Understanding States' Failure in Sustained Innovation from the Diffusion Perspective:

The Empirical Study of the Diffusion of EFOIA in the US States

by

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A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved April 2014 by the
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May 2014

ABSTRACT

It is now fashionable to seek innovation in the public sector. As routine government practices have failed to solve complex policy problems, innovation is increasingly seen as the key to establishing public faith in government agencies' ability to perform. However, not surprisingly, governments have often failed to support and maintain innovation over time.

The purpose of this study is to examine what accounts for sustained innovation in government transparency. This is an in-depth analysis of the diffusion of the Electronic Freedom of Information Act (EFOIA) across the US states from 1996 to 2013. With the theoretical basis of policy diffusion, this study measures the degree of innovation among states by the timing of adoption, and by the extent of implementation. The factors that influence states' adoption and implementation of EFOIA will be compared, thereby explaining why some early adopters failed to maintain the leader position in innovation in government transparency through the implementation phase. The study findings show that the failure of early adopters in sustained innovation is the result of the conditional nature of diffusion mechanisms (i.e. socialization and learning) which operate differently at the adoption and implementation stages of EFOIA. This study contributes to a better understanding of the role of the legal environment created by the federal government, and the relationships between state governments in sustaining innovation in government transparency.

DEDICATION

To my parents and my husband

ACKNOWLEDGMENTS

I would like to express my respect and appreciation to my committee — Dr. Johnston, Dr. Schugurensky, and Dr. Mossberger. For their excellent guidance, caring, and encouragement, the doctoral program has been the most precious and valuable period in my life. I'm also indebted to my academic cohorts at Arizona State University for their warm and unchanged support and friendship. I would like to express my deepest gratitude to my parents and husband. Without their love and persistent help, I could not see this long journey though, and this dissertation would not have been possible. Finally, I would like to acknowledge the financial support of Korea Military Army for my doctoral program.

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CHAPTER 1

INTRODUCTION

There is nothing more difficult to plan, more doubtful of success,

nor more dangerous to manage than the creation of a new order of things

Niccolo Marchiavelli, *The Prince* (1513)

Background

Over the past few decades, it has become fashionable to seek innovation in the public sector. As routine government practices have failed to solve complex policy problems, innovation is increasingly seen as the key to establishing public faith in the ability of government agencies to perform. However, not surprisingly, the governments have often failed to support and maintain innovation over time.

The purpose of this study is to examine who maintains the leader position in innovation in government transparency. To identify the factors influencing sustained innovation, this study employs theory of *policy diffusion*. The diffusion literature has paid great attention to the way in which a new policy spreads from one government to another, providing numerous insights into "interdependence" among governments in policy adoption. This diffusion approach tends to measure the degree of innovation between states by the timing of adoption (Walker, 1969; Gray, 1973; Berry & Berry, 1990).

In recent years, however, diffusion scholars have emphasized the importance of studying diffusion at the implementation stage of a policy. This new approach to diffusion examines whether adopters continue to keep pace with state-of-the art

developments in the field over time, focusing on the scope of implementation (Tolbert, Mossberger, & McNeal, 2008). Indeed, policies are reinvented or evolve through their implementation. Thus, investigating the implementation stage of a policy can provide a more accurate portrayal of how policies spread from one government to another (Graham, Shipan, & Volden, 2012).

Employing both of perspectives on diffusion, this study investigates the differences in diffusion between adoption and implementation to explain why not every early leader in adoption maintains the leader position in innovation over time. This is an in-depth analysis of the diffusion of the Electronic Freedom of Information Act (EFOIA) across the US states from 1996 to 2013. This policy area is an appropriate case for this study because there are distinct differences in diffusion between states' adoption and implementation of EFOIA; some early adopters have failed to achieve satisfactory performance or extensive use of EFOIA in implementation, thereby limiting it to a *symbolic* policy. Comparing the differences in diffusion between two stages of EFOIA may deepen the understanding of innovation in an area of transparency policy.

In addition, this study will demonstrate that such differences in diffusion between states' adoption and implementation of EFOIA result from the conditional nature of diffusion mechanisms operating differently at two stages; one diffusion mechanism may influence states' adoption of EFOIA, but its influence may fade in the states' implementation of EFOIA. To identify the appropriate mechanisms associated with the diffusion of EFOIA, this study will use the constructivist and the rationalist perspectives on policy diffusion. Those theoretical points of view suggest two potential mechanisms

through which the diffusion of EFOIA takes place: *socialization* and *policy learning*. Therefore, this study will examine the nature of socialization and policy learning that is conditional on the stages of the adoption and implementation of EFOIA.

Research Questions

With state-years as the unit of analysis, this study will identify the factors influencing sustained innovation in government transparency. This study will begin with a review of the diffusion of EFOIA in the adoption and implementation stages, and describe differences in the diffusion patterns of EFOIA in the two stages. This study will then test possible theories of why some states adopted EFOIA before or with greater success than others. Those sub-questions are based on the assumption that states do not respond uniformly to the diffusion of EFOIA. Finally, this study will compare the determinants between states' adoption and implementation of EFOIA, thereby finding the clues to how differently diffusion mechanisms operate at two stages of EFOIA.

To sum up, the research questions explored by this study are as follows:

"What accounts for sustained innovation in government transparency?"

Sub-question 1: Why did some states adopt EFOIA earlier than others?

Sub-question 2: Why have some states implemented EFOIA more successfully than others?

Sub-question 3: Why have some early adopters failed to implement EFOIA successfully?

Significance of the Study

This study makes several contributions to the scholarly research to practice.

First, the study findings will contribute to a better understanding of the role of the legal environment created by the federal government, and the relationships between state governments in sustained innovation in government transparency.

Second, this study will shed light on the *conditional* nature of diffusion mechanisms in different stages of the policy process. Some scholars have investigated the conditional nature of diffusion mechanisms by relying either on the endogenous aspects of jurisdictions (Shipan & Volden, 2008), or on the sub-phases of policy adoption consisting of pre-adoption (i.e. the agenda-setting and proposal formulation), and adoption (Cohen-Vogel & Ingle, 2007; Damanpour & Schneider[1], 2006). Yet, little is known about the conditional nature of diffusion mechanisms depending on the policy process that consists of adoption and implementation. Therefore, this study will be the first to examine the different responses of diffusion mechanisms to the adoption and implementation phases of the policy process.

Third, this study will extend the policy diffusion literature beyond policy adoptions by including the analysis for states' implementation, providing a rich case study of EFOIA. Almost all policy diffusion studies to date have been limited to the adoption

[1] It is difficult to see that Damanpour and Schneider (2006) appropriately analyzed the implementation phase of a policy because they defined implementation simply as the degree of the employment of a program by using dummy variables (not implemented, 0; sometimes implemented, 1; always implemented). According to the communications model of intergovernmental policy implementation, implementation is conceptualized as a process, meaning that implementation involves a number of activities related to carrying out the intent of the law (Goggin et al., 1990). In this point of view, if implementation is described dichotomously, as Damanpour and Schneider did , one could not say that implementation has occurred.

stage in which decision-making units determine the adoption or rejection of a policy (Karch, 2007; Moynihan, Shipan, & Volden, 2012). However, policy processes do not end at adoption, but rather evolve in the course of their implementation (Moynihan, Shipan, & Volden, 2012). Moreover, simply discussing dichotomous choices of states concerning policy initiation prevents diffusion theory from serving to evaluate *outputs* or *outcomes* the states have produced (Goggin et al., 1990). Thus, this study can help scholars and practitioners understand why some states have limited themselves to a symbolic policy when there has not been extensive use of the policy by their members, thereby offering a larger picture of policy diffusion (Damanpour, 1987; Graham, Shipan, & Volden, 2012).

Fourth, this study will empirically investigate norm diffusion across the United States. Despite early suggestions by Walker (1969) that socialization processes could be of great importance in policy diffusion, most diffusion researchers have set aside key points about the diffusion of norms across governments (Graham et al., 2012). Although the literature in international relations and comparative politics has examined the role of norms in the reinvention or evolution of international politics, it was based mostly on case study research (Goodman & Jinks, 2005). Therefore, this study can empirically clarify how policy diffusion takes place through socialization processes.

Finally, this study returns transparency debates to the policy diffusion literature. Many studies have examined the influences of government transparency on trust, corruption, or economic consequences. Applying the diffusion approach to an area of transparency policy can be useful in conducting a comparative study that can be a lens for

understanding jurisdictional differences in adopting and implementing a policy. Thus, this study will be the first step towards an empirical understanding of the diffusion of a transparency policy in the states of the US.

Outline of the Study

This dissertation consists of six chapters. The first chapter introduces the background, goals and significance of the study, and research strategy.

The second chapter will provide an overview of EFOIA, and then describe how EFOIA spread across the US states in the adoption and implementation stages. This chapter also describes characteristics of diffusion in the adoption and implementation stages of EFOIA, and identifies the differences in diffusion patterns in the two stages.

The third chapter explores the previous literature that has conceptualized policy diffusion, and suggested various diffusion mechanisms. In addition, this chapter reviews the theoretical logic that can explain why some states are leaders in adopting or implementing EFOIA, and why some early adopters failed to maintain the leader position in innovation through the implementation phase. Moreover, this chapter presents the conceptual framework and develops hypotheses for answering the research questions.

The fourth chapter presents the research design and methodology used to answer the research questions. Specifically, this chapter includes detailed descriptions of the sources of data, instruments for measuring dependent, independent and control variables, grouping strategy, and statistical techniques for data analysis.

The fifth chapter presents the results of data analysis for answering the research questions as well as the statistical findings. These results and findings will generate insight into the factors that enable state governments to maintain the leader position in innovation.

The final chapter summarizes the empirical findings, and then discusses the implications of the findings, contributions, and limitations. This discussion will be associated with the states' legal environment, their relationship with other states, and what role the federal and state governments should play in sustaining the innovation. This chapter concludes with suggestions for future research.

CHAPTER 2

DIFFUSION OF EFOIA IN THE US STATES

This chapter introduces the Electronic Freedom of Information Act (EFOIA) of 1996. Next, it describes the diffusion of EFOIA in the adoption and implementation stages. This chapter concludes with a discussion of the characteristics of diffusion in the adoption and implementation stages of EFOIA, and the differences between them.

The Electronic Freedom of Information Act

The past several decades have brought greater attention than ever to the importance of government transparency. The emphasis on enhancing public access to government information has to do with the rhetoric of citizen sovereignty, and the need for citizens' informed oversight of governmental activities (Doty, 2000). According to the principle of democracy, the actions of government bodies must be traced back to be held accountable to the public because these bodies are legitimated only indirectly; they are not directly elected (Liem, 2007). Furthermore, increased skepticism about the government's working has put substantial pressure on the government to open its activities to public scrutiny, highlighting citizens' responsibility to challenge the government's operations (Relyea, 1987; Doty, 2000).

Passage of the Electronic Freedom of Information Act (EFOIA) in 1996 was an important first step by Congress to increase government transparency, in response to the information and electronic age. Indeed, as early as 1976, public agencies began refusing requests for electronic information by arguing that FOIA did not mandate the agencies to disclose government information in digital formats. Agencies insisted that government

costs would soar as a result of requesters' demands for information in electronic versions, and that the agencies should not bear the burden of the costs (Halstuk, 2008). Although some courts held that electronic data may be subject to FOIA, they also ruled that government bodies were not obligated to provide members of the public with public records electronically (Halstuk, 2008). Thus, policies regarding public access to electronic data were decided on a case-by-case basis.

In 1996, President Clinton signed the EFOIA into law, after five years of congressional hearings[2], floor debates, and compromises (Halstuk & Chamberlin, 2001). In the 1996 EFOIA statement, President Clinton emphasized that open access to government information is crucial in preserving and fostering democracy. The EFOIA amendment of 1996 established a legal basis for the public's *online* access to government information, by updating FOIA that did not ensure the provision of computerized materials. Much of the discourse surrounding the EFOIA assumed that the incorporation of digital technologies would enhance government accountability by enabling a greater and immediate public access to government information (Oltmann, Rosenbaum, & Hara, 2006).

The EFOIA required government agencies to provide public access to information in an electronic format, and post on the Internet (i.e. electronic reading room) commonly requested information about government operation, such as statements of

[2] In 1985, Congress held its first hearings on collecting public records in an electronic form and its dissemination by the federal agencies. The resulting House Report warned that agency control over electronic information was tantamount to a government information monopoly (Halstuk, 2008).

agency rules and policy, agency annual reports, and FOIA handbooks[3]. Furthermore, the EFOIA supplemented the definitions of "governmental record" and "public body" (U.S.C.§552(f)(2)) to include all information produced and maintained by a public body, regardless of physical form or characteristics by which the information is stored, recorded, or reproduced. In addition, the EFOIA encouraged government agencies to exert all reasonable efforts to make public records available to requesters in the medium requested (U.S.C.§552(a)(3)).

Since the EFOIA amendment by the federal government in 1996, almost all state governments[4] have followed the federal model along with the expressed purpose of providing parity with the federal movement toward government transparency (Open Government Guide[5], 2011). At present, each of the 50 states has a governmental transparency website to create the environment in which citizens can access government data and government can deliver services 24 hours a day via the Internet.

The diffusion of this type of innovation is unique in that it is irrelevant to diffusion mechanisms frequently employed in the previous literature to explain policy diffusion; the diffusion of EFOIA is not associated with economic competition between states over tax revenue, or federal mandates (or incentives such as federal grants) to coerce states to take actions in compliance with federal policy preferences. Furthermore,

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[3] Electronic Freedom of Information Act Amendments § 5.

[4] Before the federal EFOIA of 1996, West Virginia (1992), Indiana (1993), Kentucky (1994), and Texas (1995) already had their own law on electronic records to guarantee that the public would have access to public records of government bodies at all levels. A fundamental philosophy of the state law on electronic records is that the ultimate goals of agency responsibility and popular control of government are best-served by maximum public access to governmental records regardless of the type of data (Open Government Guide, 2011).

[5] Retrieved from http://www.rcfp.org/open-government-guide

the movement toward increasing public access to government information has shown different patterns across the states, depending on two stages of EFOIA; adoption and implementation.

US States' Adoption of EFOIA

Since the 1996 EFOIA amendment by the federal government, states have responded in different ways to the federal move toward increasing transparency. In terms of timing, some states adopted EFOIA earlier than others. In addition, the state statutes were designed differently in response to their political climate, although the basic format was similar to the federal model.

Subsequent to the enactment of the federal EFOIA of 1996, in the same year, several states supplemented their FOIA by adding legal statements on public access to government information through a digital form. The Colorado General Assembly enacted legislation requiring public agencies to keep public records only in miniaturized or digital form. Furthermore, Colorado's Open Records Act declared that it is necessary for state agencies to assist the public in locating any record sought by providing portable disk copies of computer files or direct electronic access via online bulletin boards. Similarly, Maryland’s Public Information Act contained the legislative statements that state agencies need to prepare electronic images of public records to enable all persons to have access to information about the affairs of government. As a practical matter, the electronic imaging of government documents by state agencies has made it significantly easier for public records to be accessed through agency websites.

Mississippi has updated its public records law for the electronic age. The Mississippi Public Records Act offers members of the public the right to request public records in digital formats: records must be electronically maintained and available for inspection by the public. According to this mandate, state agencies were forbidden to contracts for information services in the absence of public access to the information provided by those services.

In a similar vein, Vermont recognized as a matter of common law that the public has a fundamental right to inspect the public records of any government body. Vermont's 1996 amendment to the statute, for the first time, granted state agencies the authority to recover costs and fees for offering information; state agencies might charge the actual cost associated with providing the copy, including the costs of mailing or transmitting the record electronically. In North Carolina, no official legislative organ was associated with public access to government information. However, the state court confirmed that public records cover all materials that government agencies made or collected at their discretion in conducting government business, and had to be made available for public inspection.

Meanwhile, in Nebraska, online access by the public to government information was a matter of hot debate for several years. In 1995, the State Library Commission contracted with a private entity to access to electronic records without legislative approval, angering many senators during the 1996 legislative session. Yet, as a result of this move, a bill was passed that established a committee charged with studying the topic of public access to government information in a digital format.

In 1997, Alabama, Florida, and Delaware continued to follow the federal model of EFOIA. The Alabama trial court recognized that computers added a great amount of value to the creation of public records, and ensured public access to the records. By quoting with approval an Ohio Supreme Court opinion, the trial court confirmed that the public should not be required to expend massive amounts of time and resources to access information which public officials had already created. In Florida, public records should be also provided where they are easily with available to the agency and could have been released with a minimum of expense or time. In addition, the agencies in Florida had the discretion[6] to furnish electronic records in a format other than the format routinely employed by the agency.

At the same time, the Delaware Freedom of Information Act did not specify online access to public records, only defining public records that would include all information regardless of the physical form or characteristics. In Delaware, government bodies are responsible for enacting their own rules and regulations pertaining to the public's online access to government information and fees. Such discretion[7] allowed government entities to refuse to provide public records unless members of the public seeking information physically visited the government office, and inspected the information there.

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[6] Yet, in that case the cost of converting the information should be imposed on requesters.

[7] This was changed in 2011 with the adoption of a standardized form for requesting public records across the state, thereby eliminating much of the discretion of a governmental body. http://spotlight.blogs.delaware.gov/2011/10/20/a-standard-foia-form/

Similar to Delaware's Statute, the Access to Public Records Act (APRA) of Rhode Island in 1998 indirectly dealt with online access to government information by broadly defining public records as those maintained by any public body regardless of their physical form or characteristics. Although the Rhode Island's APRA provided online access to public records, the Act denied access to non-residents or non-citizens: In 2006, however, the United States Court of Appeals for the Third Circuit in Lee v. Minner rejected the denial of FOIA requests based on state citizenship, requiring the states[8] limiting access to state citizens to provide public records to all US citizens.

In 1999, Georgia's statute contained the declaration regarding online access by the public to government information. Georgia had a long tradition of encouraging openness in governmental records. The philosophy behind Georgia's Open Records Law was that a democratic government enables those who elect public officials to have free access to what those public officials are doing, thereby allowing them to participate in democratic processes and to hold government officials accountable. The Georgia Open Records Law required state agencies to maintain public records available by electronic means. However, in accordance with the Georgia Administrative Procedures Act, governmental bodies cannot use the Open Records Law to access public records pertaining to the proceeding without the prior approval of the presiding administrative law judge.

[8] Delaware, New Jersey, Virginia, Arkansas, and Pennsylvania, retrieved from http://ballotpedia.org/Delaware_Freedom_of_Information_Act#Transparency_report_card

In 2000, Illinois, Nevada, South Carolina, and Wisconsin joined the transparency movement in providing online access to government information. While the state acts of public records enacted in previous years gave the authority for enforcing the act to the Attorney General, these states allowed civil enforcement by any person. Furthermore, these states tended to specify legal statements regarding fee provisions for access to public records or limitations on refusal to disclose.

When it comes to fee provisions, the Illinois Attorney General issued an opinion saying that county recorders could not charge a fee for access to online records posted on a governmental website. The South Carolina Freedom of Information Act declared that fees for access to public records had to be uniform, and that the records had to be provided at the lowest possible cost which could not exceed the actual cost of searching for the records.

With respect to exemption in disclosing information for public interest, the Nevada Supreme Court declared that the public bodies must establish the existence of a privilege as to public records when the refusal to disclose is based on confidentiality. Similarly, the Wisconsin Supreme Court held that public employees whose reputational interest would be influenced by disclosure of public records had to be notified of the decision on the release of the records with a reasonable amount of time so as to seek circuit court review of the decision.

In 2001, Arkansas, California, and Michigan updated their FOIA for the electronic age by requiring state agencies to make public records available in digital form. These states have two prominent features of their state laws on electronic records. The

public records acts formerly amended in other states did not allow requesters to choose a format for receiving public records: rather, that right lay with public agencies. However, the act of these states granted requesters the right to determine the format in which public records were made or provided. For instance, the California Public Records Act required public agencies to make information available in an electronic format when requested by any person in that format. This statute, effective January 1, 2001, superseded portions of an earlier statute that granted public agencies to determine the form holding the information if requested. Similarly, the Arkansas FOIA[9] declared legal intention that any person is allowed to request public records in any medium if those records are readily available.

As another distinct feature of theses states' laws on electronic records, the imposition of prohibitive fees to discourage requesters was constrained. Many public bodies were routinely assessing search fees for every request, in an attempt to deter requesters. For example, a Georgia county government attempted to bill a citizen almost $2,300 for copying fees and $90 an hour for legal review of public records. On one occasion, South Carolina agencies sought to prohibit information requests by requiring exorbitant advance deposits.

[9] The Arkansas FOIA did not formerly mention electronic records until its amendment in 2001. The Electronic Records Study Commission created in 1999 examined the Arkansas FOIA, and provided the General Assembly with recommendations for addressing various issues surrounding electronic access in the 2001 session.

However, Arkansas', California's, and Michigan's laws on electronic records recognized such routine labor charges as illegal. To combat these fees, the Michigan FOIA stipulated that

> "[a] fee shall not be charged for the cost of search, examination, review, and the deletion and separation of exempt from nonexempt information . . . unless failure to charge a fee would result in unreasonably high costs to the public body because of the nature of the request in the particular instance, and the public body specifically identifies the nature of these unreasonably high costs." (Michigan Attorney General. Op. No. 7083, 2001).

In a similar vein, the Arkansas FOIA and the California Public Records Act[10] contained declarations that public agencies are not allowed to impose prohibitively high copying charges to discourage information requests.

After the terrorist attacks of September 11, 2001, the George W. Bush administration altered its position on FOIA requests. The centerpiece of the George W. Bush administration's change in the direction of FOIA releases was the Justice

[10] Although the CPRA prohibits fees in excess of the "direct costs of duplication," many public bodies, especially at the local level, routinely overcharge. More problematic are the charges associated with releasing public records in a digital format. "While costs for compiling or extracting and related programming necessary to produce electronic records not otherwise routinely generated by the agency are allowable under Section 6253.9 of the CPRA, such costs have often placed access beyond the reach of most requesters, with agencies often demanding many thousands of dollars for anticipated programming costs. It also has become a new way for agencies bent on nondisclosure to discourage requesters from pursuing their access rights." (Open Government Guide, 2011, p. 8).

Department's FOIA policy memorandum issued by Attorney General *John Ashcroft* on October 12, 2001. Ashcroft's memo addressed concerns about national security associated with access to government information. Ashcroft identified fundamental values that included safeguarding national security, enhancing the effectiveness of the law enforcement by agencies, and protecting personal privacy and sensitive business information (Feinberg, 2004).

Ashcroft also pointed out that, prior to making any decisions to release public records, government agencies should fully take account of the institutional, commercial, and personal privacy interests that could be influenced by the records. Ashcroft's memo allowed public agencies to defend their decisions to withhold government information from the public, "unless they lack a sound legal basis or present an unwarranted risk of adverse impact on other agencies' abilities to protect their records." (Anderson, 2003, p. 1622). This was almost the opposite of the FOIA guidelines issued by the Clinton administration, stating that public agencies could not defend their decision to withhold records merely based on a substantial legal basis (Feinberg, 2004).

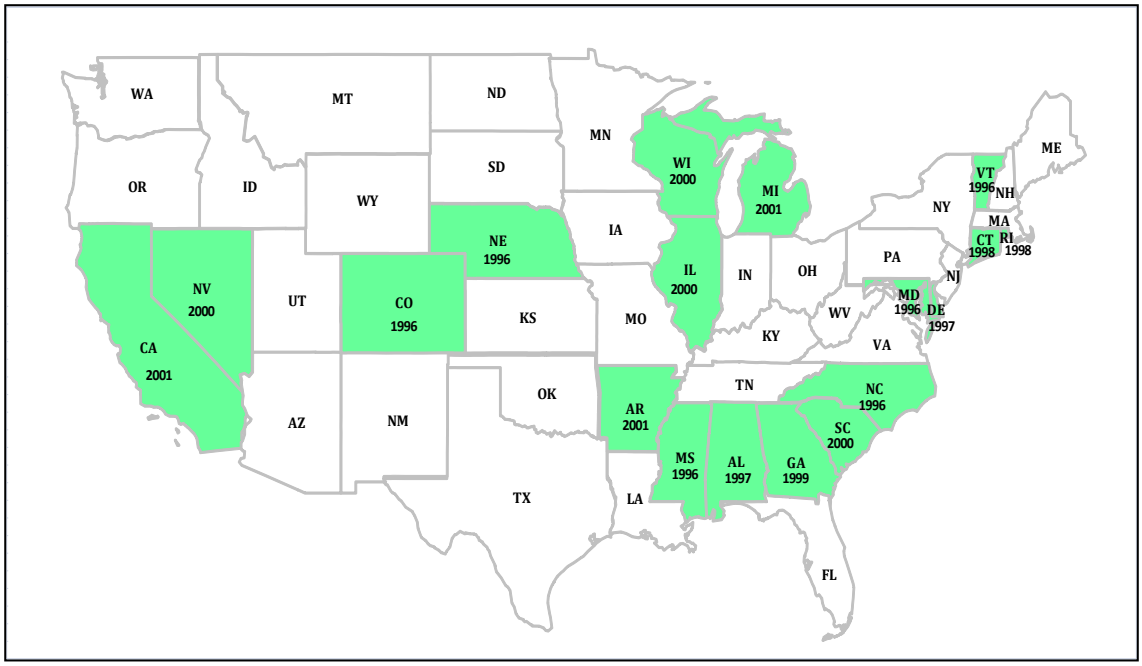

Figure 1 Adopters of EFOIA from 1996 to 2001

This new chapter to the FOIA story created in the aftermath of the 2001 terrorist attacks influenced states' decisions to update their public records acts, sending out "contradictory" guidelines; requiring public agencies to make more information available electronically, while urging the agencies to remove broad categories of information from their transparency websites (Feinberg, 2004).

In 2002, the governors of Connecticut, New Jersey, and Minnesota signed into law a new open public records act to provide a uniform system for responding to requests for electronic records. The new statutes preserved the common law right of access, and provided for access to government information stored or maintained electronically. Yet, these state laws specified legal statements about an exemption for public records when there were reasonable grounds to believe disclosure might pose a safety risk. Since there

was no integrated or coherent government policy to balance access, privacy, and secrecy, each state had discretional standards regarding an exemption from disclosing public records. However, in general, the amended section of these states addressed security concerns regarding disclosure of sensitive information associated with engineering drawings, operational specifications, security training manuals, and emergency plans of government-owned or government-leased facilities, or risk management plans of water companies.

Virginia (2003), Missouri (2004), Montana, Ohio and Utah (2005), and Oklahoma (2006) subsequently amended the section of their state FOIA to deal with creation or maintenance of an electronic database. These states encouraged but did not require public bodies to maintain an electronic data processing system of nonexempt records, and produce the records at reasonable cost as well as in any tangible medium requested by the requester, including posting the records on a website or delivering them through e-mail. However, these states simultaneously sought to remove some materials from public records based on the discretion about exemption. For example, under the Utah Government Records Access and Management Act, the following information is exempt: records created or maintained for civil, criminal, or administrative enforcement purposes or audit purposes, and private information on certain government employees. Meanwhile, the Montana Public Records Act contained the privacy "exemption" analysis[11] used for determining whether records may be kept confidential.

[11] The privacy exemption analysis includes a following three-part test: 1. Did the person involved have an actual or "subjective" expectation of privacy; and, if so 2. Is that expectation

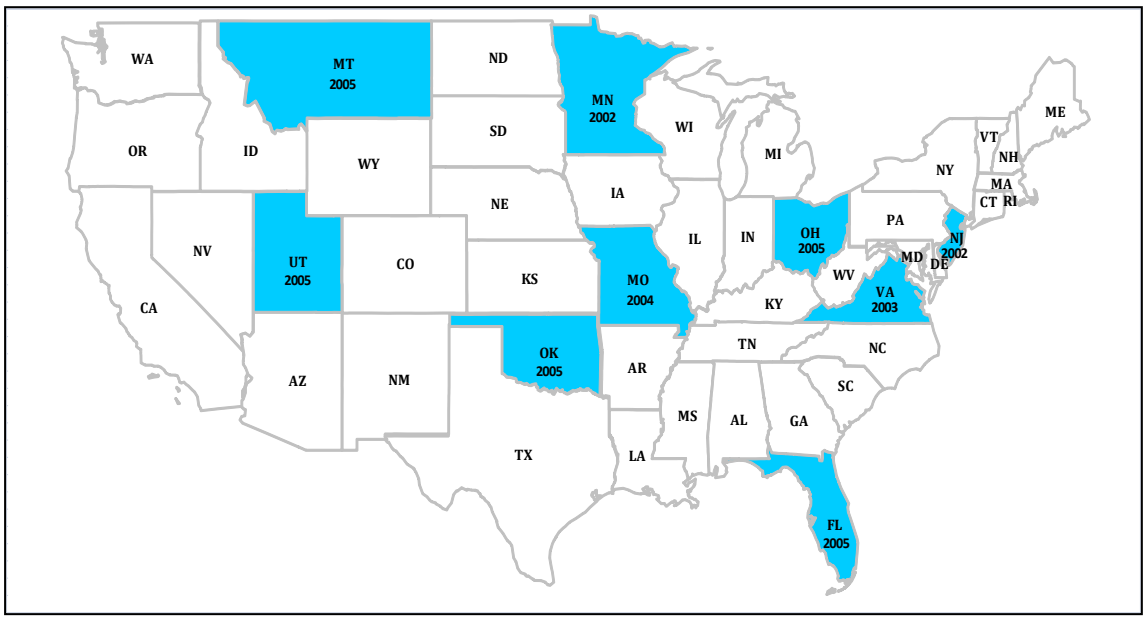

Figure 2 Adopters of EFOIA from 2002 to 2006

With regard to EFOIA management between 2001 and 2004, the GAO reports[12] noted that public agencies modified or removed government information, even frequently requested records, from their websites in response to concerns about national security (GAO, 2001, 2002, 2004). Indeed, the number of exemptions cited to support denials rose by approximately 73% from 2001 to 2002, including exemptions of law enforcement records, and personnel and medical files. Moreover, a change in policy climate characterized as moving from "a right to know" to "a need to know" was reported along with a drop in requests (Feinberg, 2004).

"reasonable"? 3. If the answers to paragraphs 1 and 2 are affirmative, then the documents containing private information may be withheld if the demands of individual privacy clearly outweigh the merits of public disclosure. If the answer to either 1 or 2 is negative, then the documents are available for public inspection.

[12] Although the GAO reports focused mainly on the federal agencies, state governments cannot be isolated from such policy climate regarding exemption of public records.

In 2007, political attention turned to the promotion of accountability for agency decisions to withhold information under FOIA. Senators Patrick Leahy and John Cornyn introduced the OPEN Government Act in the 110th Congress on March 13, 2007. This bill was expected not only to help members of the public obtain timely responses to their information requests, but also provide an alternative to costly litigation for information requesters and the government. The need for this bill resulted from the major delays[13]encountered by information requesters. In April, 2007, the bill was placed on the Senate Legislative Calendar (No. 127) under General Orders, and political debates continued.

