Diffusion of Electronic Government Technology: An Empirical Study of American Urban Places

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THESIS

Submitted as partial fulfillment of the requirements for the degree of Doctor of Philosophy in Public Administration in the Graduate College of the University of Illinois at Chicago, 2021

Chicago, Illinois

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ACKNOWLEDGEMENTS

Thank you to my advisor and dissertation chair, Professor Yonghong Wu. Your patience, support, and knowledge helped make this research possible. Thank you to Professor Michael Siciliano for your unwavering support and encouragement. Without both of you, this would not have been possible. Thank you, Professor Karen Mossberger, for your knowledge and insight. Thank you to my other committee members, Professor Benjamin Clark and Kelly LeRoux, who stayed and supported me. I am also thankful to Christina Maimone, who helped tremendously with the R code and modeling.

None of this, of course, would have been possible without my family. My mother and father never gave up and always encouraged me. My father worked with me side by side, collecting the data. My parent's love was always there, and for that, I am forever grateful. Thank you to my two wonderful kids, Stella and Vivian, who have known nothing else than their dad working on his dissertation. From the wonders of birth to now, I am so proud of you. I cannot wait to see all your accomplishments and be there for you like all these people have been for me.

And, of course, a deep and teary thank you to my wife and best friend, Melissa Mullarkey. Your encouragement, support, and belief in me kept me going even when I doubted myself. This achievement is not mine alone, but ours. We did it together, and it would not have been possible without you. This research has been challenging, and I have wanted to quit many times, but now that this chapter has come to an end, I would not do it any other way. My sincerest thanks, and I am forever grateful for all those that helped me on this journey. I am on to the next challenge.

KJR

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SUMMARY

The research examines digital era governance (DEG) policy using a descriptive and mixed methods approach. The research uses a fixed-effects regression model and geospatial analysis to examine the determinants of DEG policy adoption. The dissertation examines three phases of DEG (Web 1.0, Web 2.0, open data portals, and 311 systems) across 231 cities. The model uses 693 variables and nearly six thousand text-mined and geographically linked data points over a 10-year time frame to inform our understanding of internal and external factors influencing DEG policy adoption. This research introduces a new way of understanding digital governance diffusion by testing electronic government technologies over time. The research also offers a new means for collecting historical data regarding adopted technology. It is comprehensive in scope, collecting thousands of data points for cities over time. The research builds on diffusion theory as applied to digital governance. The dissertation also tests diffusion theory in a large N-study and applies it to technology policy at the city level – a gap in the diffusion literature.

The analysis finds a strong significance and reaffirmation that cities adopted more technologies over time. In addition to the hypothesis testing, the research finds that professional networks have slight significance as a predictor of digital governance adoption. When accounting for time, the fixed-effect analysis does not reveal any independent variables to have a strong significance on technology adoption over time. The dissertation concludes with a discussion of the policy implications of examining DEG policy diffusion, its limitations and then offers potential future research areas.

"Human beings, viewed as behaving systems, are quite simple. The apparent complexity of our behavior over time is largely a reflection of the complexity of the environment in which we find ourselves."

Herbert Simon, the Sciences of the Artificial, 1969 p. 53

1: INTRODUCTION

1.1 Statement of Problem

The adoption and proliferation of mobile networks and devices, and the Web of Things (WoT)[1] have resulted in public, private and research communities offering increasing transparency by providing information regarding their operations and internal policies. The rapid expansion of technology is changing not only our daily lives but our civic lives as well. Across the country, governments are turning to technology to engage their constituents. This technology has evolved dramatically within a relatively short time frame.

Electronic government technologies' effectiveness has been examined heavily in the literature (Bertot et al. 2010, Pina et al. 2010, Grimmelikhuijsen et al. 2013). Specifically, the literature and research in public administration and political science have focused a significant amount of its effort on electronic government technologies' potential benefits. This dissertation contributes to the electronic government, public administration, and political science literature with a unique look at how technology has diffused over time across 231 governments in the United States. To date, there is no research done on the temporal change of electronic government technology over time. Understanding this change in how governments use technology to better themselves and their citizens is crucial.

[1] The Web of Things (WoT) describes digital approaches, software architecture, and programming that allows real-world objects to be linked together via the internet.

Electronic government is a field in need of constant inquiry, given the expansion of technology in our society and continuous technological change. Over the last three decades, the internet has transformed government as it's known today. The application of information and communication technologies (ICT) can improve the interaction between citizens and government. However, technology's impact and a complete understanding of its adoption are often constrained to a specific technology or single period. This research aims to address this gap in the literature.

During the last decade, public administration and political science have dedicated significant research to electronic government policy adoption's social, political, and economic determinants. However, the research is typically limited to a single technology or point in time. This research aims to contribute to that literature by enlarging the scope by including over 200 cities, three phases of electronic government technologies, and over three time periods spanning ten years. To date, much of the research into policy diffusion has relied on the work of Berry and Berry (1990). Mallinson (2020) examines over 30 years of policy diffusion research, over 180 articles, and over 500 policy adoption models. His research finds a heavy reliance on event history analysis (EHA) of a single policy at the state level. Mallinson, and other diffusion scholars such Maggetti and Gilardi (2016), point to an over-reliance on EHA and, in general, a propensity to "recycle" the research design within the policy diffusion literature. This research intends to present an original and innovative approach that moves the diffusion research towards larger-N studies and new directions.

1.2 Three Waves of Digital Governance

The internet's role in shaping society is one of the most critical policy innovations of the past century. Technology's rapid, widespread, and sustained diffusion of Web 1.0 and Web 2.0 have changed society forever. This research offers an in-depth look at these levels of electronic government technology in large urban areas – done in conjunction with the emergence of technologies like open data portals and 311 systems that are crucial to our understanding of how governments interact with their citizenry today and in the future.

Margetts and Dunleavy (2013) outline the emergence of digital era governance (DEG) and that this movement concept has superseded New Public Management (NPM) as the predominant governance structure. The proliferation of the internet and their associated Web-based technologies enabled these digital changes. These digital tools have become the focal point of advanced industrial states and their governments. NPM stressed disaggregation, competition, and incentivization. DEG has created innovation and changed how governments operate from 2002 forward. The organizing themes of DEG are reintegration, needs-based holism, and digitalization (Margetts and Dunleavy 2013).

Reintegration reverses the NPM trend of fragmentation that gave government agencies more autonomy, creating silos through the agencification of government functions creating "micro-local agencies" (Margetts and Dunleavy 2013). Needs-based holism moves away from government competition as a way of improving efficiency. The focus is on creating client-focused structures for departments and agencies that create a single location for citizens to interact with the government. In DEG, agile and resilient government structures create efficiencies. These replace the outsourcing or deregulation of NPM.

Digitalization is the public sector's move to completely embrace and imbed electronic delivery as a central part of the government's service delivery model. DEG replaces the incentivization mode in NPM that advocated for privatization and public-private partnerships. DEG realizes efficiency through digitization efforts, not through incentivization or competition. Automation is the key to reducing redundant services and improving the efficiency of public services. Part of this process is having citizens interact online with government and contributing data through platforms such as 311 systems.

The role and evolution of DEG are critical here. According to Young (2020) the DEG framework has three principal themes: (1) digitization of public service delivery, (2) reintegration of public sector processes, and (3) reversing organizational fragmentation which occurred under NPM to greater address public needs (Dunleavy et al. 2006). Fishenden and Thompson (2013) stress that DEG reshapes preexisting relationships between government and technology. The intent is for governments to leverage open technology standards to digitize public services efficiently.

Jeong (2007) defines electronic government and its associated other titles (e-gov, digital government, online government, or connected government) as technology that deals with electronic interactions between citizens and their government, governments and their citizens, between governments and their government agencies, government, and the private sector. Brown (2005) characterizes the ways of public service delivery as (1) pushing information out over the internet, (2) two-way communication, i.e., use of online forums, to interact with citizens, (3) electronic transactions, paying taxes, parking tickets or applying for jobs online, typically through the government's website, (4) being a location for citizen involvement by informing them of what is happening inside the government. The distinction is that electronic government is more about putting information out on the web in digital or electronic format with the intent and, at times, hope that citizens and the private sector will use it to improve public services. This research refers to all these policies as digital era governance or DEG.

