trained and given the same talking points as the previous confederates, so that the groups would generally not fall below three confederates. However, there were two instances where one confederate did not show up for the discussion group. Therefore, there were sixteen discussion groups with four confederates, sixteen with three confederates, and two with two confederates. I found no significant differences based on the number of confederates.
Appendix K

Details for Behavioral Measures

For the purposes of this analysis, three independent raters measured ten specific participant behaviors that allow me to understand basic behavioral differences between those that change their opinion and those that do not. Specifically, the raters counted the number of times each participant responded verbally, asked questions, made pejorative statements, told a joke, and raised their voice. Additionally, raters measured positive and negative body language. Examples of positive body language include smiles and head nods in agreement, whereas examples of negative body language include headshakes in disagreement, folded arms, and crossed legs. Finally, raters coded ordinal measures of the participant’s eye contact while listening and responding, whether they use hand gestures, and whether they appear to become angry during the discussion.

I used the same three raters for each video and de-meaned each count measure within rater, to correct for differences across raters. I then took the average of the de-meaned measures for each participant and used the modal category for the ordinal and dichotomous measures. Finally, I rescaled the de-meaned measures so that they range from 0 to 1, which makes the results easier to interpret.
Appendix L

Breakdown of opinion change in the treatment and control groups

This appendix supports Figure 6.3 in the main body of the paper. It describes how I coded opinion change for both the treatment and control groups. As noted in the paper, I collected a participant’s opinion at multiple points during the experiment. For both groups, I have the initial opinion provided in the pre-test survey which asked participants “given what is known regarding the Jerry Sandusky incident at Penn State, the Board of Trustees was justified in firing Head Coach Joe Paterno?” Respondents answered using a five-point Likert scale ranging from Strongly Agree to Strongly Disagree.

For the control group, I then asked them to read the information sheet (see Appendix F) from the treatment condition, as well as the arguments that are counter to their initial opinion (see Appendix G and Appendix H). Control group participants that answered “Neutral” to the initial opinion question were provided both sets of arguments. After reading through the material, I asked the control group participants again whether they believed Paterno should have been fired. This time, they answered the question in two parts. The first was either a “yes” or “no” and the second asked them the strength of their opinion from “neutral” to “strong.” I assigned treatment group participants to five sub-categories based on the possible opinions and opinion strengths for each set of questions. Figure L.1 shows the percentage of the treatment group that feel into each sub-category. First, 54 percent of the treatment group provided a clear opinion (i.e., not neutral) to the initial opinion question and then provided the same clear opinion after
reading the additional information. A total of 8 percent of the group responded to the information in some way. Four percent changed their opinion from one side to the other (Information Change), while the other four percent initially provided a neutral opinion, but then took a clear stance after reading the information (Information Decision). For the remaining 37 percent of the control group, some participants held the same opinion before and after the information, but it either gained or lost intensity. Specifically, 29 percent weakened their opinion and 8 percent strengthened it. I collapsed the two information categories into a single category of Opinion Change (8 percent) and collapsed the remaining three into No Opinion Change (92 percent).

Figure L.1: Opinion changes for control group participants by subcategory
For the treatment group, I have three sets of recorded opinions. First, there is the initial opinion from the pre-test survey. Second, I have the yes or no answer provided after reading the information sheet and before starting the discussion period. Third, I have the “anonymous” ballot (yes or no) provided at the end of the discussion. I also have the verbal appearance of change coded from the video recordings, however since we are interested in actual opinion change for the main finding, I do not evaluate this for calculating overall change for Figure 6.3.

Given these three different opinions, I again have five sub-categories, but they are slightly different given the lack of intensity measure for the final vote. Figure L.2 displays the percentages of the treatment group falling into each sub-category. The largest group, once again, is the one that did not change their opinion at any time (44 percent). However, like the control group, there were some individuals that changed or decided their opinion based solely on the information presented before the discussion. Three percent changed from one clear opinion to another between the pre-test survey and the pre-discussion voice vote (Information Change) and fifteen percent moved from a neutral position to a choice of yes or no that they then maintained in the secret ballot (Information Decision). Relatedly, fifteen percent of the treatment group started as neutral in the pre-test, took a position on the initial ballot, and then changed that position after the discussion (Information Decision and Discussion Change). Finally, 24 percent of the treatment group had the same opinion in the pre-test survey and the initial voice vote, but changed that opinion after the discussion.
Given that I am interested in the extent to which individual changed their opinion during the treatment group discussion, I merged the first three categories into No Opinion Change (62 percent) and Opinion Change (38 percent).\(^5\)

Figure L.2: Opinion changes for treatment group participants by sub-category

\(^{57}\) Slight differences from totals based on Figure L.2 are the result of rounding.
References


Desmarais, Bruce A., Jeffrey J. Harden, and Frederick J. Boehmke. (Forthcoming). Persistent Policy Pathways: Inferring Diffusion Networks in the American States. *American Political Science Review*.


Rehm, Diane. 2014. "Understanding ALEC And Its Influence In U.S. Politics." In *The Diane Rehm Show*: NPR.


Vita

Daniel J. Mallinson

Academic Employment

Assistant Professor, Richard Stockton College of New Jersey (2015-Present)

Education

Ph.D. Political Science, Pennsylvania State University, 2015
  Major field: American Politics
  Minor fields: Political Methodology, Public Policy

M.A. Political Science, Pennsylvania State University, 2012

M.A. Political Science, Villanova University, 2009

B.A. Political Science, Elizabethtown College, 2008

Publications


Honors and Awards


2012: Exceptional Achievement Award, Office of the Inspector General, Department of Health and Human Services.