In this political atmosphere, Idaho's and Ohio's legislatures determined to include electronic information as governmental records. As other states had done in previous years, these states recognized that some types of public records associated with privacy and safety should not be available for public inspection and copying. However, the statutes of theses states — rather than simply following the federal EFOIA model[14] — identified the actual types of records exempt from public disclosure with a greater degree of specificity. In addition, these states sought to interpret their public records statute and enforce the law comprehensively, rather than taking a case-by-case approach.

[13] The government Accountability Office found that federal agencies and 43 percent more FOIA requests pending and outstanding in 2006 than they had in 2002 (the 110th Congress report, 2007).

[14] In the federal EFOIA, a small number of exemptions are loosely defined, along with the parameters of the exemptions left to agency regulations and judicial interpretation (Open Government Guide, 2011, Retrieved from http://www.rcfp.org/open-government-guide).

The Idaho Public Records Act refused to give government agencies the discretion to withhold public records from the public on the basis of judicial interpretations. This approach was especially appropriate in Idaho, a state with a small population, and therefore expecting infrequent judicial interpretations of the open records statutes (Open Government Guide, 2011). In Oregon, the State Department of Justice played a central role in interpreting its public records statute and in aiding in the enforcement of the law. The public records manual published and updated by the Attorney General every two years could serve as a useful desk reference for many records questions: the manual contained a summary of all public records statutes, the Attorney General's opinions, and valuable commentaries about frequently asked questions.

On December 31, 2007, President George W. Bush signed the OPEN Government Act into law. The OPEN Government Act enhanced public and press access to information about inner workings of the government in several important procedural ways: to strengthen and speed agency compliance with FOIA requests; to establish tracking numbers for each FOIA request so that users can follow the progress of their requests online; to identify agencies that rejected requests for capricious and arbitrary reasons; to prohibit an agency from assessing search and copying fees if the agency failed to release requested information within statutory time limits (Open Government Act, 2007).

After the enactment of the OPEN Government Act of 2007, states responding to the electronic age sought to amend their by focusing exclusively on "procedural issues" of information requests. In 2008, New Hampshire, New York, North Dakota,

Pennsylvania, and Tennessee amended their statutes to make explicit the application to governmental records in electronic form. These states addressed the issues of time frames for responses to requests, the provision of the new programming to provide the information, and the standard of a reasonable price for copies of records.

For instance, the New Hampshire Right to Know Law stipulated that an agency had to respond to a request for records within five business days. The New York legislation contained a new provision requiring an agency to use a new program — rather than manually manipulate or redact the data — either to retrieve a record maintained electronically, or to convert that record to the medium requested. North Dakota's statute contained provisions setting a reasonable price for copies of records: if locating records requires more than one hour, the entity may impose a fee not exceeding $25 per hour per request, excluding the initial hour, for locating records, including electronic ones.

Meanwhile, the statutes of Pennsylvania and Tennessee created institutions to assist public officials and the public, thereby expanding upon the procedures increasing the civil judgments that would be awarded against an agency acting in bad faith. Under the Pennsylvania Right to Know Act, the Office of Open Records was created to disseminate information, handle appeals, issue advisory opinions, create a mediation program, and ensure compliance with the Act’s requirements.

In a similar vein, Tennessee formed the Office of Open Records Counsel as a department of the State Controller, thereby assisting and advising public officials and the public. The Open Records Counsel[15] was also an ombudsman that would mediate disputes and opinions regarding open records issues.

In 2009 and 2011, remaining states[16] that had not designated legal statements on electronic records finally amended their FOIA: Arizona, Iowa, Kansas, Louisiana, New Mexico, Massachusetts,[17] South Dakota, Washington, Wyoming, and Maine. Some of these states created an office of an "ombudsman." In Arizona, any citizen may complain to the Office of the Ombudsman-Citizens Aide about the actions of public agencies. When responding to a complaint, the Ombudsman-Citizens Aide had the power to investigate the administrative acts of agencies and make recommendations to the governor, the legislature, and/or the appropriate prosecutor. The Iowa legislature also created the office of the Ombudsman-Citizens Aide that would investigate, on complaint or on the citizens' aide's own motion, any administrative action of any agency.

However, these late adopters, ironically, retreated from advances in the creation or maintenance of an electronic database. The statutes of these states did not have statutory language concerning procedural issues of FOIA requests, such as response time

[15] The office of Open Records Counsel, and its Advisory Committee, may also review and make comments to the General Assembly on any legislation affecting open records. The Act has no provision for allowing the requester to choose a format to receive records. The Supreme Court held that if there is information that is stored on computer but not in the format desired by the requester, the agency is required to provide the information in the format requested (Open Government Guide, 2011).

[16] Maine included legal statement regarding electronic records in 2011.

[17] The public records law of Massachusetts is among the weakest in any of the 50 states (Open Government Guide, 2011, http://www.rcfp.org/open-government-guide).

frames and the provision of electronic data processing system. For example, although the Arizona Public Records Law required public records to be promptly furnished, it did not designate a specific number of days within which a public body had to furnish the records. Thus, the state courts had to rely on a dictionary definition of "promptly" to require that public records be produced at once or without delay. Under the Kansas Public Records Act, a delay was not recognized as denial for appeal purposes.

Therefore, in Kansas, a public agency was simply required to give a detailed explanation of the cause for delay, and the place, time and date that the record would be available for inspection, unless a request is granted immediately. Furthermore, these states did not provide even statutory language stating that online access to public records in electronic form may be made available at the discretion of the public agency: instead, they implicitly designated online dissemination by broadly defining[18] "public record."

Finally, none of the statutes of these states mentioned the format for receiving the records requesters can choose, and customized searches of computer databases. The state statutes merely noted that reporters, as a matter of practice, have been able to determine a format for receiving records, if the format is available. In the statutes, statutory exemption did not specify the records or information that the legislature considered private.

[18] Public record is defined as all existing documents, papers, letters, maps, books, tapes, photographs, films, sound recording or other materials, regardless of physical form or characteristics (Open Government Guide, 2011, Retrieved from http://www.rcfp.org/open-government-guide).

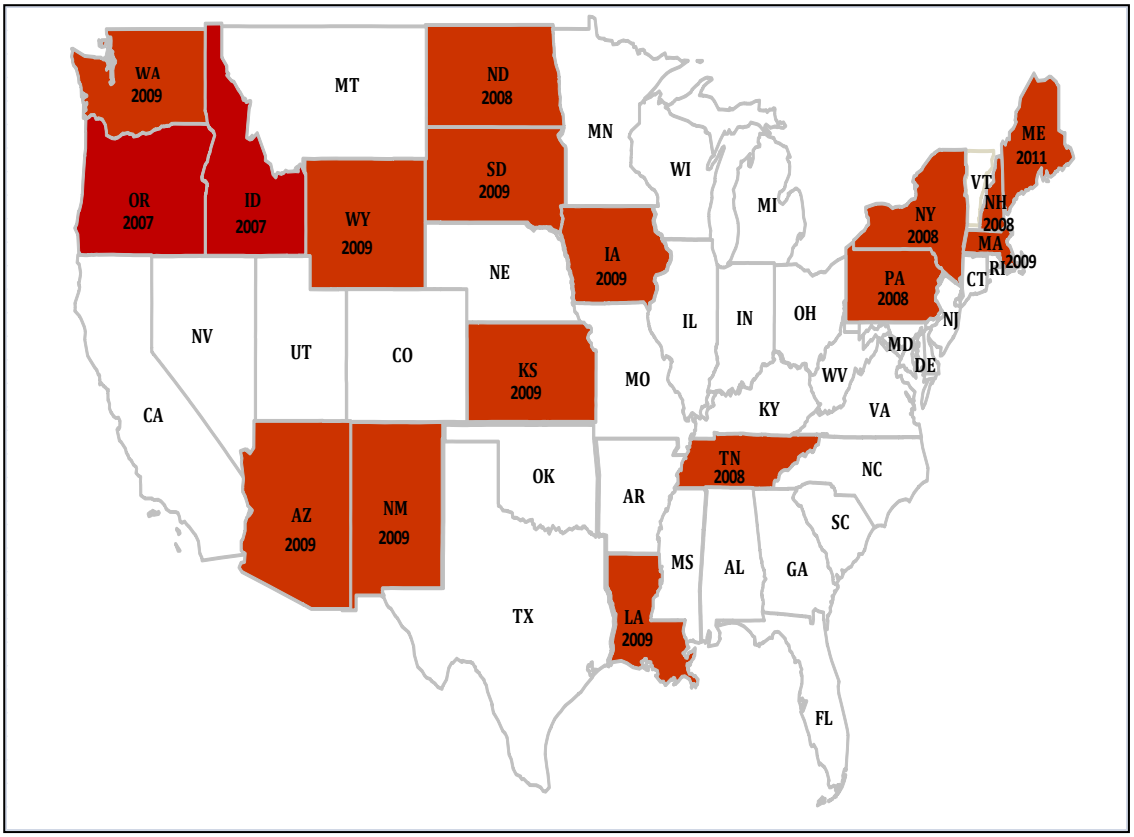

Figure 3 Adopters of EFOIA from 2007 to 2011

US States' Implementation of EFOIA

State governments across the US have established a legislative environment for public access to government information, but there is a great deal of variation in terms of the extent of implementation of EFOIA (U.S. PIRG, 2010, 2011, 2012); some states managed their transparency websites by excelling in living up to the spirit or the letter of EFOIA, while others failed to achieve progress in their transparency portals.

In 2010, 32 states allowed residents to access online databases of government expenditures such as tax subsidies and economic development grants. Seven of these

states were "leading states" or "advancing states[19] " in the transparency movement, hosting websites that provided comprehensive information on government spending: Kentucky, Ohio, Texas, Illinois, Minnesota, Missouri and Pennsylvania. These states set user-friendly portals enabling visitors to quickly and easily search government spending data by vendor's names and types of services purchased.

In addition, transparency websites of leading and advancing states contained detailed information on government contracts, such as the purpose of contracts, the amount of each contract, and contract information for vendors. Kentucky's website offered visitors both a detailed summary of state spending and PDF versions of the contracts. Furthermore, a few of the leading transparency sites had unique features designed to increase citizen involvement. For example, Illinois' website listed the number of jobs created by tax subsidies or development grants, thereby allowing visitors to determine the efficacy of the allocation. Similarly, Kentucky's website enabled users to submit suggestions about improving spending efficacy.

Yet, the transparency websites of these leading and advancing states still had room for improvement. They did not contain information that citizens needed to assess the efficacy of government spending. Some of these websites gave only a short description (two or three words) of the purpose of government contracts. In addition, most of the transparency portals had no information prior to fiscal year 2009.

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[19] The US PIRG evaluated state transparency websites in terms of data availability, usability, and accessibility, and then drove through the review of state agencies administering the transparency websites for accuracy. Leading and advancing states refer to those who achieved a grade of A (>=90) and B (>=80), respectively in online transparency.

Unlike the seven leading and advancing states, 25 states[20] either offered less comprehensive information (i.e. emerging states), or failed to provide spending data in a searchable format (i.e. lagging states) For instance, the transparency websites of Georgia, Nevada, and Oklahoma did not specify the purpose or output information of government spending, providing only the vendor's name, the contracting agency, and the obligation amount. Alaska, Oregon, and Tennessee offered information on grants, local expenditures, and tax expenditure reports, but visitors already had to know what they were searching for to find the information.

The remaining states — failing states — were left behind by the transparency movement for increasing public access to government information. Fourteen of the failing states[21] did not have transparency websites. Arizona, New Jersey, South Dakota, and Washington had transparency portals, but they offered either limited or superficial information about government expenditures. The transparency websites of Arizona and New Jersey specified only aggregate spending amount for departments and agencies, offering no description of the types of services purchased or the amount of each individual transaction. In South Dakota and Washington, visitors could view information on the contracts for professional services, but search for much less summary information on general contracts.

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[20] Alabama, Hawaii, Nevada, Colorado, New York, Virginia, Kansas, Mississippi, North Carolina, Utah, Rhode Island, Delaware, Oklahoma, Louisiana, Florida, Maryland, New Mexico, Oregon, Wyoming, South Carolina, Nebraska, California, Georgia, Tennessee, and Alaska

[21] Arkansas, Connecticut, Idaho, Indiana, Iowa, Maine, Massachusetts, Michigan, Montana, New Hampshire, North Dakota, Vermont, West Virginia, and Wisconsin

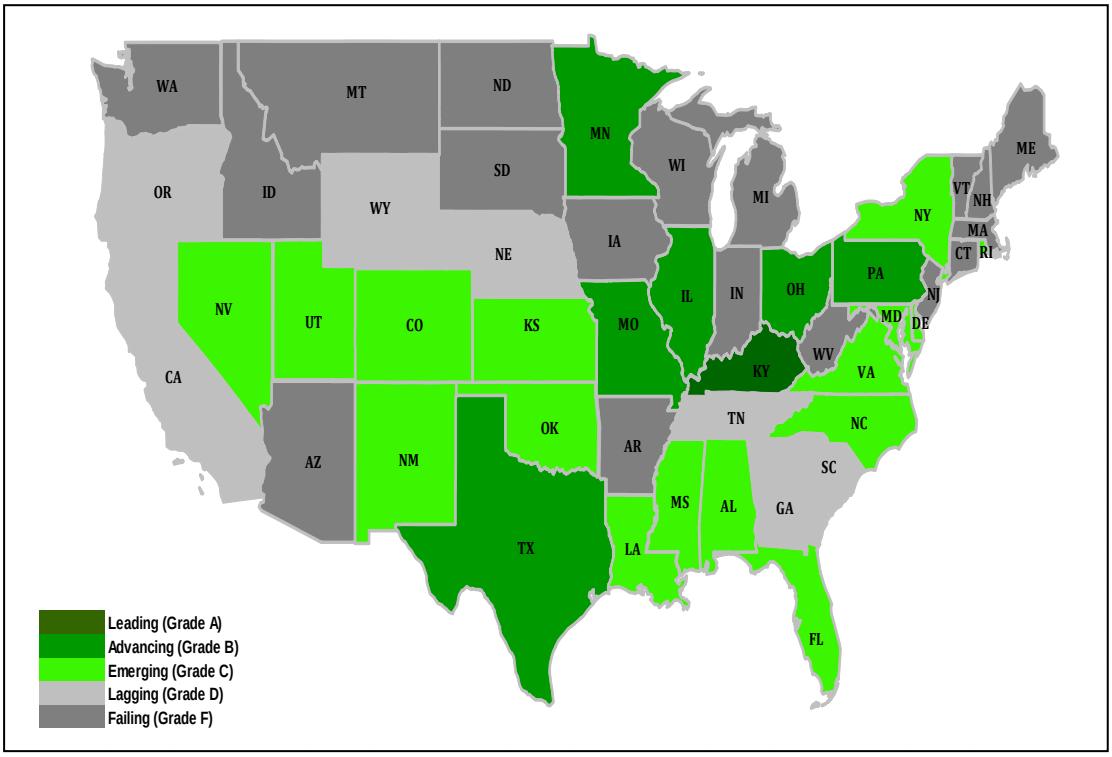

Figure 4 States' extent of Implementation of EFOIA in 2010

In 2011, Indiana, Louisiana, Arizona, Massachusetts, North Carolina, and Oregon were highly ranked in terms of providing online access to government spending data, newly involving the group of leading states or advancing states. These leading and advancing states made distinctive improvements in the detail of the information available. The states' websites posted details about past contracts, a link to its tax expenditure report, and information about economic development incentives, thereby allowing visitors to evaluate specific expenditures.

Another remarkable feature of transparency portals of leading and advancing states was the ease of use. Each of the portals offered tools enabled citizens to make

targeted searches and sort the data. For example, on Indiana's transparency website, visitors could search for information by the types of payments spent with vendors (e.g. Grant, Lease, Professional/Personal services, Contracts) along with the typical keyword search box. Louisiana's website provided separate search sections for grants, contracts, and economic incentives. On North Carolina's website, users could also search for spending data by the vendor's location, and thus see how government expenditures were geographically distributed.

As in the previous year, Kentucky, Ohio, and Texas were at the leading edge of enhancing public access to government information by making up for the weak points of their transparency portals. In Kentucky, Ohio, and Texas, visitors could access information about the purpose of economic development incentives and grants, outcome data about the number of jobs created from a specific incentive, and historical financial reports. However, as a result of the rise of new leading states, Illinois, Minnesota, Missouri, and Pennsylvania went through a small drop in online transparency scores and rankings although they maintained levels of comprehensiveness and searchability similar to the previous year.

Meanwhile, New Jersey, Michigan, South Dakota, and Wisconsin broke away from the group of failing states. These states made dramatic improvements to their transparency portals, raising their annual transparency total score by at least 50 points. In 2010, New Jersey and South Dakota posted only aggregated spending numbers for departments and agencies on their transparency websites. However, these states upgraded their portals by allowing visitors to track specific payments made to individual vendors

(e.g. general contractors, subcontractors, consultants, business entities). Michigan and Wisconsin — which did not host transparency portals in 2010 — launched their websites that would offer users information about sales, income, and property tax expenditures through easy-to-use search tools.

The rest of the states, such as Arkansas, Iowa, Idaho, and Maine, did not show clear improvement or change in the provision of online access to government information in comparison to the previous year; the other states tended to remain roughly at the previous transparency scores or rankings.

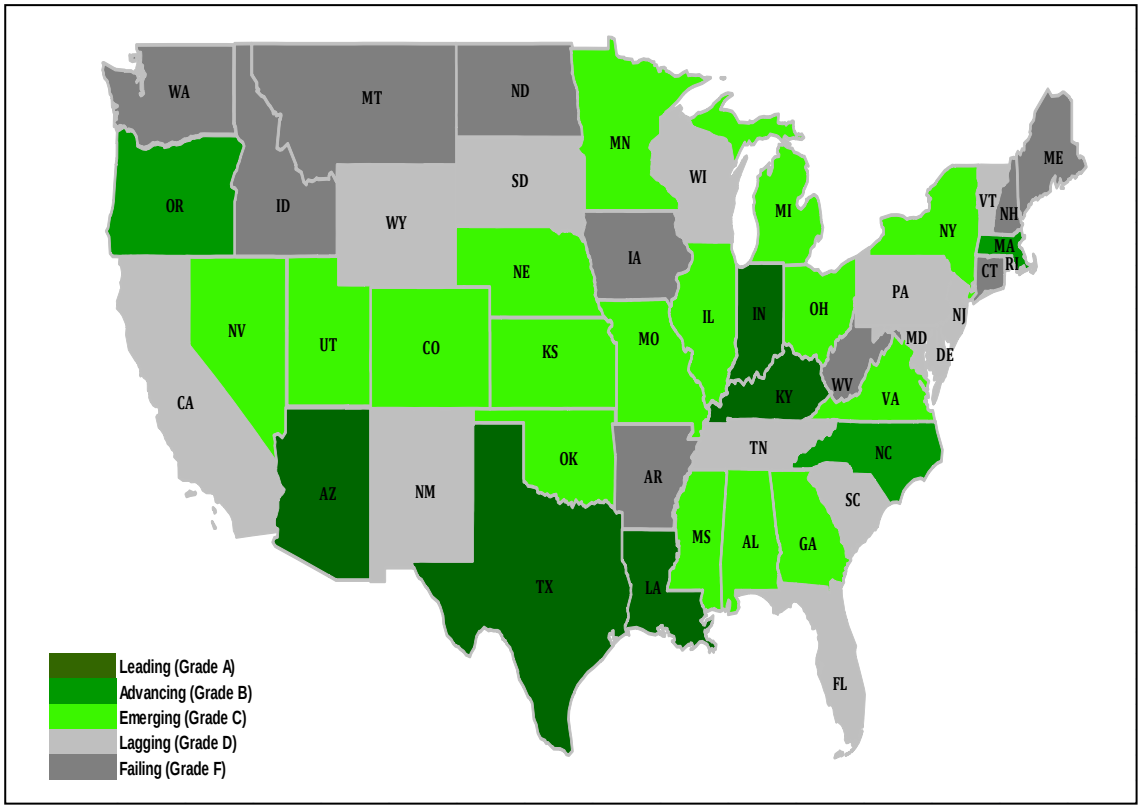

Figure 5 States' extent of Implementation of EFOIA in 2011

In 2012, Texas, Kentucky, Indiana, Louisiana, Massachusetts, Arizona, North Carolina, and Oregon continuously made progress in increasing public access to government spending data. These leading and advancing states expanded the online spending data they contained on transparency websites by including government contracts with private entities, subsidies, tax expenditure data, and transactions by quasi-public agencies. In addition, these states' transparency websites enabled visitors to search easily and quickly for information by inscrutable layers of subcategories, recipients' names, purchasing departments or agencies, types of good or service purchased, or directed keywords.

The most distinctive feature of transparency portals of these states was the ability to allow users to download datasets of vendor-specific information and compare state spending over time. Such functions of transparency websites made it easy for visitors to uncover "whether some companies are historically favored over others and whether the state is paying an appropriate amount for the goods and services purchased in a certain year as compared to others." (U.S. PIRG, 2012, p. 32). However, all leading states provided either the projections of the number of jobs created, or other intended benefits of economic development awards, failing to specify the number of jobs or other benefits which were "actually" created.

In addition to these states, Connecticut, New York, Utah, Washington, and West Virginia excelled in providing online access to government spending data, entering the group of leading or advancing states. These states updated their transparency portals to make government spending data far more accessible, not just (technically) available to

the public. For example, on Connecticut's website, the layout was intuitive and understandable to an ordinary Connecticut citizen, along with clear links for the types of state payments (e.g. "Contracts", "Grants", or "Compensation") and simple search criteria (e.g."2010" or "2011"). Thus, visitors did not need to be tech-savvy budget experts to search for information. New York's and Utah's websites were directly linked to tax expenditure reports of the states, thereby allowing users to see tax exemptions, credits, deferrals, and preferences that would affect state budgets.

Meanwhile, compared to the previous years, some states made significant improvements to their transparency websites with a noticeable increase in the score of online budget transparency: Delaware, Michigan, Nebraska, New Mexico, North Dakota, Mississippi, and South Dakota. These states redesigned their transparency websites to incorporate more detailed information on government expenditures and searchability. For instance, Delaware's website gave visitors a one-stop place to find government spending information from the Office of Management and Budget, Government Support Services, and county governments. North Dakota opened the state's checkbook specifying the payments made to vendors. The checkbook was updated monthly and included expenditure information dating back to 2007. On New Mexico's website, most pages had a sidebar that explained the page and provided helpful links, along with a glossary for ambiguous terms.

However, when it came to making their spending data available and accessible online, several states were a little behind the transparency movement. Ohio and Rhode Island dropped about 20 points from the previous year. Although Ohio was the second-

highest scoring state for online budget transparency in 2010, it failed to innovate at the pace of its peers. Ohio disconnected the link from the state's Recovery Act spending portal, thereby losing the access to important expenditure information. Furthermore, Ohio lacked tools for targeted searches by companies, the purchasing department, or agency, making it difficult for citizens to scrutinize the benefits for specific companies, and evaluate the efficacy of the expenditures. Similarly, Rhode Island failed to make its checkbook searchable, and thus dropped in the rankings. Although Wisconsin launched its transparency portal, the website did not allow visitors to view the individual payments made to vendors, and thus earned a low score of spending transparency.

California took the biggest step backwards from online budget transparency. In November 2011, Governor Jerry Brown shut down California's transparency portal, making California's spending picture vague. Brown's administration rationalized this action by contending that citizens ought to use the primary sources of information such as agency websites. However, with the state's spending data scattered across multiple agency websites, it would be difficult to access the data because of its different formats and locations. Therefore, although the state's spending data were technically available, this shutdown of California's website rendered the data inaccessible by removing a central searchable location for government information.

Meanwhile, Alaska, Florida, Tennessee, Vermont, and Wisconsin were still lagging in the transparency movement. On transparency websites of theses states, visitors were not allowed to access spending data with easy-to-use search tools. No state was easily searchable by the kind of good or service; Florida's and Tennessee's portals were

searchable only by the purchasing department or agency. Beyond the difficulty of searching spending data, the transparency websites of these states did not make important government spending data — such as information on the state revenue forgone through tax code spending — available online.

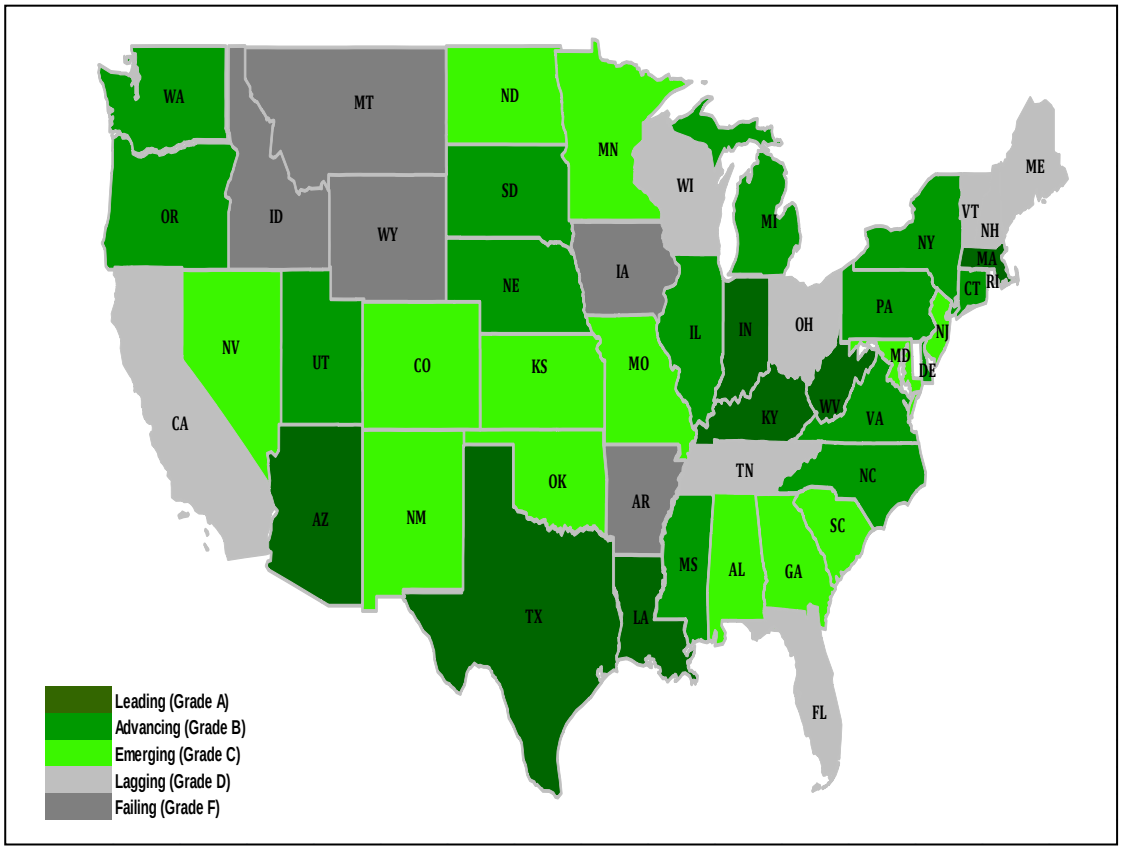

Figure 6 States' extent of Implementation of EFOIA in 2012

The rest of the states, Arkansas, Idaho, Iowa, Montana, and Wyoming, were failing in online transparency, although they took a small step toward increasing public access to government spending data over previous years. For example, on Wyoming's portal, the state's checkbook was searchable only by vendor. Thus, users could not view

the individual payments made to vendors unless they already knew the name of the vendor they were looking for. Moreover, Wyoming's website lacked information on historical expenditures, grants, economic development subsidies, and local spending. In a similar vein, Idaho's, Iowa's and Montana's transparency portals provided little information on government expenditures, and made it difficult for visitors to sort the data.

Characteristics of EFOIA Diffusion at the Adoption Stage

Most of all, the early adopters, the states adopting EFOIA in the late 1990s and the early 2000s[22], tended to follow the federal model of EFOIA; their statutes stipulate that they use the same basic format as the federal model of EFOIA, including the scope of public records, fee provisions, and characteristics of exemptions.

Another distinctive feature of the early adopters is that precise improvement continued along with the state laws on electronic records. In 1997, the definition of "public record" (or governmental record) was more clearly specified than before in order to encompass information that was electronically maintained or produced. In 1998, with respect to the decisions on the rules pertaining to online access, the state laws were able to constrain the discretion of public agencies and their refusal to fill information requests, thereby increasing online access to public records. Moreover, in 1999 the state statutes extended the right to online access to non-citizens. In 2000, the state statutes allowed for civil enforcement by any person, simply beyond giving the authority of enforcing the act to the Attorney General. Finally, the state statutes of 2001 granted requesters the right to determine the format in which information was made or provided.

[22] before the 9/11 terrorist attacks in 2001

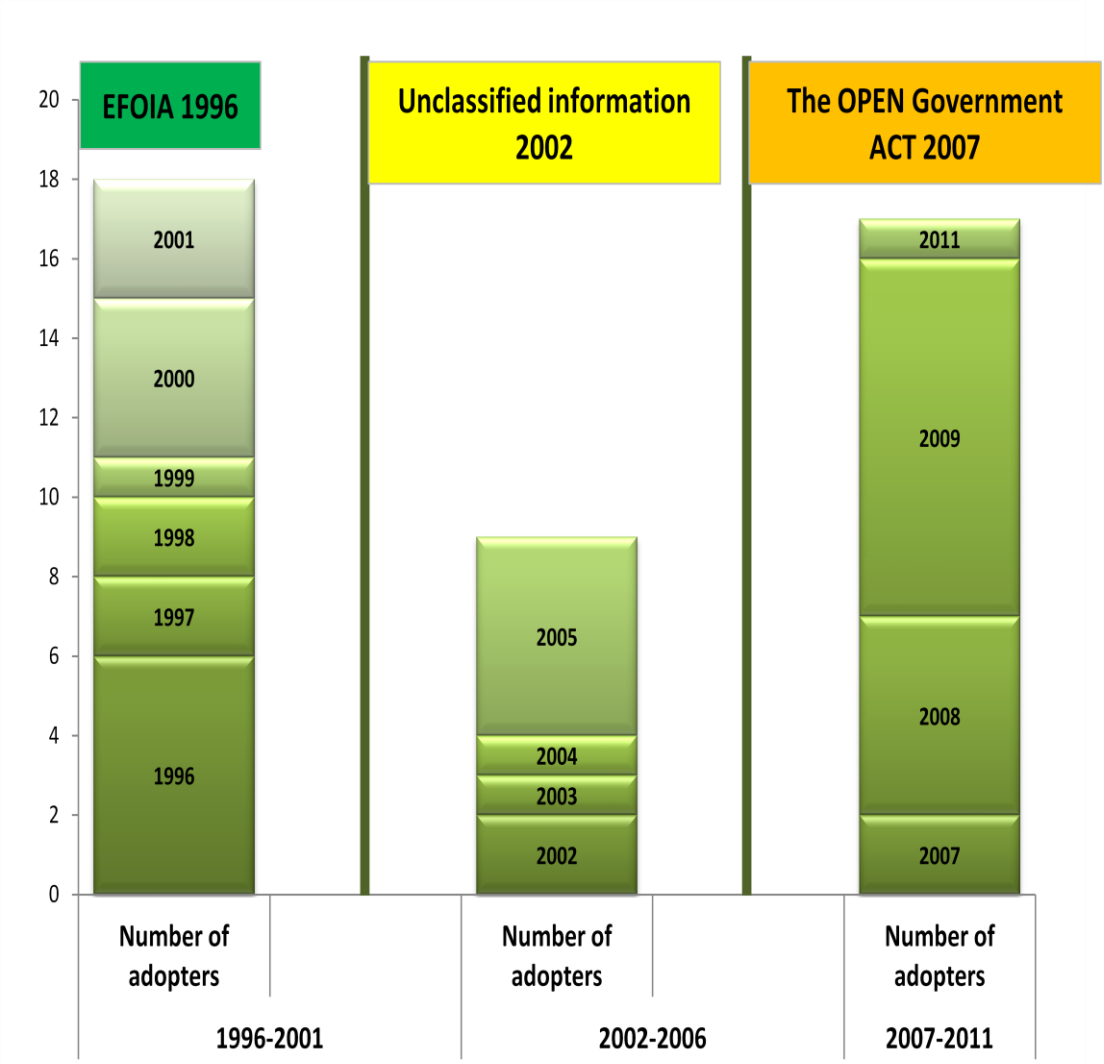

Figure 7 Numbers of Adopters

At the same time, there has been considerable variation in the timing of adoption among the states. After the September 11 terrorist attacks, there was a sharp drop in the number of the adopters of EFOIA; while 18 states adopted EFOIA before the 9/11 attacks, nine adopted the law from 2002 to 2006. Such a retreat from offering online access to government information might be associated with the political climate under the George

W. Bush administration in which public agencies withheld government information from the public out of concern for national security[23]. Since the OPEN Government Act in 2007, however, the number of EFOIA adopters nearly doubled from 9 to 17, reflecting a statutory language of the Act.