Indeed the future of public services is being shaped more and more by the development of worldwide, Internet-enabled digital platforms. As discussed DEG highlights the union between evolving technology and technology-driven behaviors of citizens whos expectations are that

DEG is central to citizen government interaction (Fishenden and Thompson 2013). This dissertation breaks this into three phases. These phases are 1.0, 2.0, and 311 and open data portal. The dissertation explains each phase as well as offering operational examples in practice of each.

The first phase of electronic policy adoption is 1.0. These technologies focus on establishing an online presence and opportunities to get in contact with an agency. Layne and Lee (2001) identify these as technologies with little complexity and sparse integration across agencies. Technologies in 1.0 deal with information dissemination (posting of meeting minutes, interactive map of services), two-way communication (email), and offering service and financial transactions (online bill pay) (Moon 2002). 1.0 technologies are early examples of creating client-focused structures that allow citizens to contact and interact with their governments using email directly. The operational examples of these technologies in practice are online bill pay, meeting minutes/agendas, email link/address or contact us, and GIS/interactive map. These technologies represent early adoptions of electronic government technologies representing an early wave of governments moving toward DEG.

In the second phase, the dissertation characterizes electronic government technologies as 2.0 technologies. These technologies correspond to what Margetts and Dunleavy (2013) call DEG wave 2. This phase begins around 2010; these technologies account for the social web's advent through social media technologies. Whereas 1.0 technologies like posting meetings and agendas online push out information in a one-way direction, these technologies are interactive and multidirectional, allowing for greater depth of communication. Jackson and Lilleker (2009) and Sharma and Kharel (2015) broadly define 2.0 technologies that cover social networking sites, video sharing sites, blogs, and wikis. Web 2.0 deals with interacting with online content, such as adding comments to a blog, or uploading documents to a website (Jackson and Lilleker

2009). Thus, these technologies are less about the top-down provision of information from the government and more towards a partnership with shared ownership over the content.

Social media has created an environment where citizens and the private sector incorporate new technologies far more quickly than governments can can. It also introduces more dynamic ways of getting government information, like YouTube live stream videos and recordings of government meetings. RSS feeds are another technology that has streamlined and made the consumption of government information more convenient. In addition, two-way interaction between government and citizens takes place through private services like Facebook and Twitter.

The last phase of electronic government technologies features collaborative technologies such as the 311 systems and open data portals. These open data initiatives are gaining interest and influence in government. Davies et al. (2013) found that open government data has spread globally, evidenced by their existence on every continent and in an increasing number of cities and international institutions. These complex systems require vertical and horizontal integration, capturing critical themes of the DEG literature: reintegration, the holistic approach, and the digitization of government.

311 and open data portals represent more recent developments in DEG technologies, and they carry the prospect of a new level of engagement with citizens. These technologies are complex and feature near-complete integration across government services. Using the framework of Layne and Lee (2001), the dissertation provides examples of vertical integration - local systems connect with higher-level systems, and systems are also horizontally integrated across different functions. This phase brings into the discussion the potential for co-production of services. The

co-production of services falls into the themes of holism and digitization of services (Dunleavy and Margetts 2010).

Both 311 and open data portals require institutional capacity and knowledge to implement these complex technological ecosystems of related software, hardware, and information – typically, this has been performed by the private sector. These challenges, aside, the opportunity and potential for change, have motivated many cities to implement open data portals. Even governments like Detroit, which experienced historic bankruptcy, made open data a priority going forward. Dawes et al. (2016) state that the prospect of open government data is "undeniable" given that it has the potential of improving democratic governance along with political participation as well as creating opportunities for the private sector and civic innovation.

Both systems can take in citizen feedback and produce measurable outcomes when done effectively. 311 systems allow for the reporting of non-emergency issues by citizens to their governments. These platforms offer a single destination for citizens to take part in the reporting process. Rather than reliance on the government to find issues, citizens become direct participants in the service delivery process. Cities currently and historically collect and store large amounts of data that have public value. Traditionally, data is stored in static form, filed away in a government building, and retrieved in the event of an FOIA request. This data was typically inaccessible to a vast majority of the public. Access to data by the public has the prospect of improving with these systems. Open data portals provide access to primary or source data previously isolated within individual departments or organizational units. Citizens and the private sector can then consume this primary data.

As a result, open data portals make a direct impact on how governments provide services. 311 and open data portals are operational examples of what Margetts and Dunleavy (2013) call 'do-it-yourself-government.' These two technologies exemplify the complete embrace of electronic service delivery by digitizing interactions with citizens and businesses. This digitization increases efficiency (citizen reports directly to the government) and increases citizens' involvement in their government.

To this point, the dissertation has outlined how to operationalize digital governance change over time by looking at these three phases: 1.0, 2.0, 311, and open data portal technologies and how they have lessened the boundaries between citizens and their governments. The focus of the 1.0 and 2.0 movements was public interaction and communication, with 2.0 being expressly about interactivity. Recent technologies like 311 and open data are focused on access to information and data. Across the three movements (1.0, 2.0, and 311/open data portal), closed systems with set boundaries are being replaced by ones that encourage openness. The dissertation next discusses digital governance's role over time and the benefit of this dissertation's time-series approach to studying its diffusion.

1.3 Importance of Digital Governance

Both practitioners and researchers have focused on the promise of ICTs and technology-related changes since the inception of digital government research over two decades ago (Andersen et al. 1994, Luna-Reyes and Gil-Garcia 2011). Morgeson and Mithas (2009) and Scholl (2020) assert that digital government is the driving force of administrative reforms worldwide. According to Layne and Lee (2001), the transformation is pervasive and drastic. These changes are fundamental according to Zhang et al. (2014) in "how public organizations are structured and operate, how public services are delivered, how policies are developed, implemented, and evaluated." In addition, it determines citizen engagement in the democratic process as a result of the introduction of various technologies (Zhang et al. 2014).

The progression of technology is consistently shaping public services. The pervasiveness of internet-enabled technologies shapes digital governance and is crucial to managing relationships with citizens (Williamson 2016). These platforms and their associated technologies are part of what Dunleavy et al. (2006) describe as Digital Era Governance (DEG). DEG requires the reorganization and consolidation of public services under government control, focusing on technology as central to the citizen-government relationship. These internal changes are responses to technologies like the social web (i.e., Facebook and Twitter) and advances in processing power (cloud computing), and the development of government-focused applications (Fishenden and Thompson 2013). DEG has "moved advanced industrial societies further toward an online civilization" (Dunleavy and Margetts 2010, p. 1). Fishenden and Thompson (2013) describe DEG as a "confluence between emerging Internet technology and emerging technology-driven behaviors and resulting citizen expectations around DEG as a channel for citizen-government interaction." Citizen behavior and expectations have only increased since we now expect these public services at every government level. Williamson (2016) emphasizes this. He outlines that DEG focuses on the movement of services from analog to new digital formats facilitate governments to gather data on citizens' activities, interactions, and transactions to provide better service in the future. Governments can then mine, analyze, and use this data to glean insights into improving efficiency and shaping public services. Governments can do this in conjunction while encouraging citizens to become responsible participants in the co-production and provision of public services.

Dawes et al. (2016) contend that there is a tendency in the public administration literature to oversimplify the complexity of providing open government data services. Oversimplification has been a topic of other past electronic government research (Dawes 2008, Brown 2005, Ho 2002). One of the critical misconceptions is that directly publishing government data online will automatically yield benefits to citizens and government services. Another critical challenge for electronic government 1.0, 2.0, and 311/Open Data Portals is the assumption that constituents can use social media, online forms, or an open data portal. Digital divide research suggests that socioeconomic factors contribute to the use of electronic government by citizens (Mossberger et al. 2013). Janssen et al. (2012) contend that open data and information do not guarantee government openness. The enhancement of democracy is not a direct result of the comprehensiveness and amount of open government data (Dawes et al. 2016).