In addition to political climate of a state, policy actions of other states may have an impact on the adoption of EFOIA by a state. When grouping the states by the period in which an event[24] influencing a state's legal environment occurred, diffusion in states' adoption of EFOIA appeared to be associated with geographical proximity. For example, according to Figure 8, Alabama, Arkansas, Georgia, Mississippi, North Carolina, and South Carolina, which adopted EFOIA between 1996 and 2001 are located in the same geographic region (i.e. BEA[25] 5 region).

Furthermore, the influence of other states on the adoption of EFOIA by an individual state is also "national" beyond geographical proximity. For instance, the Maryland Public Information Act was patterned after Colorado's state statutes (Open Government Guide, 2011).

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[23] Despite the policy mood against government transparency, legislators of some states determined to amend their existing FOIA, taking notice of the overwhelming voter support for enhancing online access information about governmental operations.

[24] the 9/11 terrorist attacks in 2001 and the enactment of the OPEN Government Act of 2007

[25] Bureau of Economic Analysis (BEA) region are a set of geographic areas that are homogeneous in terms of industrial, economic, demographic and social characteristics. The total number of the BEA regions in the US is eight.

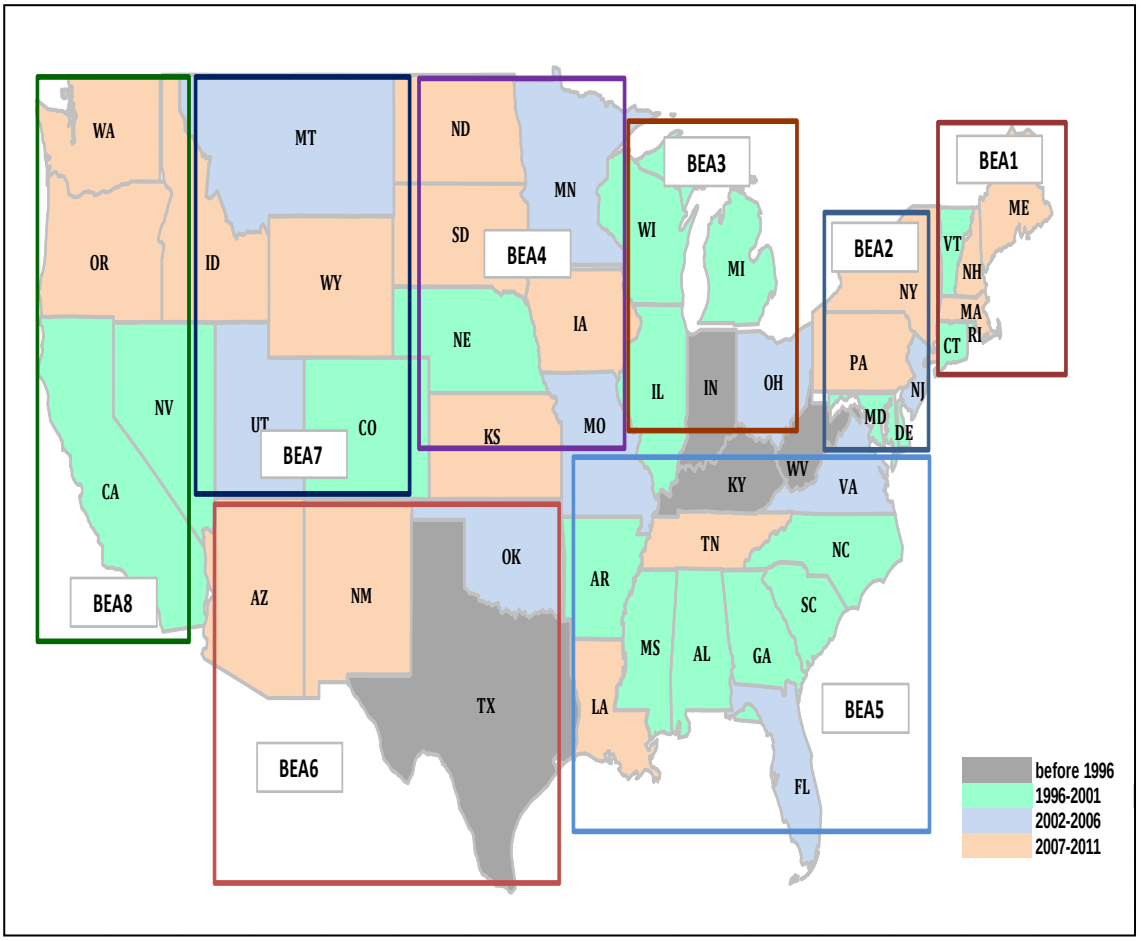


Figure 8 Geographical Location of Adopters

In conclusion, early adopters of EFOIA appear to be supportive of improving online access to public records. In addition, states' decisions in adopting EFOIA seem to have been associated with the legal practice created by the federal government, which may have affected the state's legal environment concerning transparency.

According to the legal environment theory suggested by Edelman (1990, 1992), the legal circumstance imposes *normative* pressure on organizations to change their behavior in accordance with legal practice or law. According to this perspective, legal practices of the federal government with regard to transparency, such as the policies of

the George W. Bush administration for withholding information and the OPEN Government Act of 2007, can create normative circumstances that influence a state's decision on its transparency policy. In this respect, the political environment or policy culture of a state might make it more receptive to EFOIA.

Furthermore, a state's adoption of EFOIA seems also to be affected by other states' decisions on the adoption of the law. The influence of other states that had already adopted EFOIA on an individual state can be either regional or national; an individual state's interactions with neighboring states as well as those within its geographic region through national networks may affect its decision to adopt EFOIA. Considering these characteristics of EFOIA diffusion at the adoption stage, states whose policy culture supports government transparency and/or that have involved in more interactive circumstances may adopt EFOIA earlier than others.

Characteristics of EFOIA Diffusion at the Implementation Stage.

In 2010, leading and advancing states that had shown impressive performance in providing online access to government spending data were dispersed across the United States. At a glance, in 2010, there was no distinct pattern link between states' implementation of EFOIA and their geographical proximity. However, several noticeable features of states' implementation of EFOIA were found, especially among states that saw the steepest increase in their online budget transparency score.

First, states adjacent to those that maintained a high rank in online transparency tended to show great improvement in operating their transparency portals in the following year. For example, Indiana and Michigan bordering Ohio (which was highly ranked in

online budget transparency of 2010 and 2011) were failing states in terms of online transparency of 2010. Both states, however, became new leading states in 2011, with at least a 50-point jump in their annual transparency total score.

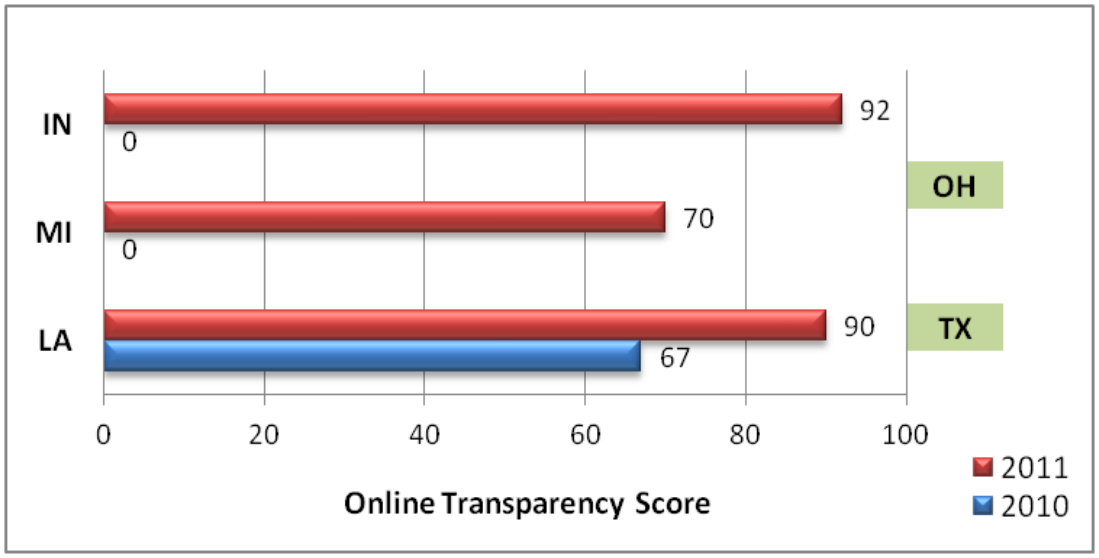


Figure 9 States with Steep Increase in Online Transparency Score (2010-2011)

A similar situation was observed in 2012 and 2013. For instance, Washington which borders Oregon, a leading state of 2011 and 2012, was highly ranked in online transparency in 2012, because of its dramatic progress in providing online access to government spending data. Oklahoma and New Hampshire — both of which were situated near leading states, Texas and Massachusetts, respectively — joined the group of leading states or advancing states in 2013.

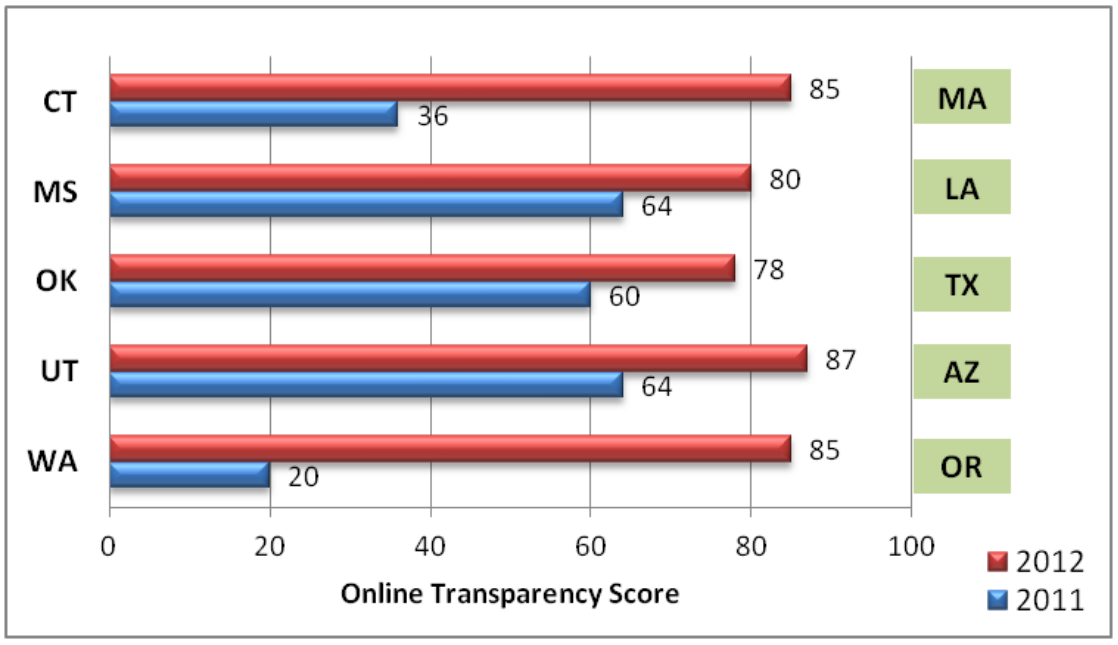


Figure 10 States with a Steep Increase in Online Transparency Score (2011-2012)

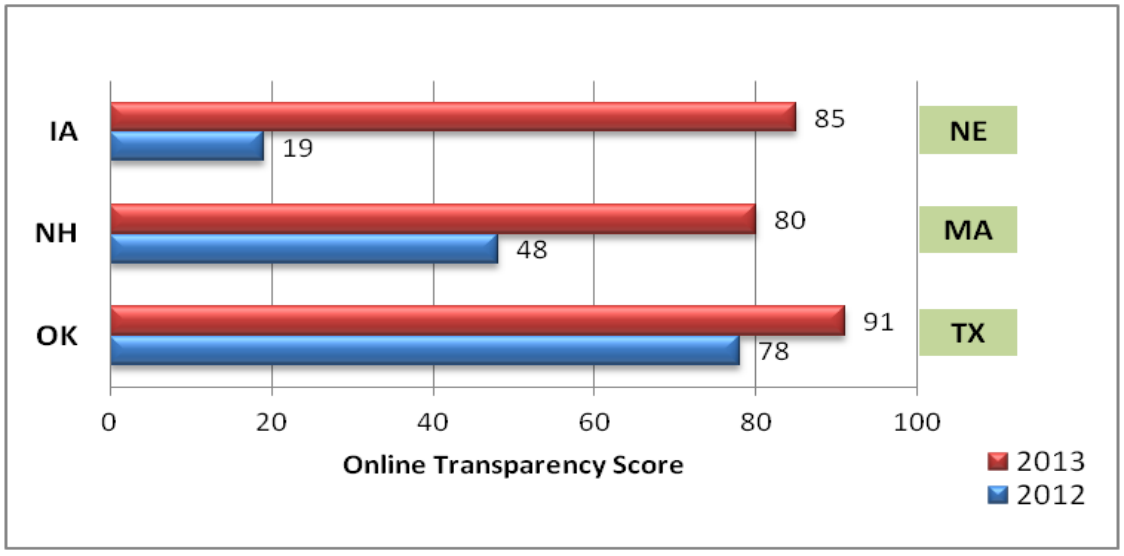


Figure 11 States with a Steep Increase in Online Transparency Score (2012-2013)

From these observations, an individual state seems to learn from the success of its neighbors or from other states in its region when implementing EFOIA. Considering that **i**nformation sharing through *interactions* is a substantial factor in the learning

process (Lee et al., 2011), interactions with successful neighbors may help an individual state learn to provide online access to governmental spending data, thereby leading to progress in online transparency.

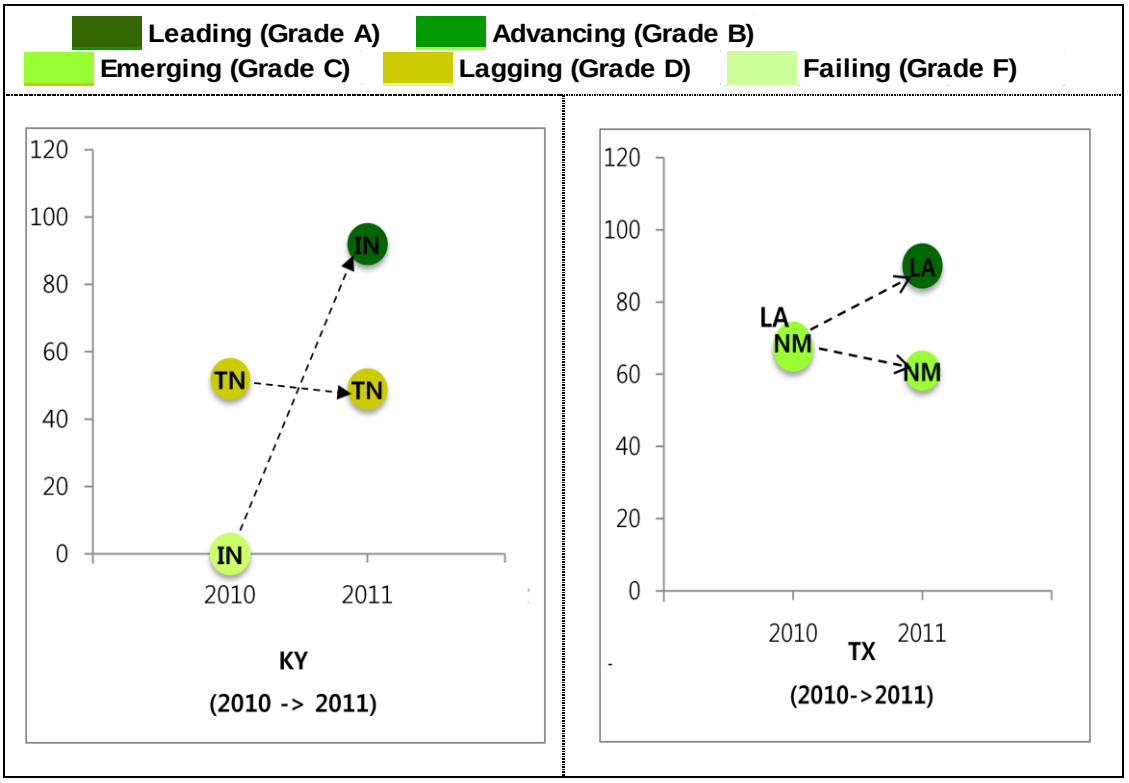
Yet, not every state adjacent to "successful" states made distinct progress in providing online access to government spending data. As described in Figure 13, Tennessee and New Mexico fell behind in increasing online access to government information in 2011, despite their geographical proximity to Kentucky and Texas, respectively, which were highly ranked in online transparency in 2010 and 2011. Likewise, among the states located near Oregon, a leading state in 2011 and 2012, only Washington saw a great improvement in online budget transparency in 2012; California and Idaho were falling behind or failing in the transparency movement. In 2013, only Iowa achieved noticeable progress in operating its transparency portal, along with Nebraska which ranked high in online transparency in 2012 and 2013.

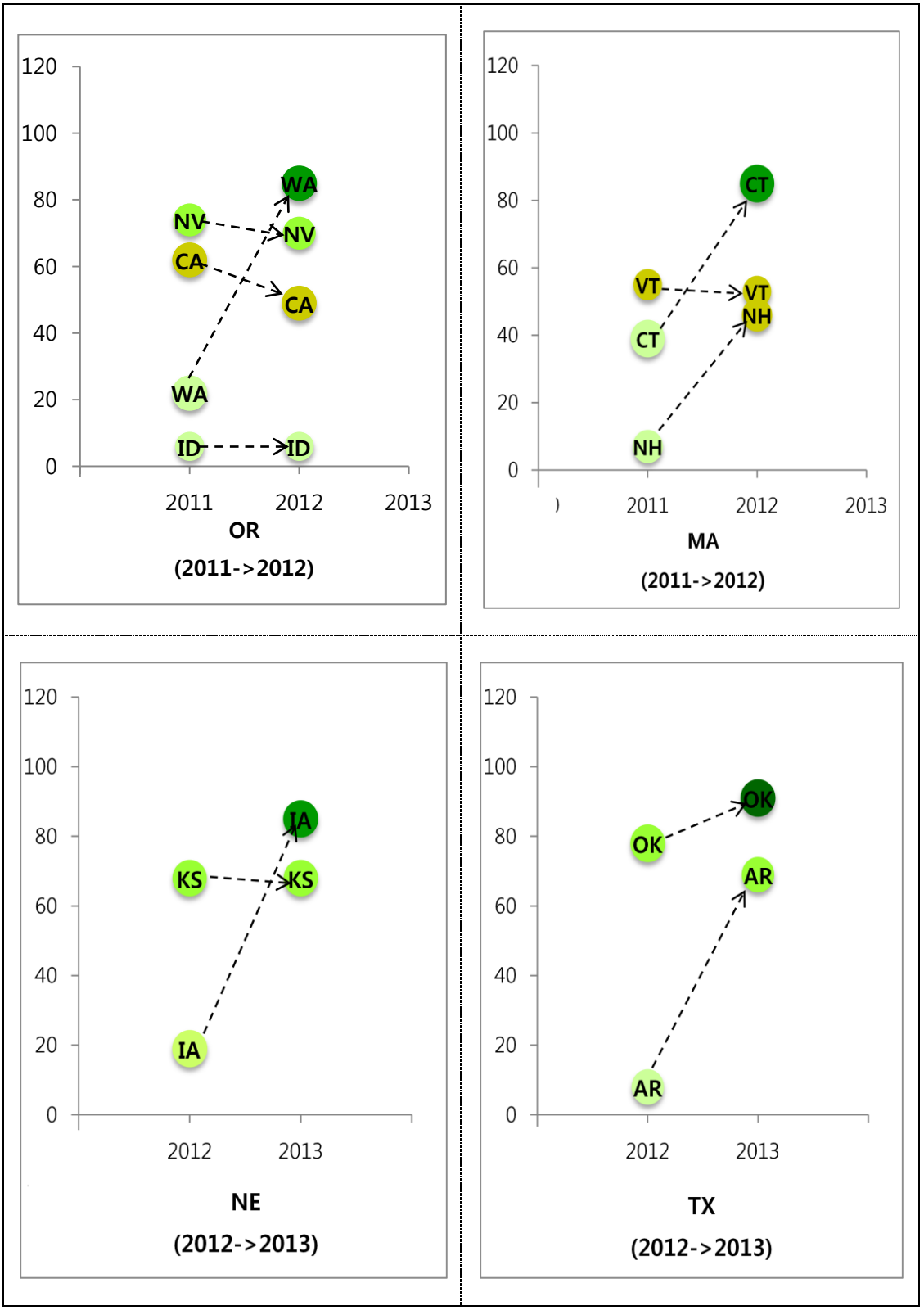
According to *the US PIRG Education Fund* (2013), many of these states were operating transparency portals within their existing budget or very limited funds[26]. The operation of EFOIA generally requires start-up and maintenance costs associated with transparency websites. Thus, when states cannot afford these costs, they are unable to institutionalize EFOIA. Indeed, *the Reporters of Committee* (2011) said that the most frequently mentioned impediment to states operating transparency websites was the lack of resources and funding.

[26] The start-up costs of California, Idaho, and Nevada were approximately $21,000, $28,000 and $78,000 respectively, while Kentucky and Louisiana spent $150,000, and $325,000, respectively (U.S. PIRG, 2013). Retrieved from www.uspirg.org/reports/usp/following-money-2013

Moreover, some states lost ground in online budget transparency. As seen with the shutdown of California's transparency website, obtaining supports from state legislators is essential for agencies wishing to maintain innovation in government transparency. In fact, in many cases political decisions of state legislators are directly connected to budgetary issues to implement and sustain a policy, practice, or program. In this regard, the learning effect may rely on slack resources which are affordable to a state for implementing EFOIA

Figure 12 Variation in Improvement to Online Transparency

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Meanwhile, a state's learning was not reduced to geography or geographical proximity to more successful states. Indeed, Arizona, Florida, Massachusetts, and Oregon are not adjacent to leading states such as Indiana, Kentucky, and Texas. Yet, these states have been able to carry out the intent of EFOIA through their transparency websites. Therefore, one could argue that the extent of a state's implementation of EFOIA may be associated with its engagement in more "nationally interactive" environment such as professional networks.

To summarize, states' success in implementing EFOIA has to do with regional and national interactions with *successful* leading and advancing states. However, states' involvement in interactive circumstances is necessary but insufficient. A state's implementation of EFOIA may also rely on its financial capacity to create and manage transparency practices. Considering these characteristics of EFOIA diffusion at the implementation stage, states that have frequently interacted with successful states along with adequate financial resources may implement EFOIA more successfully than others.

Comparison of Diffusion between Two Stages of EFOIA

Comparing diffusion between two stages of EFOIA can reveal whether or not early adopters maintain the leader position in innovation through the implementation phase. Figure 13 shows geographical location of early adopters of EFOIA as well as states that have made great performance of implementing their transparency websites from 2010 to 2013.

Many of early adopters have failed to sustain the leadership position in online transparency through the implementation stage of EFOIA; among 18 states that adopted EFOIA between 1996 and 2001, only six states belong to the group of *successful* states.

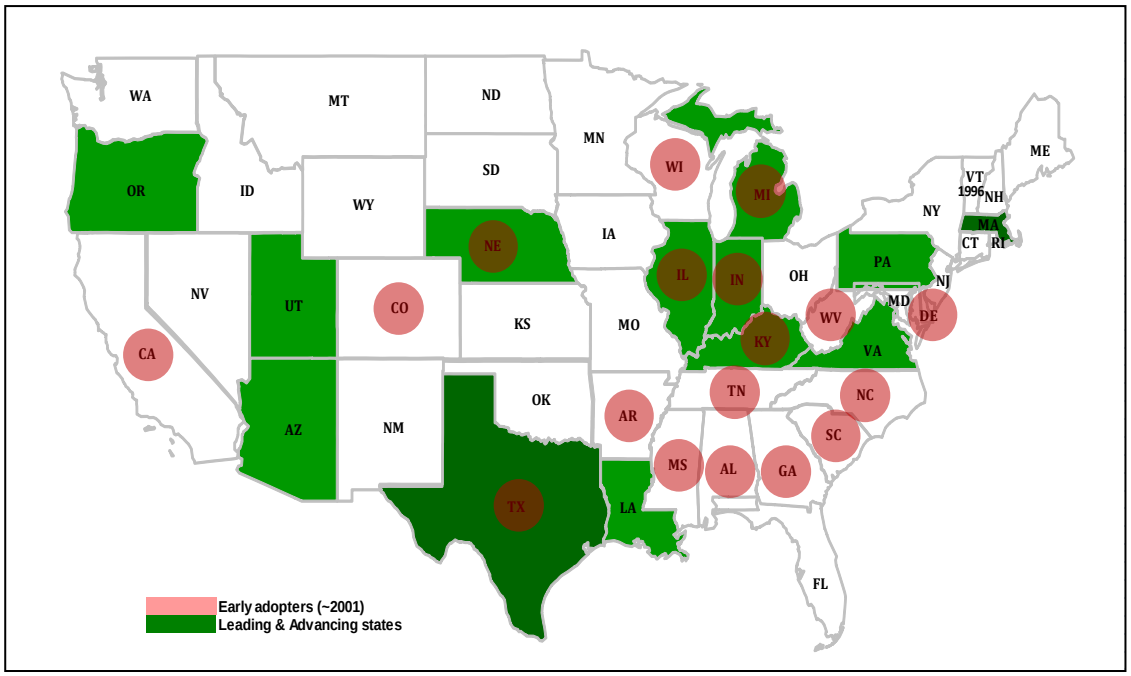

Figure 13 Comparison of the Location between Early Adopters and Success Group

Figure 14 presents the extent of states' early adoption of EFOIA and their implementation of transparency portals by using the percentage score (%). One could see that there are great variances[27] among states in adopting and implementing EFOIA.

[27] Vermont and Rhode Island adopted EFOIA in 1996 and 1998 respectively, but failed to show great performance in providing online access to government spending data: they belonged to the group of failing states with a grade of D. According to *the US PIRG Education Fund* (2013), the average rank of Vermont and Rhode in online budget transparency between 2011 and 2013 was 37th and 39th respectively. Indeed, only two early adopters — Nebraska and Illinois — were among the top ten in online budget transparency. In contrast, Louisiana and Oregon made distinct progress in operating their transparency portals although they adopted EFOIA around 2010.

Furthermore, such variance exists within the same state. For example, Louisiana has only reached 20% points[28] of the earliness of adoption along with 85% points in the extent of implementation of EFOIA. Despite 100% points of the earliness of adoption, Vermont has only achieved 61% points in the extent of implementation.

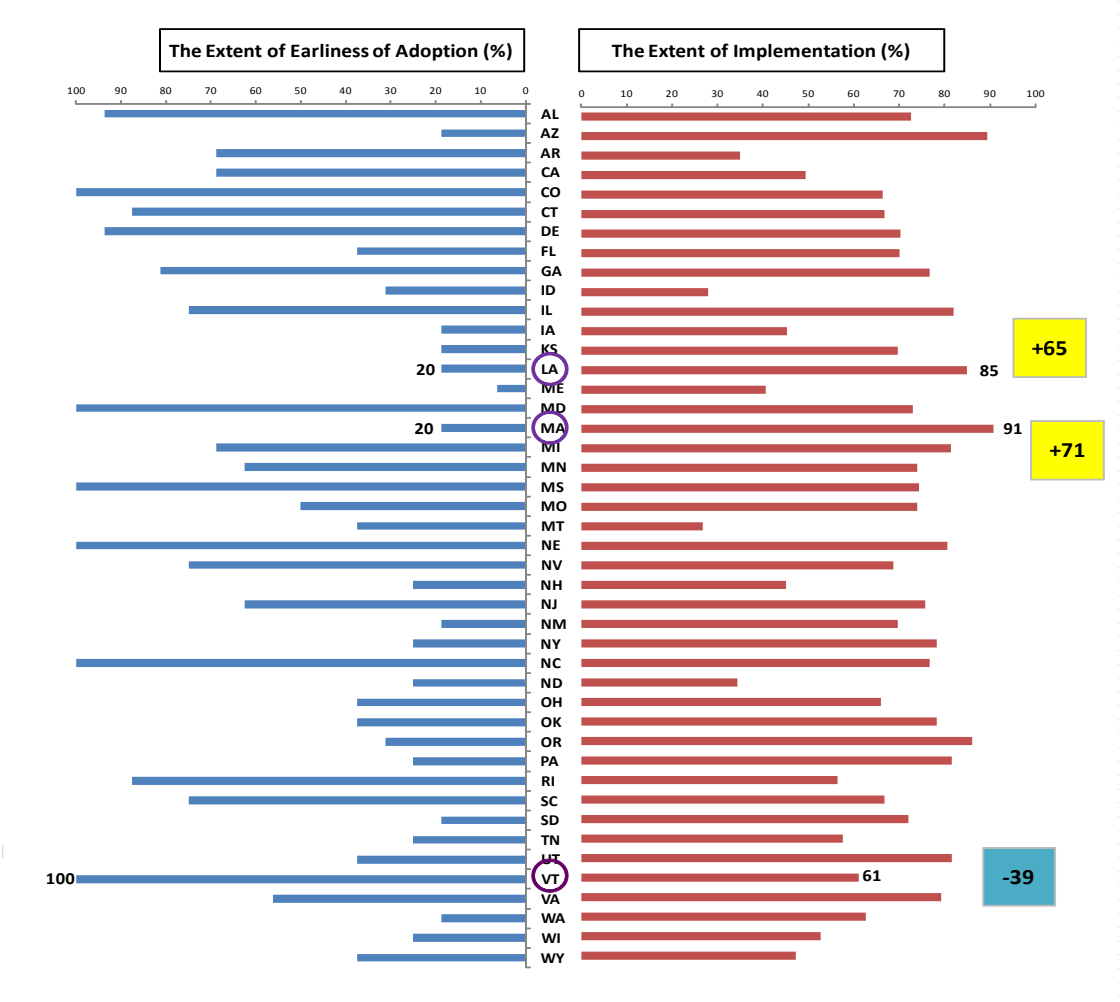

Figure 14 Earliness of Adoption & The Extent of Implementation

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[28] If a state adopted EFOIA in 1996, 100% points for the earliness of adoption will be given to the state. The percent score of online transparency serves for the proxy of the extent of implementation of EFOIA.