DEG efforts aim to create transparency and foster engagement with both citizens and the private sector. These efforts have the prospect of creating enhanced democratic outcomes (Cuadrado-Ballesteros 2014), efficiency (Navarro-Galera et al. 2016), transparency, engagement, collaboration (Bertot et al. 2010), as well as trust in government (Lourenço 2015).

1.4 Study Significance

This research makes three contributions. First, it collects, compares, and analyzes ten different technologies across ten years to identify the diffusion and adoption of urban governments' DEG policy. These ten technologies represent past and current trends in electronic government technologies. Second, the dissertation uses diffusion theory to derive testable hypotheses predicting technology adoption. The role of policy diffusion provides insights into how more recent technologies will diffuse in the future. As the research indicates, electronic government, or DEG is a policy area perfect for studying the diffusion of innovation (Jun and Weare 2011). Many of the DEG studies use innovation diffusion theory as their theoretical support for their research (Raus et al. 2009). In addition, prior literature (Al-Hadidi and Rezgui 2010, Weerakkody and Al-Sobhi 2011) uses the theory of innovation diffusion to frame their arguments and establish the challenges facing government and the factors and justification of its adoption. Third, the dissertation's analysis relies on nearly six thousand text-mined data points collected during three points in time. These points extend over ten years combined with other social, political, and demographic variables to construct a well-formulated explanation of why and when governments adopt certain technologies. This empirical model is unique in the diffusion literature in that it examines multiple cities (231) and multiple variables (693). Historically, an N-study of this size, in the innovation diffusion literature, has not been done.

Rogers proposed a theory to explain the diffusion of innovations (DOI) (Rogers 2003). These have been introduced into DEG research to explain the adoption and diffusion of electronic government. Issues of diffusion and adoption circumstances are essential for explaining the spread of innovations of both policies and ideas over time (Zheng and Ma 2021, Wijnhoven et al. 2015, Young 2020, Boehmke et al. 2020). Zhang et al. (2014), in their analysis of the diffusion of electronic government literature, find much of the existing research on the diffusion of DEG provides preliminary evidence based on theoretical consideration, reports from those working in government, case studies, and empirical research. The range of research provides an understanding of the issues of DEG diffusion. With technologies continually evolving, governments constantly need to introduce new ways to interact with citizens as part of their DEG strategy (Zhang et al. 2014, Gil-Garcia and Martinez-Moyano 2007, Norris 2011).
The result is that examining DEG policies and their associated technology and how they diffuse is of critical concern to political science and public administration research.

The goal is to build a comprehensive picture of technology adoption and diffusion at the United States city level. One of the critical components of the research is examining adoption over time. Shipan and Volden (2012) examine the role of anti-smoking policy in 675 of the America's largest cities from 1975 to 2000. Several studies have examined electronic government technology adoption but not across multiple innovations over time. Mossberger et al. (2013) examine the prevalence of social media from 2009-2011. More recently, the work of Ingrams et al. (2020) focuses on the largest cities in the "most wired" countries in the world from 2003 to

2016 to examine the stages and determinants of electronic government development. They test e-government technology adoption using cluster and regression analysis. This dissertation uses regression and is an example of empirically testing technology adoption in urban governments over time. This research uses a similar time frame (ten years versus 12) but focuses on the United States. This research also shares similarities in examining the role of population, GDP (here revenue), and competition.

Tolbert, Mossberger, and McNeal (2008) focused on innovativeness changes at the state level over five years. Historically, the work on electronic government technology and policy diffusion generally has been done at the state level. However, with the role of innovation in digital government at the local level, this has shifted. Ho (2002) focused on city websites, followed by a large body of literature focused on the city level. Mossberger et al. (2013) examined social networks and interactive tools in 75 of the largest U.S. cities; Zavattaro et al. (2015) looked at a random sample of 125, Grimmelikhuijsen and Feeney (2017) examined 500 cities. More recently, Young (2020) examined the prevalence of open data portals in 60 cities.

Of additional significance is understanding how governments think about technology and how and why different technologies are adopted. The research approach could have value looking forward as governments consider technologies like open government data portals and co-production initiatives with high financial and political costs, examining their citizens' benefits. Co-production of services has a long history in government. Co-production distinguishes itself from the classic view of government in that government is no longer the sole provider of public services. For example, police and fire departments do not provide public safety alone. Instead, a partnership between government and citizens is required to provide many of these public services. Previous examples are Neighborhood Watch programs (Musso et al. 2019), and more contemporary ones use technology like 311 report systems.

The dissertation's empirical model is also significant in the field. The model used to test technology diffusion can be adopted to examine other policies in cities and other government entities like school districts, counties, and state governments. Comprehensiveness, paired with empirical testing, should provide a unique and significant contribution to the literature in public administration and political science disciplines.

1.5 Dissertation Structure

This chapter has set forth research questions, the three waves of digital governance, how this approach adds to the literature on technology diffusion, and the significance of what this study offers over those that have come before it. Chapter two presents an overview of the literature to date in the two areas of scholarship that directly affect this study: policy diffusion and the adoption and implementation of digital governance. Chapter three lays out the hypotheses, methods, and research design. Chapter four discusses the results and outcomes from the statistical and geospatial analysis. The final chapter discusses the conclusion, offers opportunities for further research in policy diffusion and digital governance, and policy implications.

2: LITERATURE REVIEW

2.1 History of Technology and Government

The study of electronic government is not new to public administration. It dates to the 1960s and 1970s with the advent of personal computers and their use within government. Years later, the federal government invented the modern internet in 1983 with ARPANET, the network of networks. The 1980s and 1990s dramatically changed the government's relationship with technology, with increasingly sophisticated information and communication technologies (ICTs) becoming widespread across governmental organizations.

The concept of electronic government is not new to the public administration and political science literature. Initially, technology and the issues surrounding its use and access were on the periphery of government and government operation. The technology was a way to improve the managerial effectiveness of public administrators. However, this has rapidly changed. The introduction of the internet and personal computing in the 1980s increased access to technology, democratizing access, and dramatically changing the landscape of government. Today, technology can manage and improve public administration's core values – accountability, transparency, efficiency, and civic engagement.

Margetts (2012) discusses the growth in technological development in the 1990s that offered great potential to impact the citizen-government relationship, specifically the rapidly rising Internet usage across society, particularly in commerce, which led to a higher profile for information technology in general. She points out that using ICTs is widely credited as a critical driver of productivity and economic growth, particularly in the United States during this period. This growth led to the spread of the use of ICTs in government. Electronic government technology has been studied intensely by public administration scholars (Moon 2002, Ho 2002, West 2004, Brown 2005, Norris and Moon 2005).

Ma (2013) recently used diffusion theory to examine government use of technology. However, this analysis was not holistic. He looked exclusively at the emergence of microblogging (e.g., Twitter) in their assessment. Our research examines multiple periods and technologies to understand electronic government diffusion better. The work of Ma (2013) was limited in that it looked at a single government department (police bureaus) within Chinese municipalities. They found that the size of the government, area competition, internet use, and learning, and leadership pressure were positively and significantly correlated to the adoption of microblogging and being an early adopter.

Governments around the world have adopted digital governance. The goal is to improve critical values related to public policy and administration, including accountability, transparency, efficiency, and civic engagement (Pina et al. 2010, Brown 2005, Bonsón et al. 2012, Ahn and Bretschneider 2011, Dawes 2008). This movement in government has mirrored one in information technology. Technology has moved from closed to open systems of information. Chun et al. (2010) outline that the opening and publicizing of data creates a new situation that citizens can use and create information through a collaborative network of like-minded individuals. These individuals operate outside the governmental boundaries and not within the government organizational hierarchy, allowing them absolute freedom to create and analyze public data to look for solutions to government challenges. Janssen et al. (2012) found that citizens become part of the network that can process, enrich, combine or even collect relevant government data. However, there are still opportunities for further research as many findings of the effects of electronic government are mixed (Ahn and Bretschneider 2011, Moon 2002, Norris and Moon 2005, Scott 2006).

Agencies have been delivering processed information in reports or web-based query systems to search through repositories of data. Electronic government 1.0 and 2.0 initiatives have sought to improve government information access by simplifying web interfaces and online forms. These movements have focused on improving user-friendliness, citizen centricity, and universal accessibility of government data. Also, recent technology innovations in hardware, software, and file standards have emphasized explicitly reusable information.

Open data portal initiatives change how the public gets access to information. Historically, the government was reactive to the disclosure of public information. Open data initiatives allow for the proactive disclosure of information. Information is available without the need for a citizen to request it. Open data portals can also reduce the amount of time spent on complying with open record requests. With open data initiatives, citizens have on-demand access to data freeing up time for government staff to perform other duties. Kassen (2013) notes that the value of open data initiatives is that both government transparency and civic engagement will increase. Multiple other studies have found the same; Verhulst and Young (2016) and Attard et al. (2015) found that the impetus for open data portals creation was the promotion of transparency. Their creation would foster the publishing of data and the opportunity for citizens to actively participate in the government decision-making process by using this data.

2.2 The Role of Policy Diffusion

The Diffusion of Innovation Theory, initially developed in 1962 (Rogers 2003), explains how an idea gains momentum and diffuses or spreads through a particular group or social system over time. In this research, diffusion is how a policy innovation is communicated and then spread through specific networks over time within governments. The result of this diffusion is that individuals or governments adopt a new idea or behavior as part of a social system.

While Rogers (2003) studied diffusion at the individual level, many of the traits of early adopters he identified can be applied at the aggregate level, done here to examine large urban governments. Research on the adoption of policy innovations by governments is extensive. The role of policy diffusion as a mechanism for innovation in a federal system is that state and local policymaking can serve as laboratories of democracy. Governments experiment with different policies and then learn from one another. The federal government adopts successful policies from the local level (Shipan and Volden 2014).

The examination of the diffusion of policy innovations within states has a long history. Early policy innovation and diffusion research found that innovative states and particular attributes of those states could be associated with varying levels of innovativeness (Savage 1985, Walker 1969). Mohr (1969) outlined three leading indicators of innovation in organizations: motivation, number of innovation barriers, and the capacity to overcome those barriers. In addition, the presence of difficult social situations was also an important factor in the willingness of a state to innovate. One example was the motivation to innovate that arose as a result of high unemployment. More recently, Karch (2006) describes that additional obstacles to innovation. These obstacles include the high economic and political cost of a new policy idea. However, states overcome these obstacles with large tax bases or budget surpluses. These barriers to adoption will be significant later as the research builds the empirical model to test technology diffusion in cities.

Walker (1969) examined why some states adopt policy changes (innovations) faster than others, while Gray (1973) argued that state innovation varied across policy areas such as education, welfare, and civil rights. Grupp and Richards (1975) examined professional networks' role in analyzing policy diffusion in fifty states as both formal and informal communication networks. Numerous researchers have used policy variation among the states as a quasi-experimental setting to test various hypotheses about political decision-making and the policymaking process (Karch 2006).

Following Gray's (1973) argument about variation across policy areas, researchers attempted to explain innovativeness as a characteristic of state government and focused on explaining the determinants for the diffusion of a single policy over time. Subsequent research began using increasingly sophisticated statistical methods, notably event history analysis (EHA). This method allowed researchers to measure diffusion over time and account for both internal determinants and external effects within the same model (Berry and Berry 1990, Box-Steffensmeier and Jones 1997). This research allowed for richer explanatory models for particular policies but made it difficult to theorize more generally about policy innovation.

Policy diffusion is not spontaneous and independent; it is interdependent, made possible through the spreading of policy, political, and normative information as well as competitive pressures between political units (Shipan and Volden 2008). Economic characteristics like the median income of residents and the governments' resources measured as revenue tie into the slack resources that Rogers uses at the individual level. The variable median income is applied at the state level by Tolbert et al. (2008), Tummers and Rocco (2015), to name several, and is applied to the city level by Norris and Reddick (2013) and López-López et al. (2018), among others. Examining government form and participation in collaborative networks allows us to examine the role of opinion leadership outlined by Rogers at the individual level. Over decades now, a large body of research has taken this individual-level diffusion theory and applied it to policy innovations at the government level.

The focus of this research is on the adoption of multiple technology innovations over time. While the work of Rogers provides an understanding of diffusion, the work by Eyestone (1977), among others, has direct application. Eyestone defines diffusion as "any pattern of successful adoptions of a policy innovation." Thus, the research is not looking at how comprehensive a specific DEG technology is but how multiple technology innovations have spread over time. Berry (1994) finds that three significant models explain adopting a new policy (innovation). These models are the internal determinants model, which suggests internal economic, social, and political characteristics are fundamental in why government adopts a particular policy. The additional models are diffusion models indicating the influence of external factors. Two types of models address diffusion on the regional and national level. Each of these models outlines policy adoptions as actors copying the earlier adoption of the policy by other actors.

In this internal and external determinants framework, diffusion is a function of the motivations of key political actors within government, the number of resources available to the units for overcoming obstacles to adoption, the interaction with other policies already adopted by the units, and external influences (Berry and Berry 1990). Berry and Berry (1990) call this the "Unified Model of Policy Diffusion," meaning that it unifies previously disparate adoption models based on internal characteristics or external influences. In the empirical model, cities are the focus, with the external influences being other cities. Internal determinants are often political or demographic. This dissertation incorporates them into the analysis by looking at the role of median income, form of government, and government revenue (slack resources).

Shipan and Volden (2012) performed an extensive review of the diffusion literature and outlined essential lessons from the literature. They find the lessening importance of geographic clustering in their analysis. In earlier studies, Walker (1969) and Berry and Berry (1990) found geographic proximity often influenced diffusion. Geographic proximity may no longer be needed where policy actors and practitioners have an increased ability and capacity to increase their scope of information and ideas beyond nearby neighbors. The internet, social networks, and technology have made it so that merely looking at geographic clusters or what your neighbor is doing does not carry the same weight. Shipan and Volden (2012) note the limitation of focusing solely on geography. They note that with the existing low communication and travel barriers that technology now provides, the traditional view of policy diffusion being a product of geographic clustering is becoming more and more outdated.

In addition to geography's role, the earlier work by Berry and Berry (1990) reinforces other influences to policy adoption. Their work examining states finds that states imitate others' policies in three distinct ways: learning from one another, competing with one another, and responding to public pressure by citizens to adopt policies from other states. The role of competition in policy adoption has a long history in the field. Competition, emulation, and learning are more likely predictors by Shipan and Volden (2012). Competition and emulation are more likely to be geographic, whereas learning is more likely to be based on success and not necessarily proximity. There are also national networks and the diffusion of ideas through those that are not necessarily proximate exemplars.

The early work of Tiebout (1956) found that local governments compete with each other to offer the most attractive policies to citizens with the intent of keeping them within the jurisdiction. The result is that citizens will find the city that best meets their needs based on tax and spending preferences. While Shipan and Volden (2012) acknowledge that competition plays a factor in policy decisions, they also caution that the role of competition not be overstated. They note that governments often solve problems collectively through collaborative networks and multilateral agreements. Crucial to these types of agreements are governments cooperating and learning from one another as well as competing.

As they found with geographic clustering, policy innovation is not as proximity-bound as in the past. Even Walker's (1969) seminal work suggested that national networks may develop, making the regional patterns he discerned less relevant. Decades later, Shipan and Volden (2012) note that technological advances and policy networks have increased governments' ability to learn from each other across space. Specifically, the lowering of communication and travel costs has brought about this change. Also, policy advocates and entrepreneurs (Mintrom 1997, Kingdon 1984) can intervene to affect policy outcomes.

The role of politics and the capacity of government is essential for policy diffusion outcomes. Shipan and Volden (2014) found that anti-smoking policies at the local level eventually diffused out and then up to the state level. They found that state legislatures with higher capacity (they receive compensation) encouraged the diffusion of innovations from the local level to the state level. Without having to balance another job, these higher-capacity legislators would take local policies, extend them to the state level, and look at policy innovations as a means to advance their political careers. In this case, it is more about legislative professionalization than politics or political parties. While politics does matter, at least for more controversial or partisan issues, the work from Volden and Shipan illustrates for policy adoption, research indicates that professionalization is a more accurate predictor of diffusion. Government capability is an essential factor in understanding diffusion.