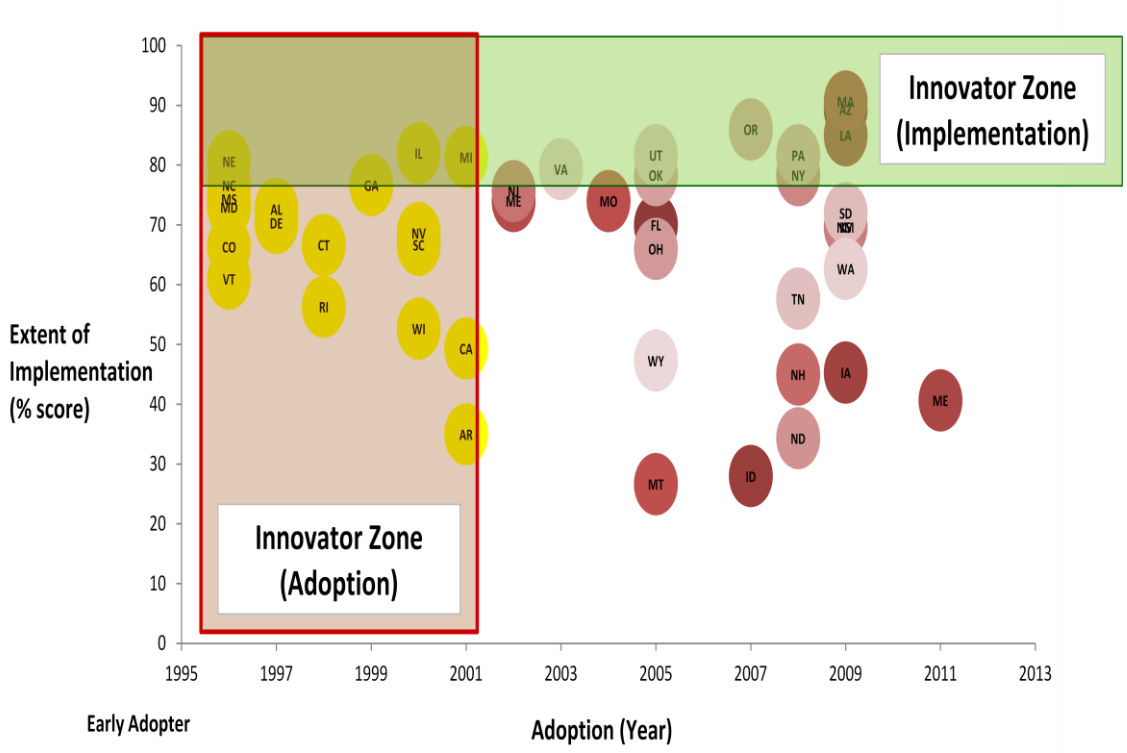

Figure 15 Innovator Zone

Figure 15 illustrates the innovator zone for those who are early leaders in adopting or implementing EFOIA. Most of early adopters involved in *the adoption innovator zone* have failed to join *the implementation innovator zone*. In this respect, not every early leader in adopting EFOIA sustains the leader position in online transparency through the implementation phase. Moreover, there is no connection between the timing of adoption and the extent of implementation. The percentage scores of early adopters range from 35 (Arkansas) to 82 (Illinois). The laggards also have a wide range of the percentage scores of the extent of implementation from 28 (Idaho) to 91 (Massachusetts).

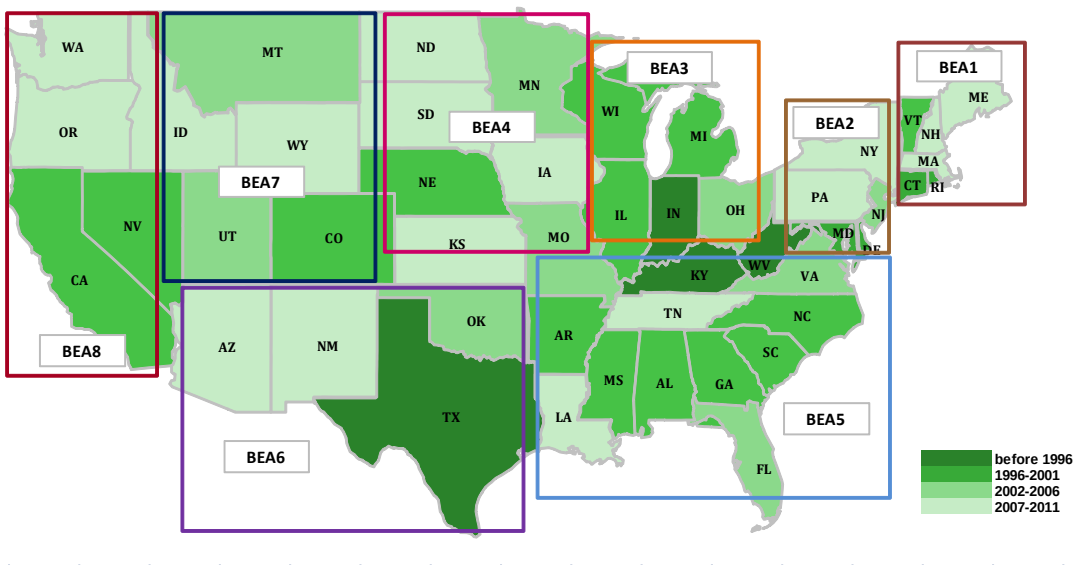

Figure 16 Regional Effects in Adoption

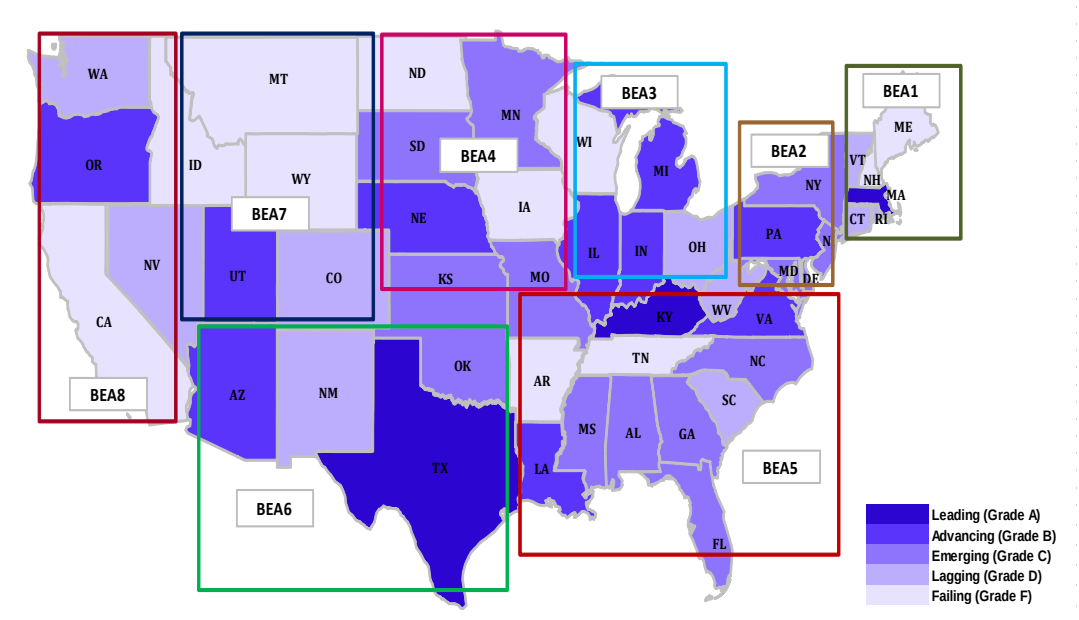

Figure 16-1 Regional Effects in Implementation

As shown in Figure 16 and Figure 16-1, states that belong to the same region tend to have a similar position in the timing of adoption as well as the extent of implementation of EFOIA. This implies that a state's interactions with neighbors (i.e. neighboring effects) may influence both its adoption and implementation of EFOIA.

To conclude, early adoption of EFOIA *in itself* does not ensure a state's successful implementation of the law. Indeed, most of early adopters have failed to show satisfactory performance in carrying out the spirit or the letter of EFOIA, thereby limiting it to a *symbolic* policy. Thus, the mechanism resulting in the diffusion of EFOIA may differ in the two stages of the law. In the diffusion of EFOIA at the adoption stage, states that have long sought to increase public access to government information tend to adopt the law earlier than those that have not. In addition, the legal environment created by federal legislative practices concerning transparency seems to affect state adoption behavior. In this regard, political climate (or policy culture) of an individual state which is consistent with the norm of transparency may play an important role in the diffusion at the adoption stage.

However, the political climate in favor of transparency does not seem to have great impact on early adopters to maintain the leader position in online transparency at the implementation stage of EFOIA. In fact, few early adopters have made great strides in providing online access to government spending data in the past four years (from 2010 to 2013). On the other hand, the effect of a state's interactions with others were still likely to be influential at the implementation stage. In this respect, the diffusion mechanisms of EFOIA seem to be "conditional," depending on the stages of adoption and

implementation: a particular diffusion mechanism facilitating the spread of norm of transparency among the states may cease to work at the implementation stage. Therefore, states may need to understand the conditional nature of mechanisms associated the diffusion of EFOIA to identify what factors contribute to sustained innovation in government transparency.

CHAPTER 3

REVIEW OF RELATED LITERATURE

This chapter begins by describing diffusion, especially in the public policy context, and four mechanisms leading to policy diffusion. These findings will be contextualized with the adoption and implementation of EFOIA in the US states. This chapter then discusses the theoretical logic that can explain the potential mechanisms through which EFOIA spread among states, and the differences in diffusion between states' adoption and implementation of EFOIA. This chapter concludes with presenting the conceptual framework and research hypotheses pertaining to the research questions of this study.

What is Diffusion?

Rogers (2003) defined diffusion as "the process through which an innovation spreads via certain communication channels over time among members of the social system." (p.11). By definition, Rogers (1962, 2003) suggested four main elements related to diffusion as follows: innovation, communication channels, time, and a social system. *Innovation* is an idea, practice, or object that is perceived as *new* (Amabile, 1988). The newness assumes that if something is new to an individual, the individual determines his or her reaction to it (Rogers, 2003). *Communication channels* are the means by which messages are transmitted from one individual to the next. In this sense, diffusion is also a particular type of communication that conveys the message content associated with a new idea. The *time* dimension is usually described either as a form of the relative earliness/lateness with which an innovation is adopted by a member in comparison with

other members of a system, or as the innovation's rate of adoption in a system usually measured by the number of members of the system adopting the innovation in a given time period (Rogers, 2003). A *social system* is a set of interrelated units involved in joint problem-solving to achieve a common goal. The units of a social system may be individuals, groups, organizations, and/or subsystems.

The concept of diffusion is widely used in fields such as physics, biology, economics, and sociology, but it commonly evokes "the image of the *spread* of something across space" (Elkins & Simmons, 2005, p. 36); the subject that is diffused over a network or throughout a community could be a disease, rumor, fad, news event, product, policy, or even culture but diffusion typically accounts for spread. For example, scholars of news diffusion have investigated the way that an extraordinarily important news story, such as the assassination of President Kennedy, or the September 11, 2001 terrorist attacks, spread among the public. These investigations have revealed that radio, television, newspaper, and interpersonal networks play a substantial role in diffusion of the story (Deutschmann & Danielson, 1960; Mayer eta al., 1990). Marketing diffusion scholars have paid great attention to the spread of a new product such as mobile telephones by tracing the rate of adoption for the product over time (Rosen, 2000; Dekimpe et al., 2000; Shermesh & Tellis, 2002). The findings of marketing diffusion literature have shown the effect of the perceived attributes of a new product, in addition to the marketing mix of advertising and personal selling, on its rate of purchase.

Meanwhile, for most sociologists and political scientists, the notion of diffusion has suggested multiple adoptions of similar practices by a population (Elkins & Simmons,

2005). In the public policy context, therefore, diffusion is seen as the spread of a policy that is new to the jurisdiction adopting it, regardless of whether or not it has already been adopted elsewhere (Walker, 1969; Gray, 1973). However, policy diffusion is not defined exclusively by the fact that a new policy has spread in that it is a consequence of "interdependence." (Gilardi, 2014) Strang (1991) defined *diffusion* as the process by which the "prior adoption of a trait or practice in a population alters the probability of adoption for remaining non-adopters." (p. 325)

Strang's (1991) definition captured the meaning of policy diffusion by implying the interdependence among units such that policy choices in one jurisdiction are influenced by the choices of others (Elikns and Simmons, 2005; Moynihan, Shipan, & Volden, 2012; Fuglister, 2012). In a similar vein, Simon et al. (2006) argued that policy diffusion at the international level takes place when government policy choices in a specific country are systemically conditioned by prior policy decisions made in other countries.

Policy diffusion in adoption. Policy diffusion scholars have studied diffusion by concentrating on the stage of *policy initiation* (Damanpour & Schneider, 2006; Graham, Shipan, & Volden, 2012). Borrowing the notion of *the innovation initiation stage*[29] suggested by Zaltman et al. (1973), the stage of policy initiation can be subdivided as follows: knowledge-awareness, formation of attitudes toward the innovation, and decision.

[29] Similarly, Rogers (2003) subdivided the initiation stage as *knowledge*, *persuasion*, and *decision.*

Knowledge-awareness substage is the stage of the innovation process in which a decision-making unit is exposed to a new policy and the opportunity to utilize that policy in a jurisdiction. With regard to which comes first, the knowledge (or awareness) or the needs of a new policy, it is debatable because research does not clearly answer this question (Rogers & Shoemaker, 1971; Zaltman, Duncan, & Holbek, 1973; Rogers, 2003). Yet, the awareness of a new policy can lead a jurisdiction to the perception of a performance gap,[30] thereby improving the jurisdiction's functioning, either internally or in its relationship with the outside environment.

Formation of attitudes toward the innovation substage implies attitudinal dimensions that a decision-making unit can exhibit about a new policy. The main attitudinal dimensions are *openness to the innovation* and *the perception of potential for innovation* (Duncan, 1972). The components of openness to the innovation include whether decision-making units are willing to consider a new policy, and whether they expect a new policy to improve the jurisdiction's functioning. The perception of potential for innovation is associated with the confidence of decision-making units concerning the jurisdiction's capacity to operate a new policy and the members' commitment to work for implementing the policy.

Decision substage takes place when decision-making units determine the adoption of a new policy. In this substage, these units assess the information about the potential policy. According to Rogers (1995), *adoption* is "a decision to make full use of

[30] It indicates a discrepancy between criteria of satisfactory performance (what decision makers ought to do) and the actual performance (Zaltman et al., 1973).

an innovation as the best course of action available." (p. 21) By this definition, the policy that is new to a jurisdiction is considered to have been *adopted* when it is enacted by legislature, or when the law supports a political decision on the policy creation (Zaltman, Duncan, & Holbek, 1973; Damanpour, 1987).

In accordance with Zaltman et al.'s approach to innovation initiation, scholars have conceptualized policy initiation as a multiphase process (Jasperson, Carter, & Zmud, 2005; Damanpour & Schneider, 2006; Cohen-Vogel & Ingle, 2007). For example, Cohen-Vogel and Ingle (2007) divided the process of policy initiation into agenda-setting, proposal formulation, and adoption. Similarly, Damanpour and Schneider (2006) looked at pre-adoption activities and the managerial decision to adopt the policy.

However, most of empirical research on policy diffusion has equated policy initiation with "dichotomous" adoption decision by treating it as a *dummy* variable — either to adopt or reject (Germain, 1996; Nystrom, Ramamurthy & Wilson, 2002). The primary concern of diffusion studies, therefore, has lay in the variation in jurisdictions' adoption of a policy as well as the timing of adoption in relation to the institutional or political characteristics of a jurisdiction or interdependence with other jurisdictions (Walker, 1969; Gray, 1973; Berry & Berry, 1990; Lieberman & Shaw, 2000; Boehmke & Witmer, 2004; Lee, 2009; Shipan & Volden, 2012; McGrath, 2013).

Policy diffusion in implementation. The diffusion approach, focusing on the temporal adoption of a policy across jurisdictions, has long been central to diffusion research. Yet, this diffusion perspective has faced severe criticism for providing only a dichotomous measure of adoption that ignores policy scope, especially, *the extent of*

implementation or *the extensive use* of a policy (Downs & Mohr, 1976; Clark, 1985; McNeal et al., 2003; Tolbert, Mossberger, & McNeal, 2008). Studies of innovation diffusion — especially on the diffusion of information technology (IT) applications — have pointed out that a political decision to adopt an innovation could not guarantee its *actual use* within a jurisdiction (Boyne, Gould-Williams, & Walker, 2005; Walker, 2006); innovation would be truly able to take place when it was actually *implemented* by members (Damanpour, 1987; Damanpour & Schneider, 2006).

For example, Jasperson et al. (2005) argued that the functional potential of an adopted IT application was underutilized due to the managerial decisions on its implementation. Such evidence demonstrated that the innovation failed in its implementation would not influence the legitimacy of a public organization, although the organization adopted an innovation to seek its legitimacy (Boyne, Gould-Williams, & Walker, 2005).

Against the single-minded attention to policy adoption, scholars have emphasized that policy diffusion should be associated with knowledge utilization in two stages: adoption and implementation (Downs & Mohr, 1976; Beyer & Trice, 1982; De Lancer Julnes & Holzer, 2001). According to this point of view, understanding the extent of implementation can help scholars and policy makers avoid limiting their jurisdictions to *symbolic policies* (Clark, 1985; De Lancer Julnes & Holzer, 2001).

According to the *communications model of intergovernmental policy implementation* developed by Goggin et al. (1990), policy implementation is considered both a *process itself* and *the result of the process*. Understanding implementation as a

process is to put already-made policy decisions into effect. In this view, state implementation behavior, at its simplest, can be described dichotomously; implementation occurred (scored 1), or it did not occur (scored 0). However, policy implementation should be assumed to involve several related activities to achieve a goal (Goggin et al., 1990). Thus, the essential aspect of implementation is "the satisfactory performance of certain necessary tasks related to carrying out the intent of the law." (Goggin et al., 1990, p. 34)

Meanwhile, implementation as the result of a process is defined in two other ways: outputs and outcomes. *Outputs* are the extent to which programmatic goals have been accomplished; *outcomes* are the change in the complex problem that the policy is intended to solve. In the conceptualization of implementation as a process, if certain activities are carried out as specified by law, implementation has taken place. However, in the notion of the implementation results, mere occurrence of certain activities is not the same as the true implementation due to a lack of outputs or outcomes (Goggin et al., 1990).

The research on policy diffusion tends to measure the extent of implementation of a policy across jurisdictions by conceptualizing implementation as a process. For instance, McNeal et al. (2007) used *Campaign Finance Disclosure Grade,* a 13-point scale ranging from F to A+, to explore the extent of e-disclosure implementation across the states. The grades were based on 120 points allocated for state activities, such as the content of the disclosure law, the enforcement of the law, and the filing schedule (Campaign Disclosure Project, 2003). Tolbert et al. (2008) used an *index of state e-*

government use to examine overall performance of state digital government. This measure was a zero to 100 point e-government index (i.e. percentage score) for each state e-government website, and was created to see how the 50 states rank. McNeal et al. (2003) used the percentage score of state government websites offering online services to citizens, including, for a comparison and validity test of the index of state e-government use, *the overall state ranking* of government websites as a secondary measure. Meanwhile, Lee et al. (2011), at the global level, used *the Web Measure Index* to measure e-government performance of nations. This indicator was "based on a questionnaire, which allocated a binary value to the indicator base on the presence/absence of specific electronic facilities/services available." (UN, 2008, p. 15)

Diffusion Mechanisms in the Previous Research

Policy diffusion is considered a product of *interdependence* (Strang, 1991; Maggetti & Gilardi, 2013). Diffusion scholars usually associate interdependence with *mechanisms* that identify how diffusion is occurring (Maggetti & Gilardi, 2013) From the various studies either of state-to-state diffusion or of the diffusion between the governments at the different levels, diffusion scholars have suggested the main mechanisms that fall into four categories of interdependence: Competition, coercion, policy learning, and socialization (Berry & Berry, 1990; Case, Hines, & Rosen, 1993; Mooney & Lee, 1995; Shipan & Volden, 2006; Graham, Shipan, & Volden, 2012). Since the diffusion of EFOIA is irrelevant to economic motivation and coercion, this section elaborates on policy learning and socialization, rather than competition and coercion.

Competition. Policy diffusion through *competition* can occur when governments react to one another either to gain an economic advantage or to avoid an economic disadvantage, thereby improving their economic conditions and the quality of the lives of state residents (Walker, Avellaneda, & Berry, 2007). This type of policy diffusion is generally associated with races between state governments for tax bases or tourist revenues (Boehmke & Witmer, 2004; Berry & Baybeck, 2005; Baybeck, Berry, & Siegel, 2011). For example, Baybeck et al. (2011) found that the diffusion of lottery business was derived by intergovernmental competition over residents' location choices either to avoid a loss of revenue or to attract residents of other states across the border to play. Similarly, Boehmke and Witmer (2004) argued that the spread of Indian gaming compacts resulted from economic competition among cities sensitive to economic spillovers across the jurisdictions.

Economic competition among states is considered either to facilitate or to hinder the spread of public policies, depending on economic spillovers across states (Shipan & Volden, 2008). If there are positive economic spillovers, states will be more likely to adopt others' policy. However, if there are negative economic spillovers, states will be less likely to adopt a policy that others lack. Thus, considering the economic effect of adoption by other states, states either defensively prevent as a loss of revenue (Alm, McKee, & Skidmore, 1993; Erekson et al., 1999; Berry & Baybeck, 2005), or proactively avoid increased costs for service provision resulting from policy choices of others (Berry, Fording, & Hanson, 2003; Bailey & Rom, 2004; Baybeck, Berry, & Siegel, 2011).

Coercion. Policy diffusion through c*oercion* can arise horizontally or vertically when one government imposes its policy preferences on others. In a horizontal setting, powerful institutions may apply pressure on targeted governments until they change their policies through collaborative efforts, such as economic sanctions or issue linkage (Schelling, 1960; Hufbauer, Schott, & Elliott, 1990). International institutions like the United Nations and the International Monetary Fund can attempt to coerce individual countries to take actions that meet common expectations. In a vertical setting, the federal government may fulfill this role (Karch, 2006; Lee, 2009). According to the scholars examining the effects of federal "top-down pressure" on policy adoptions of states, the passage of federal laws in a policy area can force specific state activities (Karch, 2006; Berry & Berry, 2007). Furthermore, Shipan and Volden (2008) contended that state-level policies can be coercive when the state law *preempts* either future local laws on the same policy.

As Berry and Berry (1999, 2007) noted, however, this type of policy diffusion through coercion seems highly uninteresting in that the federal law constrains states' discretion. A more interesting form of policy diffusion through coercion can take place when federal actions affect policy choices of states, but states retain their discretion. Subsequent studies investigated the influence of federal actions intertwined with carrot-and-stick incentives (Welch & Thompson, 1980; Allen, Pettus, & Haider-Markel, 2004; Volden, 2006; Nicholson-Crotty, 2009; Martin, Strach, & Schackman, 2013). The findings suggested that the use of fiscal incentives — often in the form of federal grants — led states to federal policy preferences. For instance, states can be encouraged to adopt

lower speed limits and higher drinking ages to avoid the lost of highway funds from the federal government (Shipan & Volden, 2008).

Policy learning. Policy diffusion through *policy learning* can take place when governments learn from others' experience to solve policy problems they in common face (Lee, Chang, & Berry, 2011; Graham, Shipan, & Volden, 2012). Policy learning generally refers to "a process whereby policy makers change their beliefs about the effect of policies." (Dobbin, Simmons, & Garrett, 2007, p. 460) When others' experiences influence these belief changes, policy learning can be considered a mechanism of policy diffusion (Gilardi, 2010). Levy (1994) describes this *experiential* learning as "the development of new beliefs, skills, or procedures as a result of the observation and interpretation of experience." (p. 283)

Policy learning is characterized as *analytic construction* (Levy, 1994). Individual states may interpret the experience of others in terms of their own analytic assumptions and worldviews. According to the rationalists' theory of policy learning, the analytic capabilities of states can be either strong or bounded. If states have full analytical capabilities and thus take into account all available information, their policy learning will be rational (i.e. Bayesian learning).

However, if states use cognitive shortcuts by looking at *relevant* information rather than at *all* information, their policy learning will be more *bounded* (i.e. bounded learning). Most analysis of policy diffusion bases policy learning on the model of bounded learning, such that states facing a common policy problem may simplify the

search for a solution through the cognitive shortcut of learning from each other (Simon, 1947; Walker, 1969; Berry & Baybeck, 2005; Walker, Avellaneda, & Berry, 2007).

When it comes to what policy makers learn from others' experience, diffusion studies have noted that they learn about success (or effectiveness) of a given policy (Volden, 2006; Gilardi, 2010; Fuglister, 2012). Yet, policy learning may be more complicated than simply perceiving success, as policy makers may have different goals (Gilardi, 2010). For example, policy makers may want to learn about a policy's political viability and public supports that are associated with their re-election and reappointment (Graham, Shipan, & Volden, 2012). Moreover, policy makers often learn about failed policies (Soule, 1999; Sharman, 2010). Therefore, policy learning can be defined as a process whereby others' experience provides relevant information on *the likely consequences* of a given policy (Gilardi, 2010).

Two notable scholars supported the diffusion through policy learning: US Supreme Court Justice Louis Brandeis and Schattschneider. Justice Brandeis praised states as *laboratories of democracy*, including the potential for federal learning from states beyond state-to-state learning (see *New State Ice Co. v. Liebmann*, 285 U.S. 262[1932], 311); governments act as laboratories where a law is enacted from the lower level of the democratic system, up to the higher level. Meanwhile, Schattschneider (1960) assumed that groups unable to prevail in one venue may *widen the scope of conflict* by seeking action in another to accomplish their goals.

According to diffusion scholars, policy diffusion through learning is associated with various channels for information flows. For example, Grossback et al (2004) and

Volden (2006) found states' geographical learning for solutions in the areas of education and criminal sentencing policies via regional interactions among the states. On the other hand, Mossberger (1999) examined the upward diffusion from the states to the federal government, concentrating on the federal Empowerment Zone and Enterprise Communities (EZ/EC) program. The findings suggested that federal policy makers learned how to coordinate the EZ/EC program from the state enterprise-zone programs[31], via professional networks — such as the Council of State Community Development Agencies and the Democratic National Committee — conveying information about general trends in the state enterprise zones.

Socialization (Normative pressure). The greatest degree of interdependence among governments accompanies *socialization*. Socialization — that is, *normative pressure* labeled by DiMaggio and Powell (1983) — is generally defined as "a process of inducting actors into the norms and rules of a community." (Siegel, 1965; Alderson, 2001; Checkel, 2005; Graham, Shipan, & Volden, 2012, p. 692) Central governments (e.g. federal government or international organizations) can engage in socialization by inducing sub-governments to change policy preferences in conformity with central norms, rules or practices that appear legitimate to citizens and policy entrepreneurs (Finnemore, 1993; Walker, Avellaneda, & Berry, 2007).

[31] Similarly, Weissert and Scheller (2008) identified the role of policy learning from states in decision-making of federal health laws. They noted that federal policy learning from the states occurred when extensive state expertise and a definite lack of federal knowledge existed.

Constructivists[32] consider socialization an important mechanism of diffusion that causes even more stable long-term policy changes (Graham, Shipan, & Volden, 2012). According to Aberg (2008), socialization is the provision of access to norms or ideals that should be incorporated so as to be recognized as members of a given society. Moreover, socialization is often called *hegemonic power* that "shapes the norms and value orientations within which policy is conducted." (Ikenberry & Kupchan, 1990, p. 288)

Socialization has two characteristics that make it distinguished from policy learning. The first distinction is that policy learning has to do with a state's learning of the likely (or anticipated) consequences of a policy, whereas socialization connotes a state's learning of norms and rules of a political community to which it belongs. The second distinction is that policy learning is consistent with *the logic of consequence*, while socialization is based on *the logic of appropriateness* (March & Olsen, 2006).

The logic of consequence implies that a state's assessment of the likely consequences of a policy may drive a change in its policy actions; states are expected to choose among alternatives by assessing the likely consequences of each for policy goals (Croidieu & Monin, 2010). However, considering states' policy actions only in the logic of consequence overlooks the substantial roles of norms, rules, and identities of a political community that may influence states.

[32] Alderson (2001) did not see socialization as a diffusion mechanism, arguing that socialization imagines states reacting in a similar way to different initial conditions, not related to the process triggering the diffusion of norms from one country to another. However, this study follows the general viewpoint of socialization suggested by diffusion scholars (Graham et al., 2012).

Within the logic of appropriateness, states' policy actions are based more on identifying the "normatively appropriate behavior" than on calculating the return expected from alternative choices (March & Olsen, 2006). It is because states do care about their national reputation and image as "normal" members of a political community (Gurowitz, 2006). According to the logic of appropriateness, states are expected to fulfill the obligations encapsulated in rules and membership in a political community since the rules are seen as *legitimate* and *rightful* (March & Olsen, 2006). Such normative pressure may compel states to change their policy preferences to conform to norms and rules of the community in which they are involved (Risse et al., 1999; Johnston, 2001; Aberg, 2008).

The primary processes[33] of socialization in which norms change behavior are *persuasion* and *acculturation* (Checkel, 1999; Goodman & Jinks, 2004; Pegram, 2010). These mechanisms are essentially based on theories of how preferences form as well as the conditions under which preferences change (Goodman & Jinks, 2004). *Persuasion* is the active inculcation of norms (Finnemore & Sikkink, 1998): persuaded states internalize new norms and rules of appropriate behavior, thereby redefining their preferences accordingly (Checkel, 1999). Persuasion theorists contend that persuasion "requires argument and deliberation in an effort to change the minds of others." (Goodman & Jinks, 2004, p. 635) In other words, persuasion can take place when states assess the content of a particular norm actively, and then change their minds along with

[33] This study does not include *strategic calculation* as a process of socialization that is typically associated with incentives (or sanctions) regarding membership (Checkel, 1999; Goodman & Jinks, 2004), as states cannot be excluded from the membership of the U.S. federal system.

confidence in the appropriateness of the norm. Thus, persuasive efforts need careful arguments and reasoned logic that prove the appropriateness of a norm, belief, or practice (Patterson, 2006).