So what specifically would influence the adoption of digital government innovations? Perceived benefits include efficiency, citizen participation, and government transparency, but understanding the factors that influence the government's adoption of electronic government technologies is crucial for realizing these benefits and passing them on to citizens. This dissertation uses the distinction outlined by Berry and Berry (1990) to classify these factors as external or internal. Work by McNeal et al. (2003) and Tolbert et al. (2008) included measures for networks, though not contiguous states. A significant number of studies use internal factors at both the local and state level of DEG policy adoption.

Seri et al. (2014) examined indicators and factors of "e-services" in Europe. Their approach longitudinally examines the drivers of e-service diffusion and usage. They outline the drivers of electronic government technology's supply at the country level as political or socioeconomic. The variables examined in their study were GDP, government expenditures, broadband penetration, human capital, and corruption. Their work found that the main driver of e-service adoption was the penetration of broadband. In addition, they found that both the demand for and the supply of broadband contributed to e-service diffusion. Education was another significant contributor to the demand and supply of e-services at the country level. In their research, corruption has an inverse correlation to the spread of e-services, which points to the importance of public trust and government accountability as a contributing factor to diffusion. While this is an international study and results may be somewhat different, we see similarities in the United States.

In addition, wealth, economic development, urbanization, education, and internet accessibility have been significant in predicting technology policy diffusion. Kneuer and Harnisch (2016) examined the diffusion of internet-based technology in government on the country level, and what they found echoed the work of Seri et al. (2014) as well as the foundational work of Norris (2001) that economic development played a crucial role in the implementation of electronic government policy adoption. The importance of human (skill) development and technology development were other crucial factors in determining what drove electronic government technology adoption by governments. Azad et al. (2010) found that the character of political institutions and national governance rules were key drivers influencing digital governance diffusion. While education and skill will differ more at the international level than in U.S. cities, it is still important to account for their use in diffusion policy studies. Gulati et al. (2014) also concluded that countries that devoted more financial resources to develop and promote such technologies had more services available to citizens. These represent international studies, but the research in the U.S. is equally strong.

The work of Moon (2002) is one of the earlier examinations of DEG in the U.S. The study used a survey from 2000 to examine the current state of DEG implementation and assess its “perceptual effectiveness.” It also uses two institutional factors as part of the analysis accounting for the size and type of government, the two variables Moon revisits in later research. The analysis finds that financial, technical, and personal capacities cause barriers to adoption.

Norris and Moon incorporate a longitudinal approach in 2005 by using two national surveys (2000 and 2002) to examine the adoption of e-government, website sophistication, impacts of technology, along with the barriers to adoption by local governments. Their research examines these against the population, type of government, geographical region, and city status (central, suburban or independent). It represents an early examination of DEG policies in the U.S. The analysis found that DEG, as measured by the deployment of websites, was multiplying.

Like the Norris and Moon study, West (2004) adopts a longitudinal approach that examines DEG and its impact on service delivery and citizens’ attitudes over three years. The analysis examines if DEG is leveraging the the internet to improve services, democratic responsiveness, and public outreach. The website content is examined and supplemented with a national survey. West examines both American state and federal government websites (not local governments) in all 1,813 websites in 2000 and then another 1,680 in 2001. The survey also incorporates sociodemographic variables (i.e., education, age, race, income). These works represent early longitudinal DEG policy analysis.

More recently, Mossberger et al. 2013 examined interactive tools utilized in websites of the largest U.S. cities from 2009 to 2011. Similar to our approach, they examined social media tools (Twitter, Facebook, and YouTube) in addition to Flickr and other phase 1.0 technologies like downloadable information materials, email updates, and RSS feed. Their research found the rapid expansion of Facebook and Twitter from 2009 to 2011, 75% and 62%, respectively. This research represents a cross-sectional study of the U.S. which is similar to this one. The methodology of this study influenced the modeling in this dissertation. Even more recently, Dubman (2019) found that key predictors of digital governance adoption in the U.S. are wealth and urbanization.

To this point, the dissertation has discussed policy diffusion as a source of digital governance innovation. Next, it examines the literature as it relates to the adoption and implementation of digital governance.

2.3 History of Digital Era Governance Research

Most of the work to date studying electronic government has been the assessment and survey of governments that have, or have not, implemented various electronic government reforms (Norris and Moon 2005, Reddick 2011, Kim and Lee 2012, Mossberger et al. 2013, van Loon and Toshkov 2015). This strand of research includes the reasons *why* governments adopt a particular technology. Reasons typically include increased transparency, accountability, and efficiency. The other significant concentration of the electronic government literature is related to the type of technology implemented, examining a single application, such as websites or social media (Norris and Moon 2005, Layne and Lee 2001, McNeal et al. 2003, Reddick 2005).

This work takes a unique approach in that it examines electronic government over multiple periods to assess the diffusion of three waves of technology. Like the two waves identified by Margetts and Dunleavy (2013), Dawes (2008) proposes a framework that classifies electronic government initiatives by looking at specific technologies. They then tie the framework to the evolution over time of these initiatives directly to several prominent public administration theories using several new and emerging analysis techniques.

In this dissertation, electronic government 1.0 deals with governments making information available online. This phase deals with governments pushing information out to citizens. Electronic government 2.0 relates to technologies like social media (Twitter, Facebook, and YouTube) seeking to engage and interact with citizens. 2.0 is a progression in that it is a back and forth between governments and citizens rather than simply pushing out information. Electronic government co-production is a concept the dissertation forwards as dealing with open data portals that seek citizens to engage on a very complex and sophisticated level in developing and analyzing government-related data. This type of engagement forms a more profound relationship than simply tweeting or posting on a government's Facebook.

Many in the electronic government literature address the evolution of governments from paper and print to websites and the use of the internet or citizens' ability to report an issue (311) (electronic government 1.0). Later research examines the eventual implementation of social media, more sophisticated distribution of information (RSS), and other interactive technologies like online forums. The literature has mainly left unaddressed factors influencing the diffusion of electronic government technology adoption and how it may differ based on the technology implemented. The "what" and "how" of this diffusion over the American government landscape is the focus of this research.

In turn, this work is advanced by examining how these pressures influence the diffusion of technology use in governments over time. The literature on digital government does well in explaining why technologies diffuse, but little on what factors have influenced different waves of technology over time. Mergel and Bretschneider (2013) created a three-stage model that outlines social media adoption by governments. Meijer's (2015) work is another example of developing a framework that outlines the parts of the government's innovation process. These studies offer insight into technology adoption by government of social media and more basic electronic government technologies. This study's framework adds to the field of research on electronic government by establishing a narrative and analysis of how technology diffuses over time. This analysis differs in that prior studies on barriers to DEG innovation used surveys as the research method (Moon 2002, Norris and Moon 2005, Ho 2002). While these studies provide insight into general trends, they do not provide depth into the specific adoption strategies. Meijer (2015) contends that only an in-depth and longitudinal case study of DEG can provide the depth necessary to contribute to the literature by highlighting policy innovation subtleties over time.

Both Meijer (2015) and Mergel and Bretschneider (2013) have created frameworks for understanding electronic government innovation. Mergel and Bretschneider suggest that social media use in government diffuses like previous technology waves due to market innovation or use outside government.

Meijer (2015) developed a framework to investigate the barriers to electronic government technology innovation and development. The intent is to understand the barriers and look for opportunities to overcome them in the adoption process. According to Meijer (2015), the critical barriers for adoption are structural, citizen concerns, and citizen issues' cultural framing. Both frameworks examine technology innovation over time; however, the one proposed in the research examines multiple technologies in multiple governments over time. The goal is to identify broader trends in government technology innovation of electronic government technologies and how those technologies diffuse over time. This dissertation trades the depth of Meijer's analysis for a more comprehensive innovation diffusion approach.

The spread of different technology policy adoption over time is a concept not well covered in the literature. Typically, research on electronic government focuses on the benefits to public ideals like accountability, efficiency, and civic engagement as reasons for adoption (Bertot et al. 2010, Chun and Reyes 2012). However, this research does not give a complete picture of the conditions and resources associated with and might facilitate DEG policies' adoption.

Ma (2013) points to technology as a critical component in enabling governments to rebuild their social image and revive public trust. With scholars and politicians alike promising that technology will fill this large and apparent gap in our social and political lives, the evidence of its ability to do so is still unclear. This gap makes the broader field of electronic government an important area of continued study. Besides, focusing on the entire movement rather than specific technologies can provide an essential narrative to technology adoption in government.

The dissertation's research intends to examine digital governance expansion over time, the similarities and differences between expansion components, and gain insights into electronic government adoption influences. The study examines a sample of government websites throughout three periods. This approach allows insights into the extent, frequency, and degree of expansion of electronic government technologies. Given the substantial investment of public monies in these technologies, it is crucial to understand the factors that influence technology policy adoption.

Norris and Moon (2005) and Norris and Reddick (2013)'s work is notable for their contribution to barriers to adoption. In both studies, they looked at the electronic government adoption at the city and county government levels. They found that lack of technology, employees, skills, financial resources, privacy, and security issues were the most often-cited examples of not being successful. Schwester (2009) found similar barriers. Organizational and employee opposition, lack of support from leadership and higher-up officials in the organization, technology barriers, concerns of security and privacy, and lack of public concern were adoption barriers.

The barriers to electronic government adoption in government are predominately related to technological barriers, the lack of factors such as security, privacy, trust, and resources.
The work of Moon (2002) and Moon and Norris (2005) examined electronic government technology implementation and found that city size, the type of government (mayor/manager), had significant influence over the adoption of technology. Their empirical work further emphasizes the lack of technical, personnel, and financial resources as significant barriers to adoption.

The work of Becker (2004) found similar early adoption issues related to trust. State government websites' navigational depth, content, and reading complexity hindered citizen trust in their websites. In examining 150 government websites, Yang and Paul (2005) found staffing a barrier to adoption. What they emphasized was the necessity and responsibility of having a software developer. Without the expertise of such a position, they find that maintaining and updating information on the government website ensures accuracy. Another barrier was the capacity of government managers to offer effective leadership in digital governance implementation.

Given the number of barriers to adoption, it is evident that successful DEG policy adoption necessitates specific characteristics to be successful.

Wang and Hou (2010) built on this to examine internal and external barriers to electronic government implementation and found that governmental and regulatory barriers and lack of communication between agencies are key external barriers to successful adoption. Internal barriers included fast technology change, the digital divide, privacy and security, and citizen beliefs were causes of internal barriers to adoption. Further, they found that many obstacles to realizing the benefits of DEG are not technical but instead occur when social, political, or legal issues arise during attempts to roll out and embrace DEG and its associated technologies.

Hossain et al. (2016) note the government's importance in getting technology initiatives adopted. They note that countries move forward with technology initiatives in an international setting when they take an active role as supporters or promoters. Huijboom and Van den Broek's (2011) work outlines the specific importance of leadership in establishing another path to technology adoption. They note the importance of developing guidelines and infrastructure and promotion through learning. The development of guidelines on how and what government departments need to do is critical, and this message commonly comes from the government's leadership.

Additionally, the government leaders must promote the benefit of technology within the government departments and the community at large. This research does not have surveys or case studies in our model to measure leadership. The analysis does have a council-manager variable to look at potential differences between council-manager and council-mayor as a measure to examine whether more political leadership from elected officials fosters this versus professionalization.

What are factors that might promote the adoption of different technologies? Early research on e-government provides some clues, though it is unclear that variables promoting adoption for digital government 1.0 are the same for open data portals. The process of diffusion should be different depending on the technology. Different technologies require different levels of economic and political investment. For example, social media like YouTube, Twitter, and Facebook are all created by private corporations. Setting up these services has a low threshold when it comes to rollout. These technologies require very little hardware aside from a personal computer. Technologies like open government data portals, 311 systems, and even GIS systems require more significant investments as they often need a substantial server and computer hardware and infrastructure to support them.

In this research, the interest is in understanding the adoption and implementation of digital governance by adopting three electronic government technology phases. Mallinson (2020) examined 30 years, 183 articles, and 507 policy adoption models on diffusion research and had two relevant takeaways. First, he found a lack of studies with large N-values, and the second few dealt with technology policy at the local government level. This dissertation addresses both of those gaps in the literature here with the empirical model. When it comes to the examination of electronic government technologies over time, there are additional gaps.

Many cross-sectional studies examine electronic government technology adoptions at a set time (Mossberger et al. 2013, Norris and Moon 2005, Moon 2002, West 2004, Welch 2004). These studies provide value in understanding the impact that electronic government has on a variable like trust (Ceron 2015, Kim and Lee 2012, Welch 2004), transparency (Lourenço 2015, de Fine Licht 2014, Pina et al. 2010), or accountability (Brown 2005, Bonsón et al. 2012, Pina et al. 2010). However, they are often limited because they do not address why a government might choose a particular technology. They also do not provide insight into what is causing electronic government technologies to be adopted and how they diffuse over time. Specifically, Ho (2002) and Moon (2002) examined what factors were associated with the adoption of DEG. While the cross-sectional analysis does not address causation with confidence in the same way that a time series analysis of a large period does, it does have a similar intent in that it is working to understand the factors that encourage adoption.

Technologies related to social media have become an often used and convenient moderator of communication between citizens and their governments (Mossberger et al. 2013). Shadbolt et al. (2012) emphasize that any government's foundation is the access and ability to use data and information as a prerequisite to gaining knowledge and producing services. An extension of this requirement is that data should be free and open to all to ensure the highest possible access. Per Hossain et al. (2016), three recent developments have catalyzed the demand for data by the public. The first being the sense of ownership that citizens have over their government and politicians. The second is the technology that has facilitated and proliferated citizens' ability to access, store, edit, analyze, link, and distribute data and information (Rohunen et al. 2014). The final is the growth in mobile networks and the proliferation of mobile devices that have resulted in the substantial rise of virtual social networks. This desire to provide data and information in a social and technical setting will not change, and the need for continued study remains. The shift in how governments operate worldwide is of continued interest to public administration researchers and practitioners alike.

This dissertation offers potential as previous studies of electronic government 1.0 and 2.0 find that socio-economics has impacted the participation in electronic government initiatives, for example, issues raised by the challenges posed by the "digital divide." However, the challenges for adopting open data portals and 311 may be different from these earlier technologies, and the next section considers them in more detail.

2.4 Collaborative Technologies and Co-Production

Co-production is delivering public services where the citizens are involved in creating public policies and services. The method contrasts the more typical transaction-based approach where public services are conceived of and provided by governments for public consumption. As a result of fiscal cutbacks in the late 1970s, co-production was promoted as a solution to meet public demand despite deficits in governmental services (Parks et al. 1981, Brudney and England 1983).

Ostrom proposed co-production to supplement the government's capacity to provide public services initially in the 1970s. This attention to co-production theory in public administration and political science would wane in the 1980s as the trend moved toward the public sector's marketization (Alford 2002). Ostrom's theory of co-production deals exclusively with public goods. These are goods that the organization cannot exclude others from using. They also are goods that can be consumed by multiple individuals at the same time, defined as "jointness" (Ostrom and Ostrom 1977). Co-production is a possible result of new digital governance platforms like 311 and open data portals that encourage citizens to take a very active and engaged role in public services.

What is unique to the theory of co-production is that those that consume services produced by the public sector are viewed as "active," meaning they participate in the production of goods and services and have a stake in their performance. Thus, the theory contrasts with public goods in the traditional sense, where consumers are typically seen as "passive," meaning the organization produces public goods, and the individual consumes them. However, since the mid-1990s, there has been renewed interest in the theory. The interest has led many academics to point out a need for research again, notably in co-production and technology.