Meanwhile, *acculturation* is the process by which states adopt the beliefs and behavioral patterns of their reference group (Goodman & Jinks, 2004, 2005). Social psychologists argue that acculturation results from cognitive pressures that are self-imposed or externally imposed. States may assimilate to a reference group to minimize *cognitive dissonance* (Goodman & Jinks, 2004). Cognitive dissonance is the *self-imposed* discomfort — such as anxiety, regret, or guilt — that is caused by holding inconsistent cognitions (Frank, 1985).

This internal pressure can motivate states either to change their behavior, or to find ways to justify their past behavior (Gibbons et al., 1997). In addition, states can be compelled to change their behavior to conform with their reference group, as they seek social legitimacy and minimize social disapproval (Petty et al., 1997). This external pressure can impose social-psychological sanctions on states through shaming or shunning (Patterson, 2006).

It has been little known about policy diffusion through socialization at the state level. Most studies of norm diffusion have employed the international or global level by assuming that the international system is an "institutional environment structured by inter-subjective cognitions and norms." (Schimmelfennig, 2000, p. 114) The diffusion of e-government and e-democracy across nations (Lee, Chang, & Berry, 2011), the diffusion of transparency across European countries (Grigorescu, 2002) and the diffusion of the

value of science policy organizations across the UNESCO members (Finnemore, 1993) offer scholars and practitioners good examples of policy diffusion through socialization.

Theoretical Logic for Understanding the Diffusion of EFOIA

The diffusion of EFOIA in the US states cannot be attributed to *competition* in that the individual state does not compete with others over the economic well-being of EFOIA. C*oercion* is also inappropriate as an explanation for the diffusion of EFOIA, as the federal government or a powerful state does not coerce targeted states to influence their adoption and implementation of EFOIA. In regard to an *indirect* effect of the federal law, some scholars have argued that political forces, such as national debates and Congressional hearings, may influence state policymaking by increasing national attention to a given policy (i.e. *visibility* or *salience*) (Karch, 2012; McCann, Shipan, & Volden, 2012).

However, this argument says little about a cognitive process through which the observation and interpretation of a certain event produce a change in beliefs, and thereby induce behavioral change (Heclo, 1974; Hall, 1993). The study finding that highly salient policies do not necessarily spread across sub-national government shows the weak explanatory power of such argument (Nicholson-Crotty, 2009; Koski, 2010).

If so, why have many of early adopters failed to sustain the leadership position in online transparency through the implementation stage of EFOIA? To identify the appropriate mechanisms associated with the diffusion of EFOIA, this study employs the constructivist and the rationalist perspectives on policy diffusion. Those theoretical points of view suggest two potential mechanisms through which the diffusion of EFOIA takes

place: *socialization* and *policy learning*. In addition, this study suggests that such differences in diffusion between states' adoption and implementation of EFOIA result from the conditional nature of diffusion mechanisms operating differently at two stages; socialization may influence states' adoption of EFOIA, but its influence does not continue through the implementation phase because of its "period effects."

Socialization as a diffusion mechanism only at the adoption stage of EFOIA. Theoretical arguments on socialization can provide the logic for explaining the diffusion of EFOIA. As the public access to government information became institutionalized by the federal government, its value as a symbol of good governance can rise. Given the reasoned logic that the adoption of EFOIA is “the right things to do” for realizing civil sovereignty, states might be persuaded to engage in increasing public access to government records. Yet, change in a state's legal circumstance poses a dilemma: an individual state should comply with the norm of e-transparency to maintain its legitimacy, but the state — in terms of the interest of efficiency — should minimize the extent to which complying with EFOIA disrupts its activities. Thus, EFOIA is more likely to be transmitted the state in which considerable societal supports for the law exist.

Borrowing the concept of *norm resonance*, constructivist theorists explain why, even holding a diffusion mechanism constant, some states are more vulnerable than others to activism invoking a new norm. Constructivist theorists define norms as a community’s shared understandings and its intentions reflecting legitimate social purposes (Ruggie, 1998; Payne, 2001). By this definition, a norm is an enabling

framework for action that offers collective expectations about proper behavior for a given identity (Jepperson, Wendt, & Katzenstein, 1996).

The notion of norm resonance is associated with the role of an existing normative framework in accepting emergent norms (Payne, 2001). According to Guido (2001), preexisting norms provide actors who pursue the introduction of a new norm with reasons to justify their argument. Thus, unless a new norm "resonates" with preexisting collective norms embedded in a political community, persuasive messages justifying a new norm cannot be transmitted (Finnemore & Sikkink, 1998; Marcussen et al., 1999). In this view, *effective resonance* occurs when a new norm fits into a given context, and thus enjoys considerable societal acceptance of its legitimacy (Goodman & Jinks, 2004).

The following empirical studies underline the importance of norm resonance for successful norm diffusion. Lee et al. (2011) found evidence that e-government and e-democracy are more likely to be developed in an area that is already highly ranked in transparency. Grigorescu (2002) attributes the unsuccessful transmission of the norm of transparency to the lack of "resonance" with the foundational norms on European institutions. The concept of norm resonance offers the expectation that EFOIA will be more likely to be transmitted to the state in which the existing normative framework (e.g. policy culture) is consistent with a norm of transparency. From the research on e-disclosure, ethics laws, and anti-corruption reforms, this study suggests several factors indicating the "internal normative climate" that is consistent with a norm of transparency: liberal ideological climate, public pressure, and innovative policy culture.

Liberal ideological climate. Government transparency is often considered an issue that lacks a strong ideological basis, as both Republicans and Democrats are supportive of it (Cornyn, 2005). Yet, this viewpoint is half right in that conservatives and liberals are both interested in transparency, but different types of transparency (Piotrowski & Van Ryzin, 2007); conservatives are more concerned than liberals about accessing security-related information, whereas liberals are more concerned with accessing government information on principle and for good governance concerns. Scholars of e-disclosure, ethics laws, and anti-corruption reforms have offered empirical findings that a liberal ideological climate in a state is positively associated with disclosure of government information since it is supportive of regulating the actions of government officials (Loftus, 1994; Rosenson, 2003; McNeal & Hale, 2010; Ríos et al., 2013). The statutes of the early adopters precisely designated that a democratic government provides the public with information they need to participate in the democratic process and request government officials to be held accountable for their actions. Also, the early adopters appeared to support openness to government information in that they made precise improvement to their laws on online access to public records. Thus, I predict that a state with a liberal ideological climate will be more likely to adopt EFOIA.

> *H1: There is a positive relationship between a liberal ideological climate and a state's adoption of EFOIA.*

Public pressure (Public demand). Collective pressure from citizens may affect state policymaking in that elected officials are very sensitive to their reelections (Berry & Berry, 1999, 2007). Skocpol et al. (1993) argued that the active engagement of citizens in enhancing their civil rights would force the government to become more supportive of civil rights reforms. From this point of view, greater engagement of citizens in democratic processes, such as referendum, may put greater pressure on states to adopt EFOIA (Gamble, 1997; McNeal & Hale, 2010). Furthermore, various scholars argued that the high levels of citizens' education and their Internet use increased public demand for e-disclosure policies of states, such as electronic campaign finance laws (Cheng, 1992; Debreceny et al., 2002; McNeal et al, 2007; Serrano et al, 2009; McNeal & Hale, 2010). Piotrowski and Van Ryzin (2007) argued that possessing the high levels of education and the Internet use may provide individuals with necessary skills for navigating a bureaucracy as well as the confidence to request information from the government. In a similar vein, Lee et al. (2011) contended that citizens became more informed and more knowledgeable about e-government and e-democracy as their level of education and Internet use increased. Therefore, I predict that a state with a greater level of public pressure to disclose information will be more likely to adopt EFOIA.

H2: There is a positive relationship between public pressure and a state's adoption of EFOIA.

Innovative policy culture. Innovative policy culture of a state refers to general climate of supporting policy change (i.e. adoption of a new policy) in the state (Soule, 1999). Many diffusion scholars argued that states with more innovative policy culture may pass new policies earlier than do those with less innovative policy cultures (Walker, 1969; Gray, 1973; Eyestone, 1977; Savage, 1978; Grattet et al., 1998). Moreover, Soule and Zylan (1997) found that states appeared to be fairly consistent over time with regard to policy decisions; early adopters of one type of policy tended to be early adopters of other policies. Thus, I predict that innovative policy culture will have a positive impact on a state's adoption and implementation of EFOIA.

H3a: There is a positive relationship between innovative policy culture and a state's adoption of EFOIA.

In addition, many scholars have supported the positive association of slack with innovative projects because slack resources not only protect organizations from the uncertain success of those projects, but also permit those organizations to more safely experiment with new strategies (Delbecq & Mills, 1985; Damanpour, 1987; Moses, 1992). Therefore, I predict that the effect of innovative policy culture will increase in the state with the high levels of slack resources.

H3b: The effect of innovative policy culture will increase in the state with the high levels of slack resources.

Period effects (Temporalization). According to the legal environment theory, the passage of EFOIA by the federal government created a normative environment in which legitimacy was conditioned on government transparency. In response to this normative environment, states may adopt EFOIA to enhance their legitimacy. However, this normative pressure on states to adopt EFOIA is a "period" or "temporal" effect that is not pervasive, but *time specific* (Walker, 1969; Gray, 1973; Edelman, 1990, 1992; Grattet & Jenness, 1998). In other words, the influences of normative pressure of law on organizations fade over time. Normative pressure from the legal environment does not easily erode long-held managerial interests (Edelman, 1992).

In addition, the meaning of compliance with law is vague. The weak enforcement mechanisms of law, such as inadequate and inconsistent feedback on what organizational practices are legal, make the meaning of compliance more obscure, thereby allowing organizations to mediate the meaning of compliance in a way that accommodates their managerial interests (Edelman, 1992). As an empirical example of the period effects of socialization, Edelman (1992) found that the ambiguity and weak enforcement mechanisms of EEO/AA[34] law weaken its capacity to influence organizations directly. In addition, Mbaye (2001) demonstrated that EU members failed to implement EU directives because they paid more attention to bureaucratic efficiency and economic power than compliance with their normative obligations. Thus, I predict that the effect of socialization is unlikely to continue through the implementation phase because of period effects.

[34] Equal Employment Opportunity and Affirmative Action

H4: There is no relationship between internal normative climate (i.e. liberalism, public pressure, and innovativeness) and a state's implementation of EFOIA.

Policy learning[35] as a mechanism at the adoption and implementation stages.

Theoretical argument on policy learning can provide the logic that explains the diffusion of EFOIA at the stage of both adoption and implementation. If a state seeks a policy solution to government transparency, but faces uncertainty about what to do, it may monitor others' experience in increasing public access to governmental records. Observing others' experience may provide an individual state with cognitive shortcuts to deal with the issue of government transparency, and thus help the states save time and resources for obtaining new information. Furthermore, learning from others enables an individual state to assess the likely consequences of EFOIA, offering knowledge about EFOIA the state can experiment with in its own jurisdictions.

Lee et al. (2011) argued that **i**nformation sharing through *interactions* could be the substantial factor leading to the learning process. A state's involvement in more interactive circumstances can increase the "opportunity to learn" through information exchange with others. Although interactions in itself do not ensure that learning takes place, scholars have argued that they might involve learning (Berry and Berry, 1999) Thus, this study also argues that states may learn from others through interactions with

[35] This study focuses on horizontal learning whereby states learn from each other through regional or national interactions among them, not considering the opportunity to learn from the federal government or vice versa.

others. From scholarly research on the diffusion of policies across state governments, this study suggests two factors associated with interactions among states: Neighboring effects and professional networks.

Neighboring effects. Neighboring effects refer to the impact of *regional interactions* among the states sharing a border or those within a similar geographic region on policy behavior of states (Hageman & Robb, 2011); neighboring effects include the notion both of *neighboring models* and of *fixed-region models* to consider *direct* and *indirect* neighboring states (Hageman & Robb, 2011). According to regional diffusion theorists, states are more likely to learn from the experience of their adjacent neighbors or those within a similar geographic region to reduce the political risk of their policy choices (Berry & Berry, 1990, 1999; Mintrom, 1997; Balla, 2001; Hageman & Robb, 2011).

Many studies have demonstrated that neighboring effects can influence policy behavior of states. For example, the scholars of civil rights legislation and anti-corruption policies demonstrated that states were more likely to emulate neighboring states regarding civil rights reforms or e-disclosure policies (Grattet et al, 1998; Rosenson, 2003). Berry and Berry (1999) also argued that learning from nearby states could lead a targeted state to similar policy outcomes, as they tended to have similar economic, political, or social environments. Similarly, Mooney (2001) contended that the bias of policy makers relying on geographical learning for policy solutions resulted from "familiarity, ease of communication, cross-mixing of media and population, and common values." (p. 105) Thus, I predict that neighboring effects are positively associated with a state's adoption of EFOIA.

H5a: There is a positive relationship between neighboring effects and a state's adoption of EFOIA.

At a glance, states adjacent to those that have maintained a high rank in online transparency tended to show great improvement in operating their transparency portals in the following year. In this respect, a state's implementation may rely heavily on evidence of success because of its greater access to information on the likely consequences of a specific policy other states have shown. According to Grossback et al (2004), the policy choices of states depend on a "function of the gain in utility the government will receive by moving away from its status quo policy and toward the innovation." (p. 523) In addition, Volden (2006) and Fuglister (2012) found that states tended to emulate only *successful* policies after having assessed how others had performed elsewhere. Similarly, Costa (2013) found that a country was more likely to strengthen its FOIA law when its neighbors had a strong FOIA law.

Furthermore, the effect of learning from the success of neighbors may be conditional on states. In fact, not every state adjacent to "successful" states shows distinct progress in providing online access to government spending data. If so, who can be more sensitive to success? If states consider innovation with inadequate slack resources, they may prefer to avoid failure in the innovation because of concerns on political risk of their policy choices, and thus pay greater attention to success from nearby states. Thus, I predict that neighboring effects will be positively associated with the implementation of the states in a lack of slack resources.

H5b: Neighboring effects will be positively associated with the implementation of the states in a lack of slack resources.

Professional networks. Geographic location should not constrain the learning process. Research has long shown that *national interactions* through formal and informal professional networks (or associations) of state policymakers, such as the National Governors Association (NGA) and National Conference of State Legislators (NCSL), may increase states' opportunity to share policy ideas and experiences with each other (Walker, 1969; Grupp & Richards, 1975; Baumgartner & Jones, 1993; Rogers, 1995).

Many studies have demonstrated that professional networks can provide an institutional environment or channels whereby policy makers exchange and learn from the experiences of others. Mossberger (2000), in her six-state case study of enterprise zones, noted that professional networks functioned as sources of information as well as influence that was independent from federal policy impetus. McNeal et al. (2003) found that professional networks of topical subcommittees formed within the NGA and NCSL played a significant role especially in the administrative reform that was not politically salient. Furthermore, Lee et al. (2011), at the global level, found that the more international professional networks a nation belonged to, the more highly ranked the nation was in e-government. Therefore, professional networks of governors or state administrators can be expected to play a significant role in the promotion of EFOIA.

H6a: There is a positive relationship between professional networks and a state's adoption of EFOIA.

H6b: There is a positive relationship between professional networks and a state's implementation of EFOIA.

Conceptual Framework

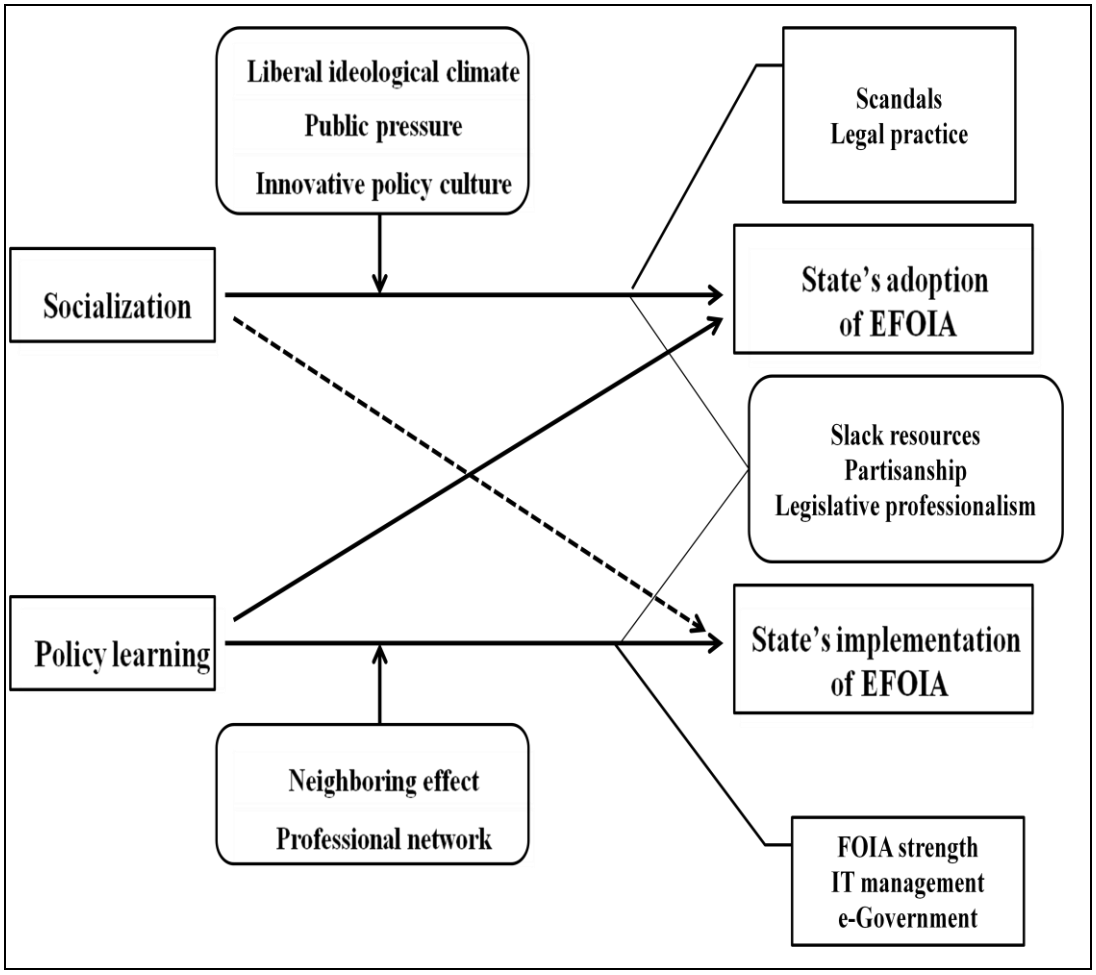

Figure 17 Conceptual Framework for Analysis

Figure 17 presents a conceptual framework for explaining the differences in diffusion between the adoption and implementation of EFOIA. This study considers socialization and policy learning the mechanisms that induce the diffusion of EFOIA. Also, this study suggests that the operations of socialization and policy learning differ, relying on the stage of EFOIA. The operation of socialization does not continue through the implementation stage, leading to the differences in diffusion between adoption and implementation.

As shown in Figure 17, states that resonate with the norm of transparency will be more likely to engage in socialization. Thus, a state with a liberal political climate, public demand for transparency, and innovative policy culture will be more likely to adopt EFOIA. Furthermore, the legal practice of the federal government concerning transparency can impose normative pressure on states to take actions in compliance with the legal environment.

At the same time, states that involve in more interactive environment will be more likely to engage in policy learning. Therefore, greater interactions of an individual state with neighbors and its participation in professional networks will have a positive impact on a state's adoption and implementation of EFOIA. Understanding the different nature of socialization and learning relying on two stages of EFOIA will answer the following questions: Why some states have adopted EFOIA earlier than others, why some states have implemented EFOIA more successfully than others, and why some early adopters have failed to implement EFOIA successfully.

In addition, based on the findings of the previous research on diffusion, this study will employ several control variables that may affect states' adoption and/or implementation of EFOIA: Slack resources, partisanship, state legislative professionalism, scandals, legal practice, FOIA strength, IT management, and e-government.

Slack resources. Scholarly literature on e-disclosure has concluded that slack resources associated with the capacity to innovate may account for states' adoption and their more extensive implementation of e-disclosure initiatives (Rosenson, 2003; McNeal et al, 2007; McNeal & Hale, 2010). The operation of EFOIA requires start-up and maintenance costs associated with transparency websites. Those apparent costs will be significant resistance to the institutionalization of EFOIA. In addition, McFarland (1976) found that citizens of wealthier states tended to have a greater desire for good-government initiatives. In this view, slack resources may affect public or social pressure for e-transparency as a symbol of good governance, thereby leading to a trustworthy, high performing, and accountable government (Hood & Heald, 2006). Thus, I predict that slack resources will be positively associated with a state's adoption and implementation of EFOIA.

H7a: There is a positive relationship between slack resources and a state's adoption of EFOIA.

H7b: There is a positive relationship between slack resources and a state's implementation of EFOIA.

State legislative professionalism. Walker (1969) argues that "the states which provide the most extensive staff and research facilities in their legislatures ought to pioneer in the adoption of new programs." (p. 885) Moreover, as legislatures become more professional, they are better prepared to deal with complex policy issues (Jones, 1994). Legislative professionalism has been considered to influence program adoption and spending levels in various policy areas, such as public assistance (Derthick, 1970), juvenile corrections (Downs, 1976), and air pollution (Downs & Rocke, 1980). Thus, I predict that state legislative professionalism will be positively associated with a state's adoption and implementation of EFOIA.

H8a: There is a positive relationship between state legislative professionalism and a state's adoption of EFOIA.

H8b: There is a positive relationship between state legislative professionalism and a state's implementation of EFOIA.

Partisanship. The Clinton administration in the 1990s promoted the idea of free access to information about the government and the actions of elected officials (Halstuk & Chamberlin, 2001). However, in response to the 9/11 terrorist attacks in 2001, the George W. Bush administration imposed tighter restrictions on the public's access to government records by creating a category of "sensitive but unclassified" information (Pack, 2004). Meanwhile, under the Obama administration, the trend toward unmitigated

access to government information has been resumed (Ginsberg, 2011). Thus, I predict that party control of the state legislature will be positively associated with a state's adoption and implementation of EFOIA.

H9a: There is a positive relationship between party control of the state legislature and a state's adoption of EFOIA.

H9b: There is a positive relationship between party control of the state legislature and a state's implementation of EFOIA.

Scandals (Applied only to the analysis for the adoption of EFOIA). Studies of legislative ethics reforms have demonstrated that scandals concerning corruption act as the catalyst for anti-corruption reform (Hofstadter, 1955; Hoogenboom, 1978; Link & McCormick, 1983; Rosenson, 2003). Rosenson (2003) argued that legislators did care about scandals due to the fear of defeat in election when they did not take aggressive action to regulate their own ethics. EFOIA is expected to regulate corrupt behavior of legislators by increasing the possibility of exposing their behavior for personal gains, such as bribery and embezzlement, to public scrutiny. In this respect, if a state struggles with scandals concerning corruption, the state may seek anti-corruption reforms. Thus, I predict that scandals will be positively associated with a state's adoption of EFOIA.

H10: There is a positive relationship between scandals and a state's adoption of EFOIA.

Legal practice (Applied only to the analysis for the adoption of EFOIA).

According to *the legal environment theory* developed by Edelman (1990, 1992), the passage of law creates a normative environment to which organizations must adapt, but its effect is *indirect*, not directly intervening organizations. Indeed, the legal environment theory views law, the legal circumstance as an important *normative* pressure on organizations to change their organizational behavior.

Moreover, this theoretical perspective emphasizes legitimacy as a major motivation for organizational attention to the legal environment; organizations respond to law because of legitimacy, not because of efficiency. From the legal environment theory, the legal practice of the federal government regarding transparency can create a normative circumstance that may influence a state's decision on its transparency policy. Such legal practices can "mediate" the effect of EFOIA of 1996 on state policymaking. This study considers two types of legal practices the federal government made: the creation of a category of unclassified information of 2002, and the OPEN Government Act of 2007.

After the 9/11 terrorists attacks, 2001, as the concerns on national security increased, the George W. Bush administration in 2002 created a new category of "sensitive but unclassified" information to constrain public access to government records (Pack, 2004). According to this new categorization, the agencies are urged to remove

broad categories of information from their transparency websites because of concerns about national security.

Meanwhile, Congress in 2007 enacted the OPEN Government Act that would address a range of procedural issues impacting FOIA administration, thereby improving the agencies' disclosure of information (McDermott, 2010). The OPEN Government Act aimed to enhance public and press access to information about inner workings of the government in several important procedural ways: to strengthen and speed agency compliance with FOIA requests. Thus, I predict that the legal practice enacted by the federal government will increase or decrease the likelihood of a state's adoption of EFOIA.

H11a: There is a negative relationship between the creation of unclassified information category and a state's adoption of EFOIA.

H11b: There is a positive relationship between the OPEN Government Act and a state's adoption of EFOIA.

FOIA strength (Applied only to the analysis for the implementation of EFOIA). Tavares (2007) argued that the introduction of FOIA could reduce corruption in that it would enable the public to observe corrupt behavior of government officials and thus punish them at elections. Similarly, Cordis and Warren (2012) contend that the "strong" FOIA laws of states had a positive impact on corruption by increasing in

detection probability (p. 5). As state FOIA legislation is stronger, it is better to force a state to provide access to government information. Thus, I predict that the strength of state FOIA will be positively associated with the scope of a state's implementation of EFOIA.

H12: There is a positive relationship between the strength of state FOIA and a state's implementation of EFOIA.

IT management (Applied only to the analysis for the implementation of EFOIA). Scholarly research on e-government demonstrated that institutional capacity in the area of information and technology (IT) policy played a significant role in sustaining e-government development (Clark, 1985; Fountain, 2001; Tolbert, Mossberger, & McNeal, 2008). According to Tolbert et al. (2008), innovation in digital government requires the institutional infrastructure and leadership capacity for its development, such as dedicated legislative committees and IT executive departments. Under the EFOIA, states that are sustained innovator allow for powerful searches, enough sources of data, and various ways to engage citizens on the transparency websites. Thus, I predict that state institutional capacity for IT management will be positively associated with the extent of a state's implementation of EFOIA.

H13: There is a positive relationship between IT management and a state's implementation of EFOIA.

e-Government implementation (Applied only to the analysis for the implementation of EFOIA). The degree of a state's e-government implementation has been often used as a proxy for state infrastructure capacity (McNeal et al., 2007). Increasing online access to government information requires great levels of infrastructure capacity associated with the use of information technology. Moreover, McNeal and Hale (2010) found the evidence that greater levels of state infrastructure capacity for e-government were strongly related to more extensive e-disclosure implementation. Thus, I predict that there is a positive relationship between the level of state e-government implementation and a state's implementation of EFOIA.

H14: There is a positive relationship between e-Government and a state's implementation of EFOIA.

CHAPTER 4

RESEARCH DESIGN AND METHODOLOGY

This chapter deals with the issues of the research design and methodology used to address the research questions of this study. First, various sources of data are briefly introduced. Second, instruments for measuring dependent variables, independent variables, and control variables are described. Finally, this chapter concludes by describing statistical techniques for data analysis.

Sources of Data

This study identifies factors influencing the diffusion of EFOIA among the US states at the stages of adoption and implementation, and examines the differences in diffusion between adoption and implementation of EFOIA. To answer the research questions, this study utilizes panel data (or longitudinal data) for the US states between1996 and 2013; panel data[36] for 44 states between 1996 and 2009 for the adoption stage of EFOIA, and panel data for 48 states between 2010 and 2013 for the implementation stage of EFOIA. The data were collected from a variety of existing data bases as follows:

the Bureau of Census, Bureau of Economic Analysis, Council of State Governments, Indiana State University - Klarner Politics, Institute for Quantitative Social Science, National Conference of State Legislatures, National Governors Association,

[36] This study excludes Alaska and Hawaii because they differ on a number of important economic and political variables that make them less directly comparable than their counterparts (Doyle et al., 2010)., In addition to these states, in the analysis for the adoption phase, this study excludes four states that already enacted the state law on electronic records before the federal EFOIA of 1996.

National Telecommunications and Information Administration, U.S. Public Interest Research Group, U. S. Department of Justice, and Reporters committee for Freedom of the Press (Open Government Guide)

Panel data[37] (or longitudinal data) typically are the data that contain time series observations of a number of units (e.g. individuals, states and nations). Panel data sampling design offers many benefits compared to either single cross-sectional or single time-series design (Frees, 2004; Hsiao, 2005, 2007).

First, panel data provide rich information in that observations in the data include both a cross-sectional dimension and a time series dimension. Thus, panel data have greater capacity for capturing complicated and dynamic behavioral hypotheses than a single cross-section or time series data.

Second, panel data offer more *accurate inference* of model parameters because of more degrees of freedom and more sample variability than cress-sectional data (with T=1) or time-series data (with N=1), thereby improving the efficiency of statistical estimates. Especially, compared to cross-sectional regression models, panel data sampling design has the ability to separate *subject-specific effects* by individual-specific error term α_i[38] from the disturbance term (or error term, ε_{it}). By separating out, statistical estimates of the variability become more precise.

[37] Panel data are also known as *pooled cross-sectional time series* and in the natural sciences (Frees, 2004)

[38] The parameters α_i vary by subject and are known as individual, or *subject-specific.*

Third, panel data may control the impact of omitted variables correlated with the included independent variables. Panel data contain information on both the inter-temporal dynamics and the individuality of the entities, and thus may enable researchers to control the effects of unobserved variables.

Finally, panel data can reduce collinearity that refers to an exact or approximate linear relationship between explanatory variables in estimating unrestricted time-adjustment patterns. For example, while time-series observations of current and lagged variables are likely to be higher collinear, panel data relying on the inter-individual differences can reduce such collinearity.

Yet, panel data sampling design can also have drawbacks since the sampling structure is complex. The most common drawback of panel data sets results from *attrition*, although the primary approach to panel data analysis generally assumes *balanced* data where each subject has the same number of observations (Frees, 2004). Attrition refers to a gradual erosion of responses by subjects: In US Panel Study of Income Dynamics (PSID), while a non-response (i.e. *missing* data) rate was 24% in the first year (1968), the non-response rate grew to about 50% by 1985 (Frees, 2004). Attrition or the existence of missing data can be troublesome because it may cause a *selection bias* that "potentially occurs when a rule other than simple random (or stratified) sampling is used to select observational units." (Frees, 2004, p. 9)

According to Little and Rubin (1987), there are several approaches for addressing partially *missing* data. One option is to treat the available data as if non-responses were intentionally planned, utilizing unbalanced estimation techniques. A

second option is to use only subjects (i.e. the units of observation) with a complete set of observations by removing unobserved observations from subjects with missing responses. A third option is to impute values for missing responses. Each option is generally easy to carry out, and may be satisfactory with small amounts of missing data (Frees, 2004).