Recent work has identified the value citizen co-production has had on public service quality (Bovaird 2007, Marschall 2004, Ostrom 1996). Both Levine and Fischer (1984) and Parks et al. (1981) found increased levels of citizenship related to co-production. Citizenship here is strictly speaking that citizens move past being consulted; it refers to more detailed and orderly participation of citizens and users in public services, where they discuss and help create those services. In addition to citizenship, it also showed greater social capital (Schneider et al. 1997, Marschall 2004,). Citizens working within these relationships are more energized, and as Ostrom (1996) pointed out, there is even the opportunity that this active engagement can have spillover benefits. She found that engaged citizens will increase the quality of the initial project and all the services they consume from multiple government agencies. Through an active and engaged citizenry, horizontal relationships are encouraged and can quickly grow, leading to a more connected and engaged society.

Janssen et al. (2012) found additional benefits by looking at three categories of open government data portal benefits. The first examined the political and social benefits that would result from improved transparency and accountability. These benefits included increased government trust, increased citizen services, satisfaction, and public sector innovations. The second category examined delineated economic benefits. The authors found that open government data could lead to growth and competitiveness, foster innovation, and create useful information for private investors and firms. The third category is related to operational and technical benefits to the government. These benefits would enable governments to reduce duplication and reuse data. Reuse enhances administrative processes, validation of data and brings together private and public data for further analysis.

More recent work by Voorberg et al. (2015) found other positive outcomes: improvements in efficiency, citizen satisfaction, strengthening social cohesion between citizens, and the greater democratization of public services. All of these issues remain a critical focus of the field and something that requires ongoing study. While this dissertation is not about the spread of co-production, it is about how DEG policies, specifically technologies like open data portals and 311 systems have co-production elements. These technologies rely on an increased level of involvement by both citizens and their governments—this interaction of government and citizens working collaboratively to create a solution.

Behind digital governance is an acknowledgment of the importance of allowing citizens to contribute their creativity and expertise. The intent is that this creativity and expertise will result in a more effective, efficient, and innovative public sector. This public sector would then be in a better position to provide services without increasing its cost. Technologies like 311 and open data portals look to citizen participation as a potential source for innovation and change in how public services are delivered. Broadly it can be seen as an actual behavior by anyone outside the government agency (Alford, 2002).

These innovative approaches to service delivery that attempt to create a better functioning public sector are at the center of this dissertation's empirical modeling of digital governance diffusion. The premise is that digital governance and the role of technologies like 311 and open data portals will improve access to data and information about government policy and will, in turn, increase the quality of public service delivery. Technology enables a new level of involvement and an evolution in how the government works with private citizens and the non-profit sectors.

The work of Sieber and Johnson (2015) categorized several forms of government data-sharing. The first is the status quo or 'data over the wall' form. In this scenario, the government is simply the supplier of open data. The government provides the physical infrastructure in the form of servers and hosting to access the data. The government also maintains the data to assure availability and ease of access to the citizenry. Within this scenario, the building of applications and products is in the hands of the private sector or individual citizens. This model requires that the private sector and citizens find uses for and determine the benefits of having access to information. The second approach is outlined in the government being a 'data activist.' Under this scenario, the government takes a promotional role. The government entities are not merely providing the platform but looking for opportunities for sharing and using data. They also actively engage with citizens, private firms, and departments within the government to use the data. An essential characteristic of this data-sharing model is that the government is an active participant in the process.

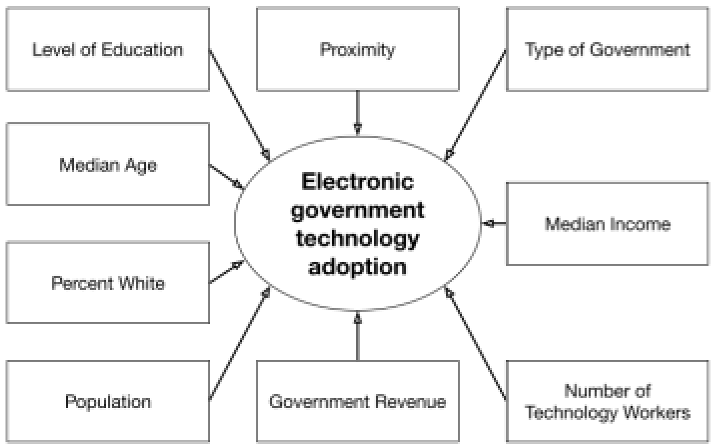
Sieber and Johnson (2015) identify a typical government role in using data as an open issue tracker. This trend was present in 1.0 and 2.0 innovations. For example, they send an email about unpicked-up trash or a pothole in a citizen's street. The intent is to use technology to improve the reporting and identification of citizen concerns. 311 systems are nearly ubiquitous in large governments in the U.S. This system allows the government to obtain straightforward responses from citizens on a narrow set of issues. Citizens as sensors are essential for this system to be beneficial. The final model outlined by Sieber and Johnson (2015) is the use of participatory open data. This model requires governments and citizens to work together in the co-production of data. These models are opportunities to improve the understanding of how electronic government has developed from 1.0 to 2.0 and, ultimately, to a co-production model of citizen services. Participatory open government data models facilitate improved open data processes and address the limitations of sole government-generated data. Providing open data, governments at the federal, state, and local level can collaborate on common goals, principally notions of greater transparency and accountability (Bonsón et al., 2012).

Chatfield and Reddick (2017) analyzed 20 open data portals, linking open data with co-production. They assert that open data portals intend to engage citizens to reuse existing data and encourage them to engage in co-production by encouraging software development that utilizes this existing data. The result is increased innovation of open services. These platforms represent the third phase of digital governance technologies in the model. The theory related to technology adoption supports the creation of a conceptual model for this dissertation to test.

2.5 Framework of Digital Era Governance Adoption

The dissertation has developed three key technology phases it wants to examine, 1.0, 2.0, and 311 and open data portal technologies as the dependent variables and how these have diffused over time based on nine independent variables. These nine independent variables are further classified if they are internal or external determinants to policy adoption. A simplified version of this framework is in the following figure. A more detailed version appears later in the dissertation.

Figure 1 Simplified Conceptual Framework



According to the research, the dissertation organizes the explanatory variables into internal and external determinants that affect digital governance adoption. Mallinson (2020) examined 28 years of diffusion literature. He found that diffusion is a function of the motivations of key political actors within government, the number of resources available to the units for overcoming obstacles, the interaction with other policies already adopted by the units, and external influences (Berry and Berry 1990). The dissertation organizes these determinants into three broader categories: organizational (internal), city environment variables (internal), and external determinants of geographic proximity and network participation.

Organizational variables are important determinants of digital governance adoption. The research has indicated that government revenue (slack resources) and leadership structure impact policy adoption. The role of resources has an extensive history in the analysis of digital governance and policy diffusion literature.

The level of resources is a predictor of digital governance adoption by organizations (Mohr 1969), regional governments (Navarro-Galera et al. 2016), states (Walker 1969, Gray 1973, Gupp and Richards 1975, Berry and Berry 1990, Tolbert et al. 2008, McNeal et al. 2003, Edmiston 2003), and cities (Musso et al. 2000, Ho 2002, Margetts 2012, Welch et al. 2016, Grimmelikhuijsen and Welch 2012). City revenue has proven to be a predictor of DEG policy adoption in the past and is prevalent in the policy adoption literature, and studies have found a definite link between wealth and electronic government initiatives. Governments with more slack resources will have the ability to innovate more extensively than those without resources. The model includes government revenue as an internal determinant of digital governance policy adoption.

Organizational revenue and the availability of resources has been shown to be an important variable when examining digital governance, another is the wealth and financial resources of a city. Tolbert et al. (2008) examined electronic government technology and policies in two distinct periods (2000 and 2004) and at the state level. They found that state institutional capacity[2] was an important factor for electronic government adoption. Their work also found that those that innovate later typically are more educated and affluent. Ingrams et al. (2020) find that one of the most common predictors of electronic government adoption is economic, measured either as GDP or taxable wealth, specifically the work of Bhatti et al.(2011) and Gallego-Álvarez et al. (2010). Further this relationship was found to be true irrespective of other environmental factors or leadership pressure. The predominate factor remained economic given the significant resources required for technology innovation to occur. Work by Edmiston (2003), Ma (2013), and Tolbert et al. (2008) further support the fact that wealthy cities are more likely to adopt DEG policies than poor ones. The analytical model operationalizes revenue like researchers have done before us. In the diffusion literature, Gray (1973) used the measure when looking at policy

[2] Tolbert et. al. (2008) defines institutional capacity as “dedicated state legislative committees, autonomous information technology executive departments, or more institutionalized information technology management and administration.”

diffusion within state governments. Wang (2001) used it in their examination of public participation in local governments.