Due to the existence of small amounts of missing data, this study will employ the second and third options suggested by Little and Rubin (1987). When examining the effect of partisanship on the diffusion of EFOIA, the missing data for the case of Nebraska will be discarded because of the state's nonpartisanship. Furthermore, with regard to the observations of variables in a given year that are not reported, I will adjust them by imputing values of the observation of the variables as an average of the observed values of the variable in a surrounding 5-year period. This approach can avoid undue weight being given to observations in a particular year (Glaeser & Saks, 2006).

Instrumentation

Dependent variable. This study has two dependent variables in the analysis. The dependent variable in the event history analysis (for the adoption stage of EFOIA) indicates the probability that a state will adopt the EFOIA in a specific year, given that the state has not already done so. It is a dummy variable; it is coded as 1 in the year a state adopted the EFOIA, and 0 otherwise. States' adoption years of EFOIA were collected by accessing the Open Government Guide.

The dependent variable in the multivariate regression analysis (for the implementation stage of EFOIA) represents the extent to which state governments implement their transparency or governmental websites in compliance with EFOIA. It is

measured by the percentage score of a state's transparency website that offers online services regarding government spending data in a given year, ranging from 0 to100. The transparency score was determined by the US Public Interest Research Group. The US PIRG Education Fund researchers evaluated a state's transparency website providing information on state government spending, in terms of data availability, usability, and accessibility. Only one website was graded for each state. If a state had a designated transparency website, that site was graded. If a state did not have a transparency website, the government website that earned the highest possible score was graded. The US PIRG Data went through the review of state agencies administering transparency websites for accuracy. In this study, the scores of 2010 and 2011 are weighted based on the score of 2012 as a standard, since state governments have improved their transparency websites by increasing their online services over time.

Independent variables. This study has a variety of independent variables associated with socialization and policy learning.

Socialization. As a proxy for socialization, three variables representing norm resonance are used: liberal ideological climate, public pressure, and innovative policy culture. *Liberal ideological climate* is measured by *government ideology index* and *citizen ideology* developed by Berry et al (1998, 2010). Government ideology refers to the mean position on a liberal-conservative continuum of the elected officials in a state, weighted according to the power they have over public policy decisions. Citizen ideology refers to the mean position on a liberal-conservative continuum of the active electorate in a state. Higher values in those ideology index imply greater policy liberalism.

Public pressure is measured by voter turnout, the public's Internet use, and educational attainment by state. Voter turnout refers to a voting rate for gubernatorial elections in each state. It represents the ability of citizens engaging directly in democratic processes to protect their civil rights and challenge the government's operations (Gamble, 1997; McNeal and Hale, 2010). The public's Internet use indicates the percent of state households with Internet access. Educational attainment by state implies the percent of state residents over age 25 with a bachelor's degree or more in a given year.

Innovative policy culture is measured by state policy innovativeness index. This index indicates the propensity of a state for policy innovativeness; a state's willingness to adopt new policies sooner or later relative to other states. This score varies from 0 to 1, with larger values indicating a quicker policy adoption rate and a higher innovation score.

Legal practice serves for a proxy of a legal action of the federal government concerning transparency, which may create the legal environment influencing a state's policy decision on transparency. This normative pressure can mediate the effect of EFOIA of 1996 on states. This measure is described as a dummy variable; it is coded 1 if a state adopted EFOA after such legal action, 0 otherwise.

Policy learning. Two variables serve as a measure of policy learning: neighboring effects and professional networks. *Neighboring effects* indicate the proportion of neighboring states and states within the applicable BEA region (without double-counting) that have previously adopted (adoption phase), or that have a grade A (leading states) or B (advancing states) in online transparency in a given year (implementation phase).

The numerator is the total number of neighboring states and states within the applicable BEA region (without double-counting) that have previously adopted (adoption phase), or that have a grade A (leading states) or B (advancing states) in online transparency in a given year (implementation phase). The denominator is the total number of neighboring states and states within the applicable BEA region (without double-counting). This variable captures the implications of both the neighbor model and fixed-region model of regional diffusion theory.

In addition, this study uses the "lagged" form of *neighboring effects* by replacing the variable with the same variables lagged by one year because the states appeared to be influenced by the performance of neighbors in the previous year. Furthermore, since this study considers neighboring effects to be influenced by slack resources, this variable is treated as an *interaction term*.

Professional networks imply a state's representation in the leadership of the National Governor Association (NGA) or National Conference of State Legislatures (NCSL) in a given year (McNeal et al, 2003, 2007). It is a dummy variable; it is coded as 1 if a state had a leadership position in a given year, 0 for otherwise. Specifically, leadership in professional networks is defined as state membership on the NCSL's Executive Committee including ex-officio members, and the NGA Executive Committee including standing committees.

Control variables. This study includes control variables in the analysis to isolate the effects of socialization and policy learning from other factors that may influence states' adoption and/or their implementation of EFOIA as follows: slack resource, party control, public opinion, state legislative professionalism, scandals, legal practice, FOIA strength, and IT management.

Slack resource. Slack resource is measured by GDP and per capita income. GDP indicates the state counterpart of the Nation's gross domestic product (GDP). GDP by state is derived as the sum of the GDP originating in all the industries in a state (Millions of current dollars). Per capita income refers to the income that is received by persons from all sources. It is measured by total personal income divided by total midyear population.

Partisanship. Partisanship or party control indicates the party alignment between the presidency and the governor of a state government. This variable is treated as a dummy variable: coded as 1 if the governor's party is the same as the president's party, 0 otherwise.

State legislative professionalism. State legislative professionalism is measured by state legislative professionalism index that Squire (2007) developed based on indicators of pay, staff resources, and session length of state legislatures. This index indicates the percent of professionalism that a state's legislature had compared to Congress in a given year, representing state institutional capacity or overall professionalism of state government.

Scandals. Scandals imply a state conviction rate per capita, representing the extent of corruption at the state level (for 100,000 people in the state population). This corruption data were derived from the Justice Department's "Report to Congress on the Activities and Operations of the Public Integrity Section." This publication lists the number of federal, state and local public officials convicted of a corruption-related crime by state. As Glaeser and Saks (2006) did, this study collects information on the number of convictions by state annually from the Justice Department's report, and then divides these convictions by state population to form an estimate of the state conviction rate per capita.

FOIA strength. FOIA strength is the score of representing the strength of state EFOIA, ranging from 0 to 10. Cordis and Warren (2012) determined the FOIA score of each state by giving one point for each of the criteria, such as the presumption for disclosure and exemptions, fee provisions, agencies' response times to a request, administrative appeal provisions, and penalties imposed for violation of the statutes. State FOIA scores are considered confidential since they are positively correlated with the scores provided by several surveys that were conducted by the Better Government Association (BGA) and the Investigative Reporters and Editors Inc. (2002), and the BGA and the National Freedom of Information Coalition (2007).

IT management. IT management serves as a measure of state infrastructure and leadership capacity, consisting of the dummy variables of *IT office* and *IT committee*. IT office presents whether a state has a separate IT office as a department unto itself; it is coded as 1 if a state has the office, 0, otherwise. IT committee presents whether there is a

IT committee in the state legislature; it is coded as 1 if either the state House or Senate has an IT committee, and 0 if neither has the committee or office.

E-government implementation. E-government implementation indicates an index of state e-government use or overall performance from 2001 to 2008. This measure is an annual index based on a composite score using the following criteria: online publications, online databases, audio clips, video clips, foreign language or language translation, advertisements, premium fees, user payments or fees, disability access, privacy policy, security policy, online services, digital signatures, and so on (West, 2008).

Conceptualization of Early Adopter and Successful Group

To define "early adopter," this study uses *the adopter categorization model* of Rogers (1962, 2003) as well as Moore's (2002) concept of *chasm*. The adopter categorization model proposes five categories of adopters of innovation according to typical behavior-based profiles: Innovator, early adopter, early majority, late majority, and laggard.

Innovators are enthusiasts who are willing to accept new ideas, technologies or policies to improve their lives, even taking a risk. *Early adopters* are open to innovation, but, unlike the innovators, they want to see the benefits of the innovation. The *early majority* group consists of pragmatists because they make their decisions on the results that are proved or supported by established references. The *late majority* members are pessimistic about the new values of innovation, and thus make decisions once the innovation becomes mainstream based on the previous experience of others. Finally, the *laggards* group consists of skeptics who feel uncomfortable with innovation (Bernstein &

Singh, 2008). According to Moore (2002), a "chasm"(or gap) between the early adopter group and the early majority group arises because of socio-economic and demographic differences between them; the early majority group waits until the innovation is proven and supported while the innovator and early adopter groups are committed to innovation. In this respect, the early majority members may change their behaviors according to a result of the innovation being introduced (Bernstein & Singh, 2008).

In 2002, the George W. Bush administration created the category of *sensitive and unclassified information* in response to the 9/11 terrorists attacks. Since 2002, states adopting EFOIA, unlike the previous adopters, stipulated legal statements that would constrain public access to government information when there were reasonable grounds to believe disclosure might pose a safety risk. In this respect, these states appeared to exhibit behavior of the early majority group, taking a much more pragmatic view of EFOIA than those adopting EFOIA in previous years. Thus, this study defines early adopters as states that are committed to EFOIA by combining the innovator group with the early adopter group — that is, states adopting EFOIA from 1996 to 2001.

Meanwhile, this study defines a" successful" group as the group of states that achieved "programmatic success" related to intended outcomes (Marsh & McConnell, 2009). Programmatic success implies that a program or a policy did achieve the intended outcomes. Since the objective of state transparency websites is to provide online access to government spending data, this study defines a successful group as the group of leading and advancing states that have achieved at least 80 % points of online transparency score.

Statistical Analysis Techniques

Data analysis is based on the event history model (especially, with a discrete-time model) for the adoption stages of EFOIA, and a multivariate regression model (with a mixed-effects model) for the implementation stages of EFOIA. Each analysis model has been generally employed in past diffusion studies. For data analysis, this study uses STATA (version 12).

Event history analysis model. This study uses the event history analysis (EHA) with panel data in determining the factors associated with a state's adoption of EFOIA. Event history models have a variety of names, such as duration models, survival models, failure-time models, reliability models, and so on. *Events* imply "changes" or represent a "transition" from one state (or position) to another, while the *history* refers to the “timing” of the occurrence of the event. In this study, an *event* is a state’s adoption of EFOIA and the *history* is the number of years leading up to the adoption of EFOIA.

Employing the EHA model can overcome the obvious shortcoming of the traditional regression model. The binary logistic regression model generally looks at the effect of "covariates” (independent variables) on the likelihood of an event's occurrence. However, this model treats units (e.g. individuals, organizations, states) experiencing a given event equally, losing *duration* information: one treats a person who held on to his/her job for 5 years before unemployment the same as someone who was out of work after only 2 months.

However, an EHA model deals with an examination of both the occurrence of an event and the history leading up to the event's occurrence. Thus, understanding the "event history" includes a consideration of not only *whether* something happens, but also *when* something happens.

The strength of the EHA model lies on its *statistical inferences* (Box-Steffensmeier & Jones, 2004; Doyle, McLendon, & Hearn, 2010). Inferences from the EHA model can be made in describing how the covariates of interest (i.e. independent variables) may influence *duration time* or *survival time* before an event's occurrence — that is, "the length of time that passes between entry into the process and occurrence of the event." (Box- Steffensmeier & Jones, 2004, p. 9) The inference is *comparative* in nature. Explicit comparative inferences can be made in terms of differences across the units (e.g. individuals, organizations, states, and so on) (Box- Steffensmeier & Jones, 2004). As long as event history data are longitudinal, and are generated across many observations, any event history model can provide comparative inferences.

A critical concept in EHA is *the risk set* representing the set of units in the sample that are "at risk" of experiencing an event. When the event under analysis cannot repeat (e.g. death), the size of the risk set will decrease over time as units in the sample experience the event; if units are annual, the size of the risk set will decrease at the end of each year. Since most government policies or programs can only be adopted once by a given jurisdiction, they are generally treated as non-repeatable events in EHA. Once a unit experienced an event, the unit in subsequent years is removed from the risk set because it is no longer at risk of experiencing the event.

Another key concept in EHA is *hazard rate*, which represents the probability that units that are at risk of experiencing an event will do so during a given time period (Berry & Berry, 1990). Thus, in this study, a hazard rate is the probability that a state will adopt EFOIA between 1996 and 2009, given that the state has not previously adopted the law at that time. Since the hazard rate is an *unobservable* variable, it is estimated from observed years of passage for a state's adoption of EFOIA. The *observable* dependent variable for estimating effects in EHA is a dummy variable (Berry & Berry, 1990); it is coded 1 when a state adopted EFOIA in a given year, 0 otherwise. The dichotomous nature of the dependent variable in EHA makes probit or logit the substantial estimation technique (Berry & Berry, 1990).

EHA models can be computed for either discrete intervals or continuous. In a *discrete time* model, the period of time of the analysis is divided into a set of distinct units (e.g. year(s)). However, a continuous time model does not make this division assuming that an event can occur anywhere in time (Berry & Berry, 1990). Berry and Berry (1990) first applied the discrete time model to the field of policy diffusion to examine lottery adoptions of states. Berry and Berry's discrete time model has been considered a standard form for event history analyses in the field of policy diffusion.

The commonly used function for the discrete time model is the logit function, which has the following form:

$$\log \{\frac{\lambda i}{1-\lambda i}\} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}$$

Where, λ_i : the probability of an event's occurrence
$1- \lambda_i$: the probability of a nonoccurrence
$\beta' x$: the covariates and regression parameters

The above model specifies in terms of the log-odds ratio of the probability of an event's occurrence (λ) to the probability of a nonoccurrence ($1-\lambda$). In addition, this model posits that this probability is a function of covariates, X. The logit coefficients, β_k, are interpreted in relation to the log-odds of an event occurrence: when $\beta_k > 0$, the log of the odds ratio is increasing as the covariate increases, and decreasing when $\beta_k < 0$. To directly retrieve the predicted probability of an event occurrence (λ), the above model can be expressed as follows:

$$\lambda_i = \exp^{\beta' x} / 1 + \exp^{\beta' x}$$

Where, $\exp^{\beta' x}$: the exponentiated logit parameters for a given covariate

The baseline hazard under the discrete time model will be equivalent to

$$\lambda_i = h_0(t) = \exp^{\beta 0}$$

Hence, the hazard probability is constant with respect to time; a distributional shape of the hazard rate over time remains *constant* and thus the probability that a state will adopt a policy is *fixed* over time. Although the discrete time model is widely used and well understood by social scientists, there are some ostensible disadvantages of this

model. Assuming a *flat* baseline hazard for the discrete time model can be inappropriate due to the problem of time dependency; the hazard rate may assume a wide variety of shapes, rather than fixed over time (Box-Steffensmeier & Jones, 2004). Moreover, if the time underlying time process is continuous, then discrete time model may be problematic to be applied.

The general way to avoid the problem of time dependency in the discrete time model is to include *k -1* temporal dummy variables. Yet, this approach has two drawbacks. First, if the number of time points in the data set is large, the temporal dummies can quickly consume many degree of freedom (Box-Steffensmeier & Jones, 2004). Second, the interpretation of the coefficients of many temporal dummies can become unwieldy, especially if the pattern of the coefficients is very noisy. Therefore, the alternative for addressing the time dependency in the hazard is the use of "the natural log transformation" or "polynomials[39]" (Box-Steffensmeier & Jones, 2004).

Meanwhile, in a *continuous time* model, an event is assumed to take place anywhere in time. There are a variety of continuous time model depending on the assumption of the baseline hazard rate, such as the exponential model, Weibull model, and Compertz model. However, arbitrary decisions regarding the nature of the baseline hazard rate have to do with *false* interpretations (Box- Steffensmeier & Jones, 2004).In this regard, the Cox proportional hazard model has been considered an attractive alternative for the event history analysis (Doyle, McLendon, & Hearn, 2010; Park, Park,

[39] Francesco (2010), Carter and Singnorino (2010), and Buckley and Westerland (2004) included three time variables, t, $t^2/10$, and $t^3/100$.

& Lee, 2010). In the Cox model, the particular distributional form of the duration times remains "unspecified" (Cox, 1972, 1975; Box-Steffensmeier & Jones, 2004); the Cox model does not have an assumption about the distributional form of the baseline hazard rate. The basic Cox model is as follows:

$$h_i(t) = \exp(\beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}) h_0(t)$$

Where, $h_i(t)$: the hazard rate for the i^{th} state
$h_0(t)$: the baseline hazard function
$\beta' x$: the covariates and regression parameters

As seen above, the Cox model does not have an intercept term (β_0) because the baseline hazard ($h_0(t)$) is assumed to be *unknown*, and thus remains *unspecified*. In this regard, the Cox model often called a "semi-parametric" model (Box-Steffensmeier & Jones, 2004). In terms of the log of the hazard ratios including predictor variables, the above model can be re-presented as follows:

$$\log \left\{ \frac{h_i(t)}{h_0(t)} \right\} = \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}$$

The hazard ratio represents the odds of an event's occurrence along with per unit of change in a covariate. Since the value of a hazard ratio is *exponentiated,* none is negative. An exponentiated coefficient of 1.0 implies that the covariate has no effect (Exp[0]=1). The coefficient larger than 1 implies that the hazard is increasing with changes in the covariate, while the coefficient smaller than 1 indicates that the hazard is

decreasing with changes in the covariate. The percentage change in the odds of an event's occurrence can be calculated by subtracting 1 from the hazard ratio and then multiplying by 100. For example, when the hazard ratio of an unemployment rate is 1.65, it indicates that increasing the unemployment rate by 1 percent makes it 65% more likely that a state will adopt a given policy.

The strong advantage of the Cox model is that the effect of covariates on a hazard rate (i.e. duration time) can be estimated, regardless of the nature and shape of the baseline hazard rate. Yet, the main drawback of the Cox model is that the estimate of the baseline hazard is so closely associated with the observed data, which makes it difficult to generalize these estimates to other settings (Gelfand & Fomin, 1963; Royston & Parmar, 2002). Royston and Parmar (2002) proposed a *flexible parametric hazard model* to addresses this drawback of the Cox model, based initially on "the assumption of either proportional hazards or proportional odds scaling of covariate effects." (p. 2176) However, the Cox model has been strongly recommended if the baseline hazard is not of central interest (Box-Steffensmeier & Jones, 2004).

This study will deploy the discrete time EHA model although event history process is usually considered to be continuous. Since state legislation operates on yearly cycles, the underlying process for policy adoption should be assumed to be discrete rather than continuous (Grattet et al., 1998; Box-Steffensmeier & Jones, 2004). Therefore, discrete-time methods are more appropriate than continuous-time methods. Furthermore, this study will include "the natural log transformation" in the discrete EHA to address the problems of *time dependency* and the unrealistic assumption of a constant hazard rate.

This natural log transformation is easy to implement as well as effective to avoid *quasi-complete separation*[40](Allison, 2008). The discrete time model of this study including the covariates of interest is as follows:

$$\text{EFOIA}_{\text{adoption}} = f(\text{Ideology}, \text{Public}_{\text{pressure}}, \text{Innovativeness}, \text{Neighboring}, \text{Network}, \text{Slack}, \text{Professionalism}, \text{Party}, \text{Legal}_{\text{practice}}, \text{Scandals})$$

$$\log\left\{\frac{\lambda i}{1-\lambda i}\right\} = \beta_0 + \beta_1 \text{Ideology}_i + \beta_2 \text{Public}_i + \cdots + \beta_{11} \text{Scandals}_i + \ln t$$

Multivariate regression model. This study deploys a multivariate regression model with panel data to test hypothesized relationships pertaining to states' implementation of EFOIA. Since the dependent variable measuring states' implementation of the EFOIA is the score of e-transparency and is continuous, OLS regression coefficients will be reported. The basic function of multivariate regression models is as follows (Eom, Lee, & Xu, 2008):

$$y_{it} = \beta_0 + \beta_1 x_{it,1} + \cdots + \beta_k x_{it,k} + v_{it}, \quad i = 1, \ldots, N; t = 1, \ldots, T; k = 1, \ldots, K.$$

Where, i : the unit of observation, t : the period of time
k : the k^{th} explanatory variable, β_0: the intercept
β_k: the coefficient of each explanatory variable
v_{it}: error term

[40] This is a major problem in logistic regression since the coefficients of covariates almost perfectly determine the value of the dependent variable, along with no-existence of maximum likelihood estimates (Allison, 2008).

In general, a basic OLS model decomposes an error term v_{it} into two error components: an idiosyncratic error term u_{it} and an subject(or individual)-specific error term a_i. In the basic regression model, an idiosyncratic error term u_{it} is assumed to be uncorrelated with regressors x_{it} (Cameron & Trivedi, 2010). A subject-specific error term a_i represents the *heterogeneity* among subjects, and is assumed to be independent of u_{it}.

When using panel data in the estimation of an OLS regression model, there are two types of considerable variations: *between* (intergroup) variations and *within* (intra-group) variations (Wooldridge, 2006, 2009). In this study, *between* variations mean variations in the average score of e-transparency from one state to another, while *within* variations refer to variations in the average score of e-transparency within each state over time. Regressions relying on *between* variations can be problematic due to the influence of unobservable differences between (or across) states — that is, *omitted variable bias*. *Omitted variable bias* occurs when the error term (i.e. the individual-specific error term) is correlated with the predictors that are included in the regression model.

In non-experimental studies, researchers often leave out certain variables, as they are difficult to measure. However, the omission of key predictors in regressions can cause severe bias in estimating the effects of the predictors (Allison, 2005). A *fixed effects* model lets researchers control for all possible characteristics of variables — even without measuring them — unless those variables are *time-invariant* (Allison, 2005). In this regard, a fixed effects model is generally seen as a powerful statistical method leading to the virtues of a randomized experiment (Allison, 2005).

The intuition behind fixed effects regressions is that the solution for removing omitted variable bias is to exploit *within* variations, assuming that there are no changes in unobservable variables within each state over time (i.e. time-invariant). The notion of *Fixed effects* implies that it holds constant or fixes the average effects of each state; the subject-specific error term (a_i) accounting for the heterogeneity is treated as a set of "fixed" parameters. Therefore, using fixed effects regressions enable researchers to control the average differences across states in any observable or unobservable predictors, thereby reducing omitted variable bias.

Yet, unfortunately, if *within* variations are little, fixed effects regression models cannot be used despite the threat of omitted variable bias. Fixed-effects models are designed to investigate the causes of changes *within* a state, and thus cannot test the effect of a time-invariant variable[41]; a time-invariant characteristic cannot cause changes within states because it is constant for each state. Furthermore, since a fixed effects model ignores *between* variations, it can yield standard errors that are considerably higher than those produced by alternative methods of analysis using both *within* variations and *between* variations (Allison, 2005). However, considering that all the variations on the independent variables are associated with *within* subjects, a fixed effects regression model can be still useful because it restricts research attention to the within-subject variation (Allison, 2005).

[41] In a fixed effects model, time-constant variables are perfectly collinear with subject-specific intercepts and hence are inestimable (Frees, 2004).

Fixed effects regression models often compare with *random effects* models. Random effects models pay attention to both *between* variance and *within* variance. The rationale behind random effects model is that, unlike a fixed effects model, the variation or heterogeneity across subjects (a_i) is "random" — not fixed — with a specified probability distribution (i.e. normal distribution), and is "uncorrelated" with the regerssors (or independent variables) included in the model (Frees, 2004; Cameron & Trivedi, 2010). Thus, a random effects model allows researchers to estimate effects for time-invariant variables (e.g. culture, religion, gender, race), while these variables in the fixed effects model are absorbed by the intercept (a_i).

Moreover, a random effects model typically has a less standard error because it utilizes both *between* variances and *within* variances. However, the drawback of a random effects model is that those estimates are inconsistent in some cases, and thus are unreliable (Cameron & Trivedi, 2010;). In addition, a random effects model does not control for unmeasured factors, as it assumes the error term (v_{it}) to be uncorrelated with the independent variables.

> "…the crucial distinction between fixed and random effects is whether the unobserved individual effect embodies elements that are correlated with the regressors in the model, not whether these effects are stochastic or not." (Greene, 2008, p.183)

If so, which is preferable, fixed effects or random effects? To decide between fixed or random effects, researchers can run a *Hausman test* that refers to a test for econometrics model misspecification based on a comparison of two different estimators of the model parameters. In a *Hausman test*, a null hypothesis is that coefficients estimated by the efficient random effects estimator are same as those estimated by the consistent fixed effects estimator (Greene, 2008); it tests whether an error term is correlated with predictors, when the null hypothesis is they are not. If same (insignificant *p-value*, Prob>chi2 larger than .05), the use of random effects will be safe, fixed effects, otherwise (Greene, 2008). According to the result of a Hausman test, this study should utilize a random effects model because *p-value* is 0.06.

However, using simple random-effect estimators ignores the fact that there are useful predictors in a fixed-effects model. Furthermore, a random-effects model has the problem of the remaining uncertainty associated with unmeasured factors. When a model is significant but does not explain all variation, using a *mixed-effects* model can be more appropriate than only adopting either a fixed-effects or random-effects model (Campbell collaboration, 2009). Mixed-effects model contains both fixed and random components.

Mixed-effects models have become very popular to address questions about changes over time in the response and changes in the relationship of the response to subjects' characteristics (Gurka & Edwards, 2008; Cheng et al., 2010). In addition, mixed-effects models are robust to missing data (Baayen, 2008). Furthermore, a mixed-effect model allows researchers to assess differences of responses from different groups — that is, *group effects*. The term *group* indicates a category of the population. The

differences in tax liability due to party affiliation (democrat/republican) or due to gender (male/female) can be a good example of group effects (Frees, 2004). A mixed-effects model has the basic function as follows:

$$E(y_{it} | a_{gi}) = a_{gi} + \beta_0 + \beta_1 x_{git1} + \beta_2 x_{git2} + \cdots + \beta_k x_{gitk}$$

a_{gi}: random, subject-specific effects among groups,

β_0: fixed differences among groups

g = 1, ... , G(groups); i = 1, ..., N_g subjects in each group

t= 1, ... , T_{gi} observations of each subject

In a similar vein, this study concentrates on the differences in the extent of implementing EFOIA among five groups (leading groups, failing groups, and so on). Thus, utilizing a mixed-effect model is appropriate to address the research questions of this study. The mixed-effects model of this study including the covariates of interest is as follows:

$$EFOIA_{implementation} = f(Ideology, Public_{pressure}, Innovativeness, Neighboring, Network, Slack, Professionalism, Party, e\text{-}Gov, IT_{management}, FOIA_{strength})$$

$$E(y_{it} | a_{gi}) = a_{gi} + \beta_0 + \beta_1 Ideology_{git} + \beta_2 Public_{git} + \cdots + \beta_{11} FOIA_{git}$$

CHAPTER 5

ANALYSES OF DATA & FINDINGS

This chapter provides an overview of how the data will be statistically analyzed to test the hypotheses of this study, and descriptions for the data and the models. This chapter then presents the empirical results of the data analysis, and discusses the findings to identify the factors that may influence states' adoption and implementation of EFOIA.

Data Analysis for the Adoption Phase

Since Berry and Berry (1990), the application of event history analysis (EHA) with panel data has become established in the field of policy diffusion. This study uses the EHA model to explain an unobservable probability (i.e. hazard rate) that a state adopts the EFOIA in a specific year. The hazard rate can change over time or remain constant. In this study, the hazard rate is treated as constant over the sample period in accordance with the general assumption of most EHA models.

Even history models can be computed for either discrete or continuous intervals. A discrete time model divides the period of time of the analysis into distinct units, while a continuous time model does not make this division (Berry & Berry, 1990). Since state legislation operates on yearly cycles, a "discrete time model" is more appropriate than a continuous time model (Grattet, Jenness, & Curry, 1998). Thus, this study employs a discrete time function that defines a year as the applicable observation period, and assumes the non-existence of within-year differences.

In a distinct observation time window, the hazard function (i.e. the probability of a state's adoption of EFOIA) is generally specified as a "logistic." However, there are several statistical weaknesses related to logit models. The first one is associated with the likelihood that the observations are temporally dependent (Mooney, 2001; Buckley & Westerland, 2004). To consider *time* seriously (Beck, Katz, & Tucker, 1998) as well as avoid the unrealistic assumption of a constant hazard rate, this study includes a log type of time (lnt) in the model.

The second weakness results from the distributional assumption of a logit model that the maximum marginal effect takes place at the value $\pi = .5$. This assumption may become problematic when the distribution of the observed values of a dependent variable (y) is particularly skewed for the presence of few 1's and hundreds of 0's. Thus, this study also performs a "complementary log-log model" to check for robustness of a logit model.

Finally, since policy diffusion is associated with spatial dependency, it can conflict with the logit model's assumption of independent observations. Following Francesco (2010) and Buckley and Westerland (2004), this study uses "robust variance estimation" to relax the assumption that the error terms are identically distributed.

I decided as starting time the year of the enactment of EFOIA by the federal government, 1996. The sample period of this study continues through 2009 (i.e. ending time) in which almost all of 50 states adopted the EFOIA. This study excludes Alaska and Hawaii because they differ on a number of important economic and political variables that make them less directly comparable than their counterparts (Doyle et al.,

2010). In addition to these states, this study does not consider four states[42] that already enacted the state law on electronic records before the federal EFOIA of 1996. Furthermore, each of these states is dropped from the discrete-time EHA model after its year of adoption because it is no longer eligible to adopt so as to avoid estimation bias (Omer & Shelly, 2004).

Table 1 Summary Statistics of IVs (Obs=616)

Independent Variable	Mean	SD	Min	Max
Government ideology	.48	.13	.24	.74
Citizen ideology	.51	.15	.08	.96
Turnout	.51	.09	.23	.74
Internet use	.51	.39	0	.83
Education	.26	.05	.14	.39
Innovativeness	.08	.08	0	.59
Neighboring	.44	.24	0	1
Network	.27	.44	0	1
Professionalism	.20	.13	.03	.68
Income(log)	10.28	.20	9.80	10.84
GDP(log)	11.66	1.06	9.58	14.10
Scandal	.32	.30	0	2.53
Partisanship	.53	.49	0	1

[42] Before the federal EFOIA of 1996, West Virginia (1992), Indiana (1993), Kentucky (1994), and Texas (1995) already had their own law on electronic records to guarantee that the public has access to public records of government bodies at all levels.

Table 1 presents summary statistics of independent variables in the analysis for the adoption phase of EFOIA. The average level of ideological liberalism in state governments as well as state residents is 48% and 51 % respectively. The percentage of state households with an Internet access as well as turnout is, on average, 51%. With regard to the propensity of a state for policy innovativeness and state legislative professionalism, there is a great deal of variation in states, ranging from 0% to 59% and from 3% to 68%, respectively.

Table2 Model Descriptions for the Event History Analysis

Model	Main IVs	Label
The effect of *Socialization* (Model1)	Government ideology Citizen ideology	Liberal ideological climate
	Turnout Internet use Education	Public pressure
	Innovativeness	Innovative policy culture
The effect of *Learning* (Model2)	Neighboring	Regional interactions
	Networks	National interactions
The effect of *Both* (Model3)	Government ideology Citizen ideology	Liberal ideological climate
	Turnout Internet use Education	Public pressure
	Innovativeness	Innovative policy culture
	Neighboring Networks	Regional interactions National interactions

As shown in Table 2, this study employs three models to examine the explanatory power of two types of diffusion mechanism (i.e. socialization and learning) on a state's adoption of EFOIA. *Model 1* is used to investigate the influence of the factors associated with *socialization* on a state's decision in adopting EFOIA. *Model 2* only concerns the relationship between the factors related to *learning* and a state's decision in adopting EFOIA. Finally, Model 3 addresses total effects of socialization and learning on a state's adoption of EFOIA.

Table 3 and Table 4 are associated with two diagnostics to detect multicollinearity between independent variables (IVs): Correlation coefficient and variable inflation factor (VIF). Multicollinearity can increase estimates of parameter variance, thereby producing models in which no variable is statistically significant in spite of large R-square(R_y^2); parameter estimates provide the "incorrect sign" and "implausible magnitude." (Belsley, Kuh, & Welsch, 1980; Greene, 1993).

Table 3 describes *correlation coefficients* between independent variables included in the event history analysis. A correlation coefficient implies the linear relationship between two variables, indicating the extent to which two variables vary together. In general, there is a multicollinearity between two IVs when the correlation coefficient is higher than .85 (Cohen et al., 2003). According to Table 3, almost all IVs appear to be irrelevant to multicollinearity, except *internet, income, and lnt*.

On the other hand, Table 4 indicates the values of VIF associated with each model after converting an *internet* variable to a dummy[43] as well as eliminating an *income* variable from the analysis.[44] The VIF provides an intuitive interpretation in terms of the effects of R-square[45] (R_i^2) on the variance of the estimated coefficient for the i^{th} IV; the VIF is $1/(1-R_i^2)$ as the reciprocal of *tolerance* ($1-R_i^2$). As rules of thumb, a VIF of 10 has been used to indicate "excessive" or "serious" multicollinearity (Neter et al., 1989; Hair et al., 1995). However, some scholars choose a more conservative threshold value of 30 (O'Brien, 2007).

[43] "net1" is dummy; coded 1 if internet >.51 (the mean), 0 otherwise.

[44] As a solution for reducing multicollinearity, researchers generally recommend to eliminate one or more of the IVs that are highly correlated with the other IVs (O'Brien, 2007).

[45] R_i^2 represents the proportion of variance in the i^{th} IV associated with the other IVs (O'Brien, 2007).

Table 3 Checking Multicollinearity by Correlation Analysis

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Gideol.	1.0000														
2 Cideol.	0.5130**	1.0000													
3 Turnout	0.0680	0.1524**	1.0000												
4 Internet	0.1982**	0.2126**	0.1706**	1.0000											
5 Edu.	0.2273**	0.4855**	0.1653**	0.4499**	1.0000										
6 Profess.	0.1101	0.4227**	-0.0733	-0.0502	0.2820**	1.0000									
7 Inno.	0.3270**	0.2273**	-0.0324	0.1844**	0.2044**	0.2423**	1.0000								
8 Income	0.3140**	0.4581**	0.1973**	0.8113**	0.6550**	0.2536**	0.2760**	1.0000							
9 Slack	0.2011**	0.3170**	-0.1729**	0.1011	0.3014**	0.7833**	0.2956**	0.3623**	1.0000						
10 Scandal	-0.1011	0.0272	-0.0093	0.0193	-0.1699**	-0.0604	0.0120	0.0073	-0.0463	1.0000					
11 Partisans-hip	0.0340	-0.0616	-0.0358	0.1409**	0.0178	0.0154	-0.1056**	0.0799	0.0301	0.0121	1.0000				
12 Network	-0.0753	-0.0245	-0.0407	0.0750	0.0110	0.1113**	-0.0479	0.0290	0.0282	-0.0473	0.0325	1.0000			
13 Neighbor	0.2261**	0.1742**	0.0088	0.6500**	0.1501**	-0.0063	0.2043**	0.5722**	0.2909**	0.1377**	0.1349**	0.0114	1.0000		
14 Legal practice	0.0449	0.0530	0.1327**	0.4393**	0.1460**	-0.2060**	-0.0355	0.2944**	-0.1797**	0.0998	-0.1311**	-0.0646	-0.2019**	1.0000	
15 lnt	0.1660	0.1691**	0.0985	0.9496**	0.3087**	-0.0577	0.1657**	0.7246**	0.0871	0.0851	-0.0678	0.1447**	0.0521	0.4253**	1.0000

Note: * *Significant at .05 level(2-tailed)***

Table 4 Checking Multicollinearity by VIF

Model	Main IVs	VIF
Model1 *(Mean VIF=13.38)*	Government ideology	21.63
	Citizen ideology	24.00
	Turnout	31.65
	Education	53.36
	Internet use	12.65
	Innovativeness	2.57
Model2 *(Mean VIF=3.96)*	Neighboring	8.34
	Networks	1.4
Model3 *(Mean VIF=12.92)*	Government ideology	22.03
	Citizen ideology	24.23
	Turnout	32.77
	Internet use	4.14
	Education	53.86
	Innovativeness	2.58
	Neighboring	9.41
	Networks	1.77

Note: No values of VIF of the other variables included in the models are higher than 10.

According to Table 4, *education* and *turnout* variables, seriously, result in "excessive" multicollinearity in that their value of VIF is higher than 30 . Although dropping a relevant variable from the equation is a general remedy for reducing multicollinearity, this solution can be problematic. Eliminating X_j from the equation

means that the model being tested has changed, and that the theory being tested by the model has also shifted (O'Brien, 2007). Thus, this study attempts to treat *education* and *turnout* variables as dummy variables; coded 1 if the observed value of the variable is more than the mean , 0 otherwise. In addition, this study drops *citizen ideology* associated with multicollinearity from the analysis. As shown in Table 4-1, multicollinearity is remarkably reduced. Since no value of VIF is higher 10, this study does not concern the issue of multicollinearity any longer.

Table 4-1 Re-checking Multicollinearity by VIF

Model	Main IVs	VIF
Model1 *(Mean VIF=4.94)*	Government ideology	2.30
	Turnout	1.93
	Education	5.90
	Internet use	3.19
	Innovativeness	8.59
Model2 *(Mean VIF=4.11)*	Neighboring	8.20
	Networks	1.42
Model3 *(Mean VIF=4.36)*	Government ideology	2.33
	Turnout	1.93
	Internet use	6.06
	Education	3.21
	Innovativeness	8.59
	Neighboring	8.13
	Networks	1.46

Note: No values of VIF of the other IVs included in the models are higher than 10.

Data Analysis for the Implementation Phase

Since the dependent variable is continuous, measured online transparency scores of states over time, this study uses a common statistical method: multivariate regression analysis. In general, multivariate regression analysis is used to estimate "a model of multiple factors that best predicts the criterion." (Abu-Bader, 2006, pp.233-234) In non-experimental studies, researchers often leave out certain variables, as they are difficult to measure. However, the omission of key predictors in regressions can cause severe bias in estimating the effects of the predictors (Allison, 2005). To relax such bias, a *fixed* or *random effects* model can be used.

To decide between fixed or random effects, researchers recommend to conduct a *Hausman test* that is based on a comparison of two different estimators of the model parameters. In a *Hausman test*, a null hypothesis is that the coefficients estimated by the efficient random effects estimator are the same as those estimated by the consistent fixed effects estimator (Greene, 2008). If *p-value* is insignificant (Prob>chi2 larger than .05), using a random effects model will be safe (Greene, 2008). According to the result of a Hausman test (Table 5), this study should employ a random effects model because *p-value* is 0.58.

Table 5 Hausman Test Results

Independent Variable	Coefficient		Differences (b-B)	S.E.
	Fixed(b)	Random(B)		
Government ideology	-.39	-.026	-.37	.95
Citizen ideology	-1.00	.07	-1.07	1.57
Turnout	.02	-.05	.08	.12
	.			
	.			
	.			

Test: H_0: difference in coefficients not systematic
Chi2 (14) = 12.27, Prob>chi2 = 0.58

However, using simple random-effect estimators ignores the fact that there are useful predictors in a fixed-effects model. Also, a random-effects model has the problem of the remaining uncertainty associated with unmeasured factors. When a model is significant but does not explain all variation, using a *mixed-effects* model can be more appropriate than only adopting either a fixed-effects or random-effects model (Campbell collaboration, 2009). Mixed-effects model contains both fixed and random components. Mixed-effects models can be useful to examine differences of responses from different groups. (Gurka & Edwards, 2008; Cheng et al., 2010). This study concerns the differences in the extent of implementing EFOIA, based on five groups in which each state is grouped according to its online transparency score. Thus, this study uses a mixed effects model for the analysis. Additionally, this study includes "year dummy variables" to reduce possible bias in the standard errors from heteroskedasticity.

This study excludes Alaska and Hawaii because they differ on a number of important economic and political variables that make them less directly comparable than their counterparts (Doyle et al., 2010). The Ordinary Least Squares (OLS) regression models in this study have four time periods (T) from 2010 to 2013 and 48 panels (N), with each state as a panel. Since the number of time periods is relatively small compared to the number of panels ($T < N$), this study also uses the OLS regression model with panel corrected standard errors (PCSE). According to Beck and Katz (1995), the coverage probabilities of the OLS estimators with PCSE are closer to nominal levels than those of the General Least Squares (GLS) estimators with associated model-based GLS standard errors. Therefore, using PCSE can reduce serial correlation in calculating the standard errors of the regression coefficients (McNeal & Hale, 2010).

Table 6 presents summary statistics of independent variables in the analysis for the implementation phase of EFOIA. The average level of policy liberalism in state governments as well as state residents is 49% and 53 %, respectively. The percentage of state households with an Internet access as well as turnout is, on average, 77% and 52%, respectively. With regard to the state legislative professionalism, there is a great deal of variation in states, ranging from 3% to 68%.

Table 6 Summary Statistics of IVs (Obs=192)

Independent Variable	Mean	SD	Min	Max
Government ideology	.49	.10	.28	.69
Citizen ideology	.53	.14	.26	.87
Turnout	.52	.08	.32	.76
Internet use	.77	.05	61	.87
Education	.28	.04	.18	.39
Neighboring (time lag)	.65	.24	0	1
Network	.31	.46	0	1
ITcommittee	.35	.48	0	1
Professionalism	.20	.12	.03	.68
E-government	25.27	14.24	1	50
Partisanship	.44	.50	0	1

Table 7 Model Descriptions for the OLS Regression Analysis

Model	Main IVs	Label
The effect of *Socialization* (Model1)	Government ideology Citizen ideology	Liberal ideological climate
	Turnout Internet use Education	Public pressure
	Innovativeness	Innovative policy culture
The effect of *Learning* (Model2)	Neighboring	Regional interactions
	Networks	National interactions
The effect of *Both* (Model3)	Government ideology Citizen ideology	Liberal ideological climate
	Turnout Internet use Education	Public pressure
	Innovativeness	Innovative policy culture
	Neighboring Networks	Regional interactions National interactions

As presented in Table 7, this study deploys three models to investigate the explanatory power of two types of diffusion mechanism (i.e. socialization and learning) on a state's implementation of EFOIA. *Model 1* is used to examine the influence of the factors associated with *socialization* on a state's extent of implementing EFOIA. *Model 2* only concerns the relationship between the factors related to *learning* and a state's extent of implementing EFOIA. Finally, Model 3 considers the effects of socialization and learning on a state's extent of implementing EFOIA together.

Table 8 Checking Multicollinearity by Correlation Analysis

	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Gideol.	1.0000												
2 Cideol.	0.6560 **	1.0000											
3 Turnout	0.1310	0.2518 **	1.0000										
4 Internet	0.0413	0.2714 **	0.4655 **	1.0000									
5 Edu.	0.2487 **	0.5260 **	0.2975 **	0.6735 **	1.0000								
6 Profess.	0.2068 **	0.3319 **	0.0455	0.1684 **	0.2860 **	1.0000							
7 FOIA strength	0.1412	0.2601 **	-0.1237	0.0419	0.1983 **	0.1108	1.0000						
8 Network	0.1078	0.0228	-0.0917	0.0164	0.0199	-0.0595	0.0096	1.0000					
9 e-Gov't	0.0513	0.2314 **	-0.0195	0.2417 **	0.2729 **	0.2824 **	0.2045 **	0.0670	1.0000				
10 Partisan-ship	0.3902 **	0.3344 **	0.0649	0.1472 **	0.3166 **	0.1887 **	0.1526 **	0.0396	0.1155	1.0000			
11 Slack	0.0935	0.0584	-0.1277	-0.2915 **	-0.0597	0.0336	0.1712 **	0.0760	0.2462 **	0.1100	1.0000		
12 IT.	-0.1075	0.0529	0.0195	-0.0574	-0.0746	0.0199	-0.1179	-0.0059	-0.1398	-0.0165	0.2272 **	1.0000	
13 Neighbor	-0.0114	-0.0549	-0.2056 **	-0.2477 **	-0.1485 **	0.0974	0.1079	0.1095	-0.0235	-0.0549	0.0306	0.0405	1.0000

Note: ** *Significant at .05 level (2-tailed)*

Table 8 shows the results of correlation analysis to detect Multicollinearity between independent variables included in the analysis. The results of the analysis indicates no problems of multicollinearity with the combination of the IVs. However, as described in Table 9, the VIF tests designate the existence of the "excessive" multicollinearity between the IVs. Almost all IVs are associated with multicollinearity because their value of VIF is higher than 10.

Table 9 Checking Multicollinearity by VIF

Model	Main IVs	VIF
Model1 *(Mean VIF=26.42)*	Government ideology	21.32
	Citizen ideology	26.19
	Turnout	13.01
	Education	26.91
	Internet use	15.31
Model2 *(Mean VIF=5.63)*	Neighboring (lagged)	8.78
	Networks	1.59
Model3 *(Mean VIF=24.15)*	Government ideology	25.16
	Citizen ideology	21.82
	Turnout	15.75
	Internet use	13.97
	Education	28.22
	Neighboring (lagged)	9.84
	Networks	1.63

Note: No values of VIF of the other IVs included in the models are higher than 10.

To address multicollinearity, this study treats *education, internet,* and *turnout* as dummy variables; coded 1 if the observed value of the variable is more than the mean, 0 otherwise. In addition, this study drops *citizen ideology* closely related to multicollinearity from the analysis. As shown in Table 9-1, multicollinearity is remarkably reduced. Since no value of VIF is higher 10, this study does not pay attention to the issue of multicollinearity any longer.

Table 9-1 Re-checking Multicollinearity by VIF

Model	Main IVs	VIF
Model1 *(Mean VIF=3.84)*	Government ideology	2.90
	Turnout	4.00
	Internet use	4.16
	Education	4.15
Model2 *(Mean VIF=3.03)*	Neighboring (lagged)	5.17
	Networks	1.59
Model3 *(Mean VIF=3.53)*	Government ideology	3.46
	Turnout	4.08
	Education	3.62
	Neighboring (lagged)	6.49
	Networks	1.61

Note: No values of VIF of the other IVs included in the models are higher than 10.

Findings

This section assesses the role of socialization and learning in the diffusion of EFOIA among the US states. This section first identifies the effects of the hypothesized correlates of these diffusion mechanisms on states' decisions in adopting EFOIA. Next, this section considers whether these mechanisms are associated with states' implementation of EFOIA.

The effects of socialization and learning on states' adoption. Table 10 shows the statistical results of the models with *logistic regression*. Model 1 investigates how well the variables associated with *socialization* explain states' adoption of EFOIA. Model 1 is statistically significant (Wald $Ch^2 = 48.17$, $p < .000$), accounting for approximately 34% (*Pseudo* $R^2 = .34$) of states' adoption of EFOIA. As the effect of socialization, *government ideology* (*Coeff.* = 1.23, $p = .014$) and *education* (*Coeff.* = 1.07, $p = .048$) are statistically significant and "positively" associated with adoption of EFOIA, while *turnout, internet,* and *slack* are not statistically significant. When controlling for the main effect of socialization, as the variables representing legal practices, *Unclassified categorization* (*Coeff.* = -4.30, $p = .000$) and *The OPEN Act* (*Coeff.*= -6.28, $p = .000$) are statistically significant, but "negatively" associated with adoption of EFOIA.

Model 2 examines the effect of *learning* on a state's adoption of EFOIA. Model 2 is statistically significant (Wald $Ch^2 = 45.40$, $p < .000$), accounting for approximately 30% (*Pseudo* $R^2 = .30$) of states' adoption of EFOIA. In the effect of learning, *neighboring* is positively associated with adoption (*Coeff.*= 3.63, $p = .001$) whereas *network* is not statistically significant ($p = .488$).

Table 10 Predicting the Effects of Socialization and Learning on Adoption with Logistic Regression

Covariates	Socialization		Learning		Both	
Model	1		2		3	
	Coefficient (s.e.)	P>|z|	Coefficient (s.e.)	P>|z|	Coefficient (s.e.)	P>|z|
Government ideology	1.23** (.50)	.014	-	-	1.23** (.57)	.032
Turnout	.42 (.40)	.300	-	-	.47 (.42)	.262
Internet use	.62 (.94)	.507	-	-	.74 (.98)	.448
Education	1.07** (.54)	.048	-	-	1.30** (.58)	.027
Innovativeness	8.58** (3.85)	.026	-	-	7.40* (4.12)	.072
Inno*Slack	-15.10** (7.18)	.035	-	-	-12.00** (5.77)	.038
Network	-	-	.30(.43)	.488	.55 (.52)	.298
Neighboring	-	-	3.63*** (1.09)	.001	3.67*** (1.36)	.007
Professionalism	-1.20 (2.21)	.587	-2.11 (1.57)	.178	-1.45 (1.84)	.432
Unclassified	-4.30*** (.90)	.000	-3.69*** (.78)	.000	-4.33***(.98)	.000
The OPEN	-6.28*** (.98)	.000	-5.42*** (.92)	.000	-6.82***(1.10)	.000
Slack	.70 (.64)	.274	.05 (.01)	.803	.07 (.75)	.924
Scandal	-.70(.67)	.295	-1.45* (.80)	.071	-1.14 (.77)	.141
Partisanship	1.09** (.48)	.023	.69 (.42)	.093	.99** (.49)	.043
t(log)	2.54(.80)	.002	1.75*** (.61)	.004	1.78** (.87)	.042
Constant	-4.56 (1.31)	.001	-2.64 (.87)	.002	-4.91 (1.38)	.000
Pseudo R^2	.34		.30		.38	
Wald Ch^2	48.17	.000	45.40	.000	52.98	.000
N	368		368		368	

Note: ** *Significant at .05 level (2-tailed)*

Similar to Model 1, the maximum likelihood (ML) estimates of the effect of Unclassified categorization (Coeff.= -3.69., p = .000) and The OPEN Act (Coeff.=-5.42., p = .000) are substantially negative, implying reductions in the log of the odds of adoption with a one unit of change in these variables (when the other variables in the model held constant).

Finally, Model 3 examines the total effects of socialization and learning on a state's adoption of EFOIA. Model 3 is statistically significant (Wald $Ch^2 = 52.98$, $p < .000$), accounting for approximately 38% (*Pseudo* $R^2 = .38$) of states' adoption of EFOIA. The ML estimates of the total effects of socialization and learning on adoption show that *government ideology*, *education*, *innovativeness*, and *neighboring* increase the log of the odds in adoption. However, *Unclassified categorization* and *The OPEN Act* decrease the odds in adoption (when the other variables in the model held constant).

Table 11 Predicting the Effects of Socialization and Learning on Adoption with Complementary Log-Log Regression

Covariates	Socialization		Learning		Both	
Model	1		2		3	
	Coefficient (s.e.)	P>|z|	Coefficient (s.e.)	P>|z|	Coefficient (s.e.)	P>|z|
Government ideology	1.01** (.40)	.013	-	-	1.07*** (.41)	.010
Turnout	.40 (.35)	.254	-	-	.46 (.35)	.202
Internet use	.48 (.75)	.523	-	-	.10 (.10)	.323
Education	1.11** (.48)	.022	-	-	1.31** (.51)	.011
Innovativeness	8.13*** (3.10)	.009	-	-	8.02** (3.15)	.011
Inno*Slack	-15.04*** (4.46)	.001	-	-	-12.52*** (4.26)	.003
Network	-	-	.28 (.35)	.426	.37 (.37)	.329
Neighboring	-	-	2.43*** (.85)	.004	2.69*** (.90)	.003
Professionalism	-.85 (1.47)	.560	-1.68(1.40)	.228	-.07 (2.25)	.973
Unclassified	-3.48*** (.75)	.000	-2.69*** (.55)	.000	-3.33***(.77)	.000
The OPEN	-5.10*** (.81)	.000	-4.04*** (.60)	.000	-5.45***(.89)	.000
Slack	.76 (.49)	.122	.11 (.39)	.724	.18 (.56)	.753
Scandal	-.57(.69)	.412	-1.06 (.74)	.146	-.98 (.78)	.213
Partisanship	.81** (.35)	.023	.69** (.34)	.040	.75** (.35)	.036
t(log)	2.11***(.53)	.000	1.51*** (.47)	.002	1.34** (.58)	.021
Constant	-4.40 (1.39)	.001	-2.88 (.62)	.000	-4.86 (.94)	.000
LR Ch^2	89.66	.000	75.85	.000	99.05	.000
N	368		368		368	

Note: **Significant at .10 level, ** Significant at .05 level, * Significant at .01 level*(2-tailed)**

Table 11 shows the statistical results of the models with *complementary log-log regression*. The *complementary log-log regression* model is used to check for "robustness" of the results in the logistic regression model. The parameter estimates in Table 11 are generally consistent with the results in Table 10. All models are also statistically significant.

In Model 1, the effects of *government ideology, education,* and *innovativeness* on adoption is positive; if *government ideology, education,* and *innovativeness* are increased by one percent, one should expect the probability of adoption to increase by 1.01%, 1.11%, and 8.13%, respectively. In particular, the effect of *innovativeness* on adoption is associated with 15.04 points increase in the states with the low levels of slack resource. However, the effects of *unclassified categorization* and *The OPEN Act* on adoption are negative; if an individual state experienced *unclassified categorization* or *The OPEN Act*, its likelihood of adopting EFOIA is decreased by 3.48% and 5.10%, respectively.

In Model 2, the parameter estimates of learning show that only *neighboring* is positively associated with adoption (*Coeff.*= 2.43, p = .004); the estimate of *network* is not statistically significant (p = .426). Similar to Model 1, the effects of *unclassified categorization* and *The OPEN Act* on adoption are negative.

Finally, the statistical results of Model 3 indicate that an increase in *government ideology*, *education, innovativeness*, and *neighboring* by one percent is associated with an increase in the probability of adoption by 1.07%, 1.31%, 8.02%, and 2.69%, respectively. However, the effects of *unclassified categorization* and *The OPEN Act* on adoption are negative.

Taken as a whole, the results of the analysis suggest that socialization and learning have a positive impact on a state's decision on adopting EFOIA. Also, the probability of a state's adoption of EFOIA is increased over time. However, a state's decision on adopting EFOIA is also strongly influenced by the legal environment to which it belongs; since the categorization of unclassified information, states are less likely to adopt EFOIA, and such tendency continued through 2009. Contrary to expectation, since the enactment of the OPEN Government Act, states are less likely to adopt EFOIA. In addition, the state legislative professionalism, GDP, and partisanship are irrelevant to a state's adoption of EFOIA.

The effects of socialization and learning on states' implementation. Table 12 presents the statistical results of the ML regression models with *mixed effects*. The mixed-effects model [46] is used when the data used in the analysis are grouped or nested in more than one category (e.g. states, countries, etc). In Table 12 the ML estimates represent the effects that vary by state groups (e.g. leading states, emerging states, lagging states, etc). The *intra-class correlation* (IC) is the correlation of the observations (cases) within a cluster. In statistics, the IC is a descriptive statistic that can be used when quantitative measurements are made on units that are organized into groups. It describes how strongly units in the same group resemble each other**.** If the IC approaches 0 then the grouping by states are of no use; one may as well run a simple regression. If the IC approaches 1 then there is no variance to explain at the individual level, implying that

[46] Mixed-effects models estimate group level averages while regular regression models ignore the average variation between entities.

every observation (i.e. state) within a particular group is the same. In Table 12, every observation within each state group is the same because the value of the IC of all models approaches 1 (IC=.94).

Model 1 examines the relationship between the variables associated with *socialization* and a state's online transparency. Model 1 is statistically significant (Wald $Ch^2 = 27.75$, $p < .000$). Except public pressure measured by *education*, none of the variables associated with socialization are statistically significant. However, the estimates of *FOIAstrength, slack,* and *e-Gov* are positively associated with online transparency.

Model 2 considers the effect of *learning* on a state's online transparency. Model 2 is statistically significant (Wald $Ch^2 = 34.94$, $p < .000$). The maximum likelihood (ML) estimates of the effect of learning show that *neighboring* (*Coeff.* = 6.92, $p = .051$) is positively associated with online transparency. Furthermore, the interaction term between *slack* and *neighboring* is also statistically significant, but the parameter estimate is negative (*Coeff.* = -11.59, $p = .008$); the effect of *neighboring* on online transparency is 11.59 points more increased in the states with the low levels of slack resources. Similar to Model 1, the estimates of *FOIAstrength, slack, professionalism,* and *e-Gov* are positively associated with state online transparency.

Finally, Model 3 examines the total effects of socialization and learning on a state's online transparency. Model 3 is statistically significant (Wald $Ch^2 = 41.11$, $p < .000$). The ML estimates of the total effects of socialization and learning on online transparency indicate that socialization is generally irrelevant to increasing online transparency score; the variables related to socialization (i.e. *government ideology,*

turnout, and Internet) are statistically insignificant. At the same time, learning is substantially associated with increasing online transparency scores. The interaction term between *neighboring* and *slack* is statistically significant at the .05 level *(Coeff*. = 9.82, *p* = .024), but its effect is negative; the effect of *neighboring* on online transparency is increased in the state with the low levels of slack resources. As shown in the other models, *professionalism, slack,* and *e-Gov* are positively associated with online transparency.

Table 12 Predicting the Effects of Socialization and Learning on Implementation with Mixed Effects

Covariates	Socialization		Learning		Both	
Model	1		2		3	
	Coefficient (s.e.)	P>|z|	Coefficient (s.e.)	P>|z|	Coefficient (s.e.)	P>|z|
Government ideology	-1.28 (1.44)	.445	-	-	-1.19 (1.17)	.981
Turnout	1.92 (1.37)	.162	-	-	.06 (1.33)	.213
Internet	-1.14 (1.34)	.394	-	-	-.96 (1.39)	.491
Education	1.58 (1.39)	.259	-	-	2.73* (1.55)	.079
Innovativeness	.05 (.10)	.619	-	-	.02 (.09)	.809
Network	-	-	.74 (1.18)	.532	.91 (1.19)	.442
Neighboring(lagged)	-	-	6.92* (3.55)	.051	4.94 (3.64)	.175
Slack*Neighboring(lagged)	-	-	-11.59***(4.37)	.008	-9.82**(4.35)	.024
Slack	3.35** (1.37)	.015	5.45***(1.81)	.003	6.43***(1.83)	.000
Professionalism	6.33(4.71)	.179	10.34** (4.90)	.035	10.99**(4.98)	.027
e-Gov	.08** (.04)	.05	.09**(.04)	.037	.10** (.04)	.021
Partisanship	.53 (1.18)	.654	.04 (1.10)	.973	1.69(1.34)	.207
FOIAstrength	2.16* (1.13)	.055	2.35** (1.20)	.050	1.72 (1.21)	.155
IT committee	-1.12 (1.16)	.314	-.74 (1.15)	.516	-1.21 (1.15)	.292
Year2011	5.11 (1.53)	.001	(omitted)	-	(omitted)	-
Year2012	3.05 (1.86)	.109	-.31 (1.31)	.811	-.09(1.58)	.951
Year2013	5.85 (1.59)	.000	1.63 (1.52)	.282	2.03 (1.54)	.187
Constant	6.28 (1.23)	.000	6.18 (1.42)	.000	6.34 (1.30)	.000
Wald Ch^2	27.75	.000	34.94	.000	41.11	.000
Intra-class correlation	.94		.94		.94	
N	192		192		192	

Note: **Significant at .10 level, ** Significant at .05 level, * Significant at .01 level* (2-tailed)**

Table 13 presents the statistical results of the regression models with *panels corrected standard errors (PCSEs)*. Following Beck and Katz (1995) and McNeal and Hale (2010), this study uses the *PCSEs* model in order to check for "robustness" of the results in the mixed-effects model; Beck and Katz (1995) argued that the OLS estimates with *PCSEs* should be used when the number of time periods (T) is relatively small compared to the number of panels (N). McNeal and Hale (2010) made a strong case for using PCSEs over random effects models for pooled data with four time periods and fifty panels.

The parameter estimates in Table 14 are generally consistent with the results in Table 13. All three models are also statistically significant. In Model 1, all parameter estimates of socialization are statistically insignificant, implying that socialization has no impact on the online transparency of a state. The effect of *FOIAstrength* on online transparency is positive *(Coeff.* = 2.18, p = .008); a 1% increase in *FOIAstrength* leads to 2.18 points more increase in the online transparency score of a state. In addition, *slack* and *e-Gov* are positively associated with online transparency. However, the parameter estimates of group dummies are negative, implying that the online transparency scores are decreased in the other groups in comparison with a leading state group. When controlling for the other variables, *partisanship, professionalism,* and *ITcommittee* are not statistically significant.

In Model 2, the parameter estimates of the variables associated with learning show that learning has a positive impact on the online transparency score of a state; both *neighboring* (*Coeff.*= 6.87, p = .056) and *neighboring*slack* (*Coeff.*= -11.49, p = .001) are

Table 13 Predicting the Effects of Socialization and Learning on Implementation with PCSE

Covariates	Socialization		Learning		Both	
Model	1		2		3	
	Coefficient (s.e.)	P>|z|	Coefficient (s.e.)	P>|z|	Coefficient (s.e.)	P>|z|
Government ideology	-1.26 (1.09)	.276	-	-	-.17(.86)	.176
Turnout	1.94 (1.45)	.287	-	-	.08 (.84)	.917
Internet	-1.11 (1.81)	.537	-	-	-.92 (1.91)	.629
Education	-1.57 (1.38)	.254	-	-	2.73*** (.79)	.001
Innovativeness	.04 (.09)	.634			.02 (.06)	.702
Network	-	-	.75 (1.46)	.606	.92 (1.04)	.545
Neighboring (lagged)	-	-	6.87* (3.60)	.056	4.93 (1.33)	.140
Slack*Neighboring	-	-	-11.49***(3.59)	.001	-9.75***(3.17)	.002
Professionalism	6.30(6.61)	.270	10.31* (5.98)	.084	10.94*(6.42)	.088
e-Gov	.08*** (.03)	.008	.09***(.03)	.007	.10***(.03)	.001
FOIAstrength	2.18*** (.81)	.008	2.37*** (.50)	.000	1.74*** (.60)	.004
Partisanship	.52 (.98)	.566	.04 (.82)	.958	1.69***(.58)	.004
IT committee	-1.13 (.74)	.287	-.76 (.77)	.320	-1.22 (.91)	.178
Slack	3.31*** (1.05)	.002	5.39*** (1.41)	.000	6.36*** (1.36)	.000
Year2011	5.08 (.93)	.000	(omitted)	-	(omitted)	-
Year2012	2.97 (1.97)	.131	-.35 (.33)	.280	-1.14 (.88)	.866
Year2013	5.78 (1.30)	.000	1.59** (.69)	.021	1.98 (.66)	.003
Group2(Advancing)	-9.45*** (1.85)	.000	-8.85*** (1.09)	.000	-7.43*** (1.26)	.000
Group3 (Emerging)	-20.40*** (1.55)	.000	-20.82*** (1.20)	.000	-19.665*** (1.17)	.000
Group4(Lagging)	-37.71*** (1.99)	.000	-37.33*** (2.32)	.000	-36.20*** (2.24)	.000
Group5(Failing)	-77.59*** (3.36)	.000	-71.10*** (3.00)	.000	-69.71*** (3.10)	.000
Constant	8.93 (2.54)	.000	8.95 (2.68)	.000	9.01 (2.56)	.000
R^2	92.58		92.88		93.77	
Wald Ch^2	4552.49	.000	17288.43	.000	4028.06	.000
N	192		192		192	

Note: ****Significant at .10 level, ** Significant at .05 level, * Significant at .01 level* **(2-tailed)**

associated with the state online transparency. In particular, the effect of *neighboring* is associated with 11.49 points increase in the online transparency score of the states with the low levels of slack resources. *FOIA strength*, *slack* and *e-Gov* are positively associated with online transparency. However, *partisanship*, and *ITcommittee* are not statistically significant.

Finally, Model 3 examines the total effects of socialization and learning on a state's online transparency. The ML estimates of the total effects of socialization and learning on online transparency indicate that socialization is generally irrelevant to increasing state online transparency; *government ideology, turnout, and internet* are statistically insignificant. As the other models show, the effect of learning on state online transparency is conditional on the level of a state's slack resource. *Professionalism, FOIA strength*, *slack,* and *e-Gov* are also positively associated with online transparency. In addition, the effect of learning on online transparency of a state is positive when the party of a state governor is the same as the presidency *(Coeff.* = 1.69, p = .004). There is a great deal of variation in the online transparency scores between state groups. For example, *lagging* states with a grade of D are associated with 36.20 points *less* increase in an online transparency score than leading states *(Coeff.* = -36.20, p < .000).

To summarize, the results of the analysis suggest that learning has a positive impact on the online transparency of a state while socialization, in general, has nothing to do with it. Especially, the conditional effect of the interactions between *neighboring* and *slack* is substantially important in online transparency of a state. The degree of the state online transparency is, in general, associated with *slack*, *FOIA strength*, and *e-Gov*.

However, *partisanship* and *ITcommittee* are generally irrelevant to increasing the online transparency of a state. Furthermore, there are a great deal of the differences between state groups in the extent of increasing their online transparency.

CHAPTER 6

DISCUSSION AND CONCLUSION

The purpose of this study is to examine what accounts for sustained innovation in government transparency. With the theoretical basis of policy diffusion, this study explores the factors that influence a state's adoption and implementation of EFOIA. The comparison of the determinants between a state's adoption and implementation of EFOIA provides the clues to explaining why some early adopters failed to maintain the leader position in online transparency through the implementation stage. From the empirical findings, this study found that the nature of diffusion mechanisms — socialization and learning — was conditional on the two stages of EFOIA. This chapter begins by summarizing the empirical findings of this study. Next, this chapter offers the policy implications of this study, and concludes with suggestions for future research.

Summary of the Empirical Findings

Determinants of early adoption. Socialization and learning are considered to be key factors in a state's adoption of EFOIA. Socialization was conceptualized along with four dimensions indicating a state's internal normative climate (i.e. liberal ideological climate, public pressure, innovative policy culture, and legal environment); learning was represented by external interactions of an individual state with its neighbors and with professional networks such as NCSL and NGA.

Consistent with the literature on e-disclosure, ethics laws, and anti-corruption reforms, liberal ideological climate and public pressure affected states' decisions to adopt EFOIA. A state's long history of democratic government seems to have driven its early

adoption of EFOIA. As expected, innovative policy culture was an important indicator of adoption. However, the effect of innovative policy culture on adoption was unexpectedly increased in the state with low levels of slack resources. As one possible explanation, slack may diminish incentives to innovate and promotes undisciplined investment in projects or practices that rarely yield economic benefits (Leibenstein, 1969; Jensen, 1993).

Meanwhile, the legal practices of the federal government, such as the creation of unclassified categories, and the enactment of the OPEN Government Act, were found to be strong indicators of adoption. Contrary to expectation, the coefficient of the OPEN Government Act was negative, implying that states under the Act were less likely to adopt EFOIA. This result might conflict with the general philosophy of the Act that would support public access to information about inner workings of the government through enhanced procedures for information requests.

Yet, this result can be acceptable. In fact, the OPEN Government Act has not solved the significant systemic problems concerning the disclosure of government information because of "secrecy" in the name of national security and privacy (Halstuk, 2008). The OPEN Government Act in itself is not about extending categories of public records that can be released, but about the procedural enhancement for public access to information such as a quick response of public agencies to a request. The Act still allows the agencies to keep the category of the sensitive and unclassified information in response to national security. Thus, if an individual state prefers secrecy to openness in the name of safety, the state will be less likely to adopt EFOIA.

With regard to the effect of external interactions on adoption, as expected, *neighboring effect* was a strong and statistically significant predictor of adoption. As Berry and Berry (1999), and Mooney (2001) suggested, states might learn from neighboring states not only because these nearby states tended to be similar in terms of economic and social characteristics, but also because the adoption of a successful policy of neighboring states could reduce the political risk of adoption.

At the same time, professional network was irrelevant to increasing the likelihood that non-adopting states would adopt EFOIA. This may result from the unrealistic assumption of national interaction models that all states are essentially the same, and that all non-adopting states are equally responding to innovation. These assumptions can be problematic in that they overlook the fundamental variances in the endogenous and exogenous factors surrounding states. Given the industrial, demographic, and political differences across states, the assumptions associated with national interactions are somewhat difficult to be supported.

As the other determinants of adoption, *state legislative professionalism* and *slack resource* were not found to be significant factors in any of the three models whereas the parameter estimation of *party alignment* was statistically significant in all three models. In this respect, party alignment between the governor and the presidency seems to be more influential in a state's decision to establish the legal environment for online transparency than state legislative professionalism or slack resources.

Determinants of successful implementation. Because of period effect of socialization, this study expects that the influence of socialization is unlikely to continue through the implementation phase; a state's internal normative climate may not influence its extent of implementation. Thus, learning is considered to be a key factor in a state's implementation of EFOIA. As expected, in general, the variables representing a state's internal normative climate were not found to be significant indicators of the extent of implementation; a liberal ideological climate, and innovative policy culture were not associated with the extent of implementation of EFOIA. This implies that policy makers tended to pay less attention to EFOIA once the legal environment associated with online transparency had been created. As suggested by the legal environment theory, normative pressure in response to EFOIA may not continue through implementation as it is short-lived or time-specific.

While household access to the Internet and voter turnout were not statistically significant, the level of educational attainment as the proxy of public pressure was positively associated with the extent of implementation. This suggests that challenging the passive response of the agents to information requests may require active participation of citizens in increasing online transparency. Annual referenda and merely visiting a transparency website have limitations in urging the agencies to make a commitment to enhancing online transparency. Citizens should become informed and knowledgeable about online transparency insofar as they can analyze the released data and assess the government's operations appropriately. In this respect, a highly educated public may be essential to successful implementation of EFOIA. This finding may also

reflect that the enforcement of EFOIA is not salient among the general public but is primarily the purview of public agencies and interest groups seeking to increase government transparency (McNeal et al., 2007).

When it came to the effect of external interactions on implementation, professional networks such as NGA and NCSL were not associated with the extent of implementation. The influence of these organizations may be too diffuse across policy areas to identify a distinct influence on online access within the area of transparency reform (McNeal et al., 2006). As expected, the effect of successful neighbors depends on the influence of the degree of slack resources; the influence of neighboring states on the extent of implementation was increased in the states with the low levels of slack resources.

As another influence factors, *slack resources* was a powerful predictor of the scope of implementation. States with greater resources and the extensive implementation of e-government were more likely to have more comprehensive e-transparency programs. These finding were consistent with earlier research with respect to resources and the influence of e-government (McNeal et al., 2007; Tolbert et al., 2008) The strength of FOIA was also significant indicator of the extent of implementation. As the state FOIA offered stricter standards and broad criteria pertaining to the disclosure of information, states were more likely to create comprehensive and user-friendly transparency websites.

Consistent with the literature on administrative reform, legislative professionalism was a statistically significant factor in providing more extensive e-transparency practices; states with more professional legislatures were more likely to be

leaders in operating more comprehensive, accessible, and user-friendly transparency websites. In addition, there was great variation in the scope of implementation among groups of states, especially between a leading and a lagging group. Finally, contrary to the research on e-government, partisanship and the operation of IT committees were not predictors of the extent of implementation of online transparency (McNeal et al., 2003; Tolbert et al., 2008). This finding may reflect that the enforcement of EFOIA is more sophisticated than e-government policies related to efficiency concerns because it is associated with public demands or government accountability.

Implications

This study has identified the factors that influence sustained innovation in government transparency, employing the case of EFOIA. This type of innovation is unique in that it is irrelevant to economic competition over tax revenue between states or federal coercive actions. Based on the diffusion perspective, the study findings provide two insights into "intergovernmental relations" between the federal and state governments, and between state governments in adopting and implementing the innovation irrelevant to economic motivation or federal mandates.

First, the analysis presented here suggests that earliness of adoption may be influenced by the variance in the norm's acceptance by states; states resonating with the norm of transparency appeared to adopt EFOIA earlier than other states. In this respect, to encourage states to accept a federal practice, the federal government may need to concentrate on "persuasive efforts" that justify a new norm pertaining to the federal practice.

According to the logic of appropriateness, persuasion can occur when states shift their minds along with confidence in the appropriateness of a norm, belief, or practice. Thus, the federal government should provide states with careful arguments and reasoned logic that prove its practice as *legitimate* and *rightful*, thereby facilitating the states' motivation for political legitimacy.

Second, the study finding indicates that spatial proximity is an important channel of influence of a federal practice on states. According to the regional effects model, states tend to learn from their bordering states because of the similarity in administrative style, socioeconomic conditions and/or political ideology. In this sense, states may need to develop the venue or the process through which they cooperate with their bordering states on the successful enforcement of a federal practice, thereby gaining political legitimacy.

Meanwhile, the most distinctive feature of the diffusion of EFOIA is that the operation of socialization and learning mechanism differ in two stages, resulting in differences in diffusion between adoption and implementation; socialization does matter only with regard to early adoption, while learning is a significant predictor of both adoption and the scope of implementation. In this respect, socialization — also called normative pressure — is characterized as "short-lived" or "temporalization."

The influence of socialization may fade over time because normative pressure is itself "the weak enforcement mechanism of law." (Edelman, 1990) Socialization creates only normative environment to which an individual state must adapt. A major motivation for organizational attention to normative environment is the quest for "political legitimacy." In the context of EFOIA, the enactment of federal EFOIA in 1996 provided

individual states with a normative environment in which the disclosure of information would be described as a symbol of good governance. In response to this federal action, states that pursue legitimacy initially construct and institutionalize forms of compliance with law.

In terms of the enforcement of law, the weakness of socialization is that it provides states with inadequate and inconsistent feedback on what this legal practice is as well as the meaning of "compliance." The ambiguous meaning of compliance, combined with the weak enforcement of law allow states to change values associated with the law in a way that accommodates their managerial interests, thereby mitigating the impact of law (Edelman, 1990). Furthermore, normative pressure from the legal environment does not easily erode long-held managerial interests (i.e. bureaucratic efficiency and economic power rather than compliance with their normative obligations) (Edelman, 1990).

Understanding the limitation of socialization as the weak enforcement mechanism of law provides several insights into sustained innovation related to normative pressure.

First, the provision of clear and adequate guidelines and consistent feedback may be important to ensure sub-jurisdictions' compliance with the value of innovation. Until the norm of transparency is appropriately settled, the upper-level government (i.e. federal government) may need to act as a teacher of norms.

Second, concerns about infrastructure and institutional capacity for maintaining innovation should be preceded by legislators in the adoption phase. According to the empirical findings of this study, slack resource and state legislative professionalism were

irrelevant to decisions to adopt EFOIA, but they were found to be powerful indicators of the extent of implementation. Thus, no legislative considerations on resources and/or responsible institutions for implementing innovation will make it difficult to sustain the innovation over time.

Third, NGOs can play an important role in facilitating and sustaining innovation in a field. For example, NGOs can publish articles and brochures in the attempt to convince the public of the need for enhancing government transparency. At the same time, they can take government bureaucrats to court in cases in which the public is refused to access information (Grigorescu, 2002). Considering that some governments often give financial aid to NGOs, they can use NGOs as active supporters of their practices.

Furthermore, increasing citizen participation in procedure may facilitate the enforcement of innovation. As seen in the philosophy of participatory governance, citizens should be able to participate in making the decisions that affect their own lives. In this respect, the agencies may need to increase the opportunity to listen to the public voice and discuss the issues of online access to government information with the public.

Finally, the political support for innovation should not be the only consideration in deciding whether or not the innovation should be continued. The shutdown of California's transparency portals shows that the governor's political decision clouded California's spending picture. In this respect, likewise the civil right movement, the government may need to consider ways to increase the societal support for innovation.

Future Research

This study focuses on identifying the factors that may influence a state's adoption and implementation of EFOIA, thereby explaining why some early leaders in adoption failed to sustain the leader position in innovation over time. Comparing the factors relevant to each stage of EFOIA, this study suggests that the failure of some early adopters in sustained innovation may be associated with the nature of socialization — that is, temporalization.

Although this study suggests several ways to avoid the weak enforcement of law, this study is just the fundamental step to address this issue. This study does not cover critical issues concerning sustained innovation. As one possible research, it is necessary to examine how states understand the meaning of compliance with online transparency, and whether there is variance in the perceptions of the meaning of compliance. In addition, it is necessary to examine the impact of legal practices on change in organizational calculus of bureaucratic efficiency.

Furthermore, future research can conduct a deep qualitative study to examine how cooperation for law enforcement between states takes place. Finally, to generalize the findings of this study, future research needs to test more cases of policy diffusion irrelevant to economic motivation and federal coercive actions at the same time, and check whether or not the similar results can be found.

Concluding remark

This study attempts to explain the diffusion of EFOIA in the absence of motivations to realize economic performance, or mandates and incentives from higher

levels of government. According to the empirical results of this study, the quest for legitimacy or a desire for enhancing organizational prestige may attract governments in sustaining EFOIA over time. In this respect, this study provides the *normative imitation framework* explaining that governments emulate others due to the desire for enhancing legitimacy regardless of functional needs (Weyland, 2005). In this view, the desire to appear legitimate or modern and comply with new norms encourages governments to emulate others' innovations even in the absence of a sufficient assessment of their advantages and problems (Weyland, 2005).

This framework can be useful to explore the diffusion of innovation in "distributive policy areas." Distributive policy decisions tend to be easily triggered by symbolic or normative concerns because they make some constituents happy but do not make anybody unhappy except for the finance minister (Weyland, 2005). For example, homogenization among hospitals may result from the fact that hospitals operate according to a norm of *social legitimation* or a desire for increasing organizational prestige (Fennell, 1980). In a similar vein, DiMaggio and Powell (1983) explain the normative isomorphism among hospitals as follows:

> Apparently, hospitals can increase their range of services not because there is an actual needs for a particular service or facility within the patient population, but because they will be defined as fit only if they can offer everything other hospitals in the area offer (p. 154).

However, the usefulness of this normative imitation framework is questionable in explaining the diffusion of innovation in "redistributive policy areas" such as pension reform. Since redistributive policy decisions tend to clearly define the categories of winners and losers, there will be the clash of interests. Thus, the quest for legitimacy does not seem to be the major driving force behind the diffusion of innovation in these policy areas although it may constrain the pursuit of interests and affect the outcome of power struggles (Kahneman et al., 1986; Weyland, 2005).

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APPENDIX A.

INSTRUMENTATION & SOURCES OF DATA

Variable	Label	Data Description & Measure		Data Sources
EFOIA $_{\text{adoption}}$	Dependent variable at the adoption stage: the adoption of EFOIA	Data indicate the probability that a state will adopt the EFOIA in a specific year, given that the state has not already done so. A dummy variable; it is coded as 1 in the year a state enacted the EFOIA, and 0 otherwise. States' adoption years of EFOIA were derived from Open Government Guide.		Open Government Guide (www.rcfp.org/open-government-guide)
EFOIA $_{\text{implementation}}$	Dependent variable at the implementation stage: the percentage e-transparency score (ranging from 0 to100)	Data indicate the percentage score of a state's transparency website that offers online services regarding government spending data in a given year. Since state governments have improved their transparency websites by increasing their online services over time, *2010score* and *2011score* are weighted scores, based on *2012score* as a standard.	Data reflect the extent to which a state implements provide online access to government spending data in a given year through its transparency website, in compliance with EFOIA. The U.S. PIRG Education Fund researchers evaluated a state's transparency website that provides information on government spending, in terms of data availability, usability, and accessibility. Data went through the review of state agencies administering transparency websites for accuracy.	U.S. PIRG (www.uspirg.org/reports/)
Liberal ideological climate (Norm resonance)	Independent variable: government ideology index	Government ideology refers to the mean position on a liberal-conservative continuum of the elected officials in a state, weighted according to the power they have over public policy decisions. Higher values indicate greater policy liberalism. Developed by Berry et al (1998, 2010)		Institute for Quantitative Social Science (stateminder.org/variables)

Liberal ideological climate (Norm resonance)	Independent variable: state citizen ideology index	Citizen ideology refers to the mean position on a liberal-conservative continuum of the active electorate in a state. Higher values indicate greater policy liberalism. Developed by Berry et al (1998, 2010)	Institute for Quantitative Social Science (stateminder.org/variables)
Public pressure (Demand) (Norm resonance)	Independent variable: voter turnout	Data indicate voting rates for gubernatorial elections in each state. Voter turnout represents the ability of citizens engaging directly in democratic processes to protect their civil rights and challenge the government's operations (Gamble, 1997; McNeal and Hale, 2010).	*The Book of States* (published by The Council of State Governments) (knowledgecenter.csg.org)
	Independent variable: the public's Internet use	Data indicate the percent of state households with Internet access.	National Telecommunications and Information Administration (www.ntia.doc.gov)
	Independent variable: educational attainment by state	Data indicate the percent of state residents over age 25 with a bachelor's degree or more in a given year.	U.S. Census Bureau (www.census.gov)
Innovative policy culture (Norm resonance)	Independent variable: state policy innovativeness index	Data indicate the propensity of a state for policy innovativeness; a state's willingness to adopt new policies sooner or later relative to other states. This score varies from zero to one, with larger values indicating a quicker policy adoption rate and a higher innovation score. Innovativeness at a given point in time, *t*, for state *i* is measured by $$R_{ij} = \frac{\sum_{t=T_0}^{T} \sum_{i=1}^{K_{it}} Y_{ikt}}{\sum_{t=T_0}^{T} K_{it}}$$ K_{it} represents the number of policies that state *i* could potentially adopt in year t. Y_{ikt}, takes on the value zero in years of non-adoption, one in the year of adoption, and is treated as missing in subsequent years. Developed by Boehmke & Paul Skinner (2012)	Institute for Quantitative Social Science (stateminder.org/variables)

Legal practice (Legal environment)	Independent variable: legal action of the federal government regarding transparency (Applied only to the analysis for the adoption of EFOIA)	Data indicate a legal action of the federal government concerning transparency, which may create the legal environment influencing a state's policy decision on transparency. This normative pressure can mediate the effect of EFOIA of 1996 on states. Dummy: coded 1 if a state adopted EFOIA after a federal legal action had occurred, 0 otherwise.	1996: the enactment of federal EFOIA 2002: the creation of a category of unclassified information 2007: the enactment of the OPEN Government Act
Neighboring effect (Policy learning)	Independent variable: the proportion of adjacent neighbors or other states within a similar geographic region that have already adopted (adoption phase), or successfully implemented EFOIA (i.e. leading and advancing states) (implementation phase)	Data indicate the proportion of neighboring states and states within the applicable BEA region (without double-counting) that have previously adopted (adoption phase), or that have a grade of A or B (>=80) (i.e. leading and advancing state groups) in online transparency in a given year (implementation phase). The numerator is the total number of neighboring states and states within the applicable BEA region (without double-counting) that have previously adopted (adoption phase), or that have a grade of A or B (>=80) (i.e. leading and advancing state groups) in online transparency in a given year (implementation phase). The denominator is the total number of neighboring states and states within the applicable BEA region (without double-counting). This variable captures the implications of both the neighbor model and fixed-region model of regional diffusion theory.	Hageman & Robb (2011)'s scale
Professional network (Policy learning)	Independent variable: state leadership positions in NGA or NCSL	Data indicate a state's representation in the leadership of the NGA or NCSL in a given year. A dummy variable; it is coded as 1 if a state had a leadership position in a given year, 0 for otherwise. Leadership in professional networks is defined as state membership on the NCSL's Executive Committee including ex-officio members, and the NGA Executive Committee including standing committees. Borrowing the scale of McNeal et al (2003, 2007)	National Governors Association (www.nga.org) National Conference of State Legislators (www.ncsl.org)

Slack resources	Control variable: GDP by state	Data indicate the state counterpart of the Nation's gross domestic product (GDP). GDP by state is derived as the sum of the GDP originating in all the industries in a state (Millions of current dollars).	Bureau of Economic Analysis (bea.gov)
	Control variable: per capita personal income	Data indicate the income that is received by persons from all sources. Total personal income divided by total midyear population.	U.S. Department of Commerce, Bureau of Economic Analysis (http://www.bea.gov/)
Partisanship	Control variable: party alignment between the presidency and the state governor	Data indicate the party alignment between the presidency and the governor of a state government. Dummy: coded as 1 if the governor's party is the same as the president's party, 0 otherwise.	Indiana State University - Klarner Politics (http://www.indstate.edu/polisci/klarnerpolitics.htm)
State legislative professionalism	Control variable: legislative professionalism index	Data indicate the percent of professionalism that a state's legislature had compared to Congress in a given year, which indicates overall professionalism of state government. This index serves as a measure of state institutional capacity and a proxy for overall professionalization of state government. Developed by Squire (2007) who used indicators of pay, staff resources, and session length of state legislatures.	Squire' scale (2007)
IT management	Control variable: IT office & IT committee (Applied only to the analysis for the implementation of EFOIA)	Data serve as a measure of state infrastructure and leadership capacity. *IT office* presents whether a state has a separate IT office as a department unto itself (1 = yes, 0 = no). IT committee presents whether there are IT committees in the state legislature (Coded as 1 if either the state House or Senate has an IT committee, 0 if neither has an IT committee).	*The Book of States* (published by The Council of State Governments) (knowledgecenter.csg.org)

e-government implementation	Control variable: e-government index (Applied only to the analysis for the implementation of EFOIA)	Data indicate an index of state e-government use (or overall performance) during the period 2001-2008. This measure is an annual index based on a composite score using the following criteria: online publications, online databases, audio clips, video clips, foreign language or language translation, advertisements, premium fees, user payments or fees, disability access, privacy policy, security policy, online services, digital signatures, and so on. Developed by Darrell West and reported in a series of studies, *State and Federal E-Government in the United States.*	Darrell West's scale (2001-2008)
FOIA strength	Control variable: state's FOIA score (Applied only to the analysis for the implementation of EFOIA)	Cordis and Warren determined the FOIA score of each state by giving one point for each of the criteria such as the presumption for disclosure and exemptions, fee provisions, agencies' response times to a request, administrative appeal provisions, and penalties imposed for violation of the statutes. State FOIA scores are positively correlated with the scores provided by several surveys that were conducted by the Better Government Association (BGA) and the Investigative Reporters and Editors Inc. (2002), and the BGA and the National Freedom of Information Coalition (2007).	Cordis & Warren's (2012) scale
Scandals	Control variable: state conviction rate per capita (Applied only to the analysis for the adoption of EFOIA)	Data indicate a state conviction rate per capita, implying the extent of corruption at the state level (for 100,000 people in the state population). This corruption data was derived from the Justice Department's "Report to Congress on the Activities and Operations of the Public Integrity Section." This publication lists the number of federal, state and local public officials convicted of a corruption-related crime by state. As Glaeser and Saks (2006) did, I collected information on the number of convictions by state annually from the Justice Department's report, and then divided these convictions by state population to form an estimate of the state conviction rate per capita.	Glaeser & Saks' s scale (2006) Department of Justice (www.justice.gov)

Weighted E-transparency Score

E-transparency Score

Year	Data availability (comprehensiveness)						Usability (easy to use)				Accessbility (link to other websites)			Weighted total score (maximum)
	checkbook (detailed expenditure information)	contract & summary information	historical expenditure	grants & economic incentives	**feedback (data request)**	tax expenditure reports	search by vendor (contractor)	search by keyword (activity)	**search by agency (department)**	**downloadable**	off-budget agencies	city and county budget	ARRA funding	
2010	0	0	0	0	X	0	0	0	X	X	0	0	0	
2011	0	0	0	0	0	0	0	0	X	0	0	0	0	
2012	0	0	0	0	0	0	0	0	0	0	0	0	0	
2010score	40 (*30/40)	10	5	10	.(zero)	10	10(*8/10)	10(*8/10)	.(zero)	.(zero)	2	1(*2)	2	87(=100-2-8-3)
2011score	35(*30/35)	10	5	10	2	10	10(*8/10)	10(*8/10)	.(zero)	2(*3/2)	2	2	2	92(=100-8)
2012score	30	10	5	10	2	10	8	8	8	3	2	2	2	100

Improvement of a transparency website	Added criteria
2010 → 2011	feedback & downloadable
2011→ 2012	search by agency (department)

Note: Since the 2013 criteria are the same as those of 2012, the 2013 scores are not adjusted.

APPENDIX B

STATE TRANSPARENCY WEBSITE URL

State	Transparency Website URL	State	Transparency Website URL
Alabama	open.alabama.gov	Montana	transparency.mt.gov
Alaska	checkbook.alaska.gov	Nebraska	nebraskaspending.gov
Arizona	openbooks.az.gov	Nevada	open.nv.gov
Arkansas	transparency.arkansas.gov	New Hampshire	www.nh.gov/transparentnh
California	www.dgs.ca.gov	New Jersey	yourmoney.nj.gov
Colorado	tops.state.co.us	New Mexico	www.sunshineportalnm.com
Connecticut	www.osc.ct.gov/openct	New York	www.openbooknewyork.com
Delaware	transparency.delaware.gov	North Carolina	www.ncopenbook.gov
Florida	www.myfloridacfo.com/transparency	North Dakota	data.share.nd.gov/pr
Georgia	open.georgia.gov	Ohio	transparency.ohio.gov
Hawaii	hawaii.gov/spo2	Oklahoma	data.ok.gov
Idaho	transparent.idaho.gov	Oregon	www.oregon.gov/transparency
Illinois	accountability.illinois.gov	Pennsylvania	www.pennwatch.pa.gov
Indiana	www.in.gov/itp	Rhode Island	www.transparency.ri.gov
Iowa	data.iowa.gov	South Carolina	www.cg.sc.gov/fiscaltransparency
Kansas	kanview.ks.gov	South Dakota	open.sd.gov
Kentucky	opendoor.ky.gov	Tennessee	www.tn.gov/opengov
Louisiana	wwwprd.doa.louisiana.gov/latrac	Texas	www.texastransparency.org
Maine	www.opencheckbook.maine.gov	Utah	www.utah.gov/transparency
Maryland	spending.dbm.maryland.gov	Vermont	spotlight.vermont.gov
Massachusetts	www.mass.gov/transparency	Virginia	datapoint.apa.virginia.gov
Michigan	www.michigan.gov/openmichigan	Washington	fiscal.wa.gov
Minnesota	www.mmb.state.mn.us/tap	West Virginia	www.transparencywv.org
Mississippi	www.transparency.mississippi.gov	Wisconsin	sunshine.wi.gov
Missouri	mapyourtaxes.mo.gov/map	Wyoming	wyoming.gov/transparency.html

APPENDIX C

ADOPTION YEAR & ONLINE TRANSPARENCY SCORE

State's adoption of EFOIA				State's implementation of EFOIA			
Rank	State (Adoption year)	Rank	State (Adoption year)	Rank	State (Avg. score)	Rank	State (Avg. score)
1	West Virginia (1992)	26	Hawaii (2004)	1	Kentucky (95)	26	New Mexico (68)
2	Indiana (1993)	27	Missouri (2004)	2	Texas (93)	27	Massachusetts (68)
3	Kentucky (1994)	28	Alaska (2005)	3	Illinois (82)	28	Hawaii (66)
4	Texas (1995)	29	Oklahoma (2005)	4	Pennsylvania (82)	29	Indiana (65)
5	Colorado (1996)	30	Florida (2005)	5	Louisiana (81)	30	South Carolina (65)
6	Maryland (1996)	31	Montana (2005)	6	Utah (79)	31	New Jersey(63)
7	Mississippi (1996)	32	Ohio (2005)	7	Oregon (79)	32	Michigan (61)
8	Nebraska (1996)	33	Utah (2005)	8	Virginia (79)	33	South Dakota (60)
9	North Carolina (1996)	34	Idaho (2007)	9	New York (78)	34	Rhode Island (60)
10	Vermont (1996)	35	Oregon (2007)	10	Missouri (78)	35	Tennessee (56)
11	Alabama (1997)	36	New Hampshire (2008)	11	Minnesota (76)	36	Alaska (53)
12	Delaware (1997)	37	New York (2008)	12	North Carolina (76)	37	Washington (53)
13	Connecticut (1998)	38	North Dakota (2008)	13	Oklahoma (76)	38	California (50)
14	Rhode Island (1998)	39	Pennsylvania (2008)	14	Nebraska (75)	39	Wyoming (50)
15	Georgia (1999)	40	Tennessee (2008)	15	Alabama (74)	40	Connecticut (50)
16	Illinois (2000)	41	Arizona (2009)	16	Mississippi (74)	41	West Virginia (48)
17	Nevada (2000)	42	Iowa (2009)	17	Maryland (71)	42	Vermont (46)
18	South Carolina (2000)	43	Kansas (2009)	18	Nevada (71)	43	Wisconsin (40)
19	Wisconsin (2000)	44	Louisiana (2009)	19	Kansas (71)	44	Iowa (34)
20	Arkansas (2001)	45	Massachusetts (2009)	20	Georgia (71)	45	New Hampshire (34)
21	California (2001)	46	New Mexico (2009)	21	Ohio (71)	46	Maine (31)
22	Michigan (2001)	47	South Dakota (2009)	22	Arizona (70)	47	Arkansas (26)
23	New Jersey (2002)	48	Washington (2009)	23	Delaware (70)	48	North Dakota (26)
24	Minnesota (2002)	49	Wyoming (2009)	24	Colorado (69)	49	Idaho (21)
25	Virginia (2003)	50	Maine (2011)	25	Florida (69)	50	Montana (20)