The form of government is also a commonly used independent variable in the DEG literature. Moon (2002) and Jun and Weare (2011) included government form when examining electronic government initiatives. The role of leadership structure and patterns of technology innovation is mixed. Moon and deLeon (2001) and Kwon et al. (2009) show that cities with manager-council form have different innovation patterns than those with a mayor. In addition, Zheng et al. (2014) found that cities with mayors are more likely to have higher involvement in electronic government services. However, Wang's (2001) survey data from 249 leaders from U.S. cities with a population greater than 50,000 found no significant citizen participation difference between mayor-council and council-manager government forms. Regardless, government type is part of the initial modeling. The following section examines the external city environment variables.

There are six external determinants related to the city's environment included in the empirical model. These variables include the educational attainment, age of the citizens, population size, percent of white population, median income, and citizens employed in the technology sector. Many of these variables are linked directly to digital governance determinants by Tolbert et al. (2008). They link institutional capacity for technology adoption to the level of urbanization, wealth, and education. Lee et al. (2011) examine electronic government adoption at the national level from 2003 to 2008, using several United Nations collected variables. While at a different scale, they find similar results as Tolbert et al. (2008) that institutional capacity matters. In this case, a human capital index is a measurement. The finding is that domestic development and citizen pressure levels account for much of a government's adoption practice of electronic government technology over time. Research reinforces this in the U.S. where it indicates that population size and density are related to innovation policy. Ho (2002), Moon (2002), and Cho et al. (2021) all found that metropolitan status, size, and density of cities were critical factors in electronic government technology adoption and policy innovation, respectfully.

Digital government requires higher education and search skills in the user population (Seri et al. 2014). The level of education attained by citizens is a typical variable used when examining adoption of electronic government technology. Previous studies by Reddick (2005), Chatfield and Reddick (2017), Jaeger (2003), Norris and Reddick (2013), West (2004), Walker (1969) and Tolbert et al. (2008) have all used educational attainment variables. These studies have found that communities with higher average educational attainment are more likely to have adopted aspects of e-government. Similarly, there is a relationship between what citizens do online and education (Mossberger et al. 2003, Mossberger et al. 2017). Research shows that education levels correlate to more demand for government information and services and more willingness to participate in public affairs (Putnam 2000). Specifically, more educated individuals have a higher likelihood of possessing the expertise and confidence in technology and navigate information and forms. The work of Mossberger et al. (2013) examines educational attainment and the role that addresses the four digital-divide gaps from the perspectives of gender, age, ethnicity, and political affiliation have on the use of digital government. The role that education plays is also relevant, as Mossberger et al. (2017) find in disadvantaged communities in black and brown communities.

Another variable of interest is age, as mentioned, Hargittai (2002) examines age and how it affects internet sophistication. The logic is that younger residents would be more interested in adopting and implementing electronic government initiatives, given that they are more familiar and exposed to digital technologies. Specifically, Hargittai (2002) found that age is adversely related to an individual's Internet skill level and that one's experience with the technology is positively associated with the ability to navigate online. The work of Prensky (2005) is the base for the thought process in defining digital natives. Digital natives grow up in the digital age versus digital immigrants who acquire familiarity with digital systems as an adult.

In addition to age and education, multiple city-level studies use population size as an explanatory variable. The argument is that local governments with larger populations will have more resources and be more prone to invest in electronic government technologies. Chatfield and Reddick (2017) found that population size is the best predictor of open data portal adoption. Earlier studies by Moon (2002), Norris and Moon (2005) found that city size was an essential organizational factor in predicting electronic government technology implementation. The population has been a variable in numerous electronic government studies (Meijer and Bekkers 2015, Jin and Cho 2015). Cho et al. (2021) found that larger cities are more likely to use online platforms for civic engagement than smaller ones. Ingrams et al. (2020) illustrate that population size is linked positively to developing a city's electronic government provisions (e.g., Ahn and Bretschneider 2011, Brudney and Selden 1995, Lee et al. 2011).

The intent of DEG is to provide equal access to everyone. The extensive literature on the digital divide has shown that a gap in access to information exists due to having access to technology. Demographic and socio-economic characteristics are linked to access to DEG. The role of race, gender, income, education, age, and geographic location, whether urban or rural, are barriers to DEG adoption. The role of race is vital in understanding DEG policy adoption. Explicitly the impact of income and education on ICT access and usage. Already included in this modeling is income, education, geographic location (urban), and to improve the explanatory nature of the modeling, it includes the percent white population of the given city, something first used by Ho (2002).

A contribution this research hopes to make is to see if cities that have a significant technology sector are more prone to the adoption of electronic government technologies than those that do not. The hypothesis is that cities with more technology-savvy citizens will demand more electronic services from their government. In addition, understanding the internal pressure presented by technology sector employees on their government services would contribute to the electronic government literature.

While the inclusion of employees in the technology sector might be new, income variables' inclusion is not. The inclusion of the median income variable is supported by existing research. Walker (1969) used the level of personal income (along with the size of the urban population) to predict the degree of participation and party competition in a state in his work on policy diffusion theory. Forestier et al. (2002) find that there is a close link between income per capita and internet access at the cross-country level. Three years later, West (2004) found that per capita income was a significant predictor in the number of state agencies offering services on the web and had a greater adoption of e-government technologies overall.

To this point, the dissertation examines the internal city environment variables of educational attainment, age of the citizens, population size, percent white, median income, and the number of citizens employed in the technology sector. The dissertation now turns to two additional external determinant variables, geographic proximity and network participation. Geographic proximity was an often used variable in past diffusion research, but its role has been waning, varying across policies. The role of network participation is another external environment variable of interest.

The measure of collaboration included in the model is the participation in intergovernmental organizations to share information about technology adoption. The interest is if collaboration within an information network would lead to significant adoption of electronic government technology. The Public Technology Institute (PTI) is a network of local government executives and elected officials who share research, education, and executive-level consulting services around technology that impact the local government. Because PTI would not make available historical membership data, the analysis accounted for membership for 2012 and ran a linear regression model and found that it was not significant in determining technology adoption.

Neighboring states may be more aware of each other’s policies and programs, and they may also share similar problems that the policies address. Early studies outlined the spread of policy innovation from one government to the next. Walker (1969) documented this early work by showing how state policy diffusion resulted in regional clusters. The work of Berry and Berry (1990) reinforced the role of geography in their analysis as well. As Shipan and Volden (2012) note, this continued into the following decades of research. The measure considers only geographic distance between units or whether they share a border, and proximity was too frequently measured simply by the frequency of geographically adjacent states that had already approved a particular policy. Maggetti and Gilardi (2016), like Shipan and Volden (2012), find that geographic proximity is not a measure of policy diffusion alone, for ideas may come from internal actors rather than emulation. However, research has found that geography is often an important diffusion component but cannot be linked directly to policy diffusion (Maggetti and Gilardi 2016). Therefore, the model treats geographic proximity as one indicator of potential external influence.

The role of geographic proximity may be outdated in some ways, given the role of information technology in sharing policy solutions. Chicago does not only innovate based on what Milwaukee, Indianapolis, Detroit, or Cleveland are doing. With the role of technology, cities and their citizens can learn of digital governance policy from cities not just in the United States but worldwide. This interconnectedness influences the final external variable, participation in a professional network.

Walker (1969) discussed the role that communication networks play in his early study of policy adoption. Early on, he and Grupp and Richards (1975) noted that “specialized communication networks” were quickening the rate of policy diffusion. Many researchers have acknowledged the impact that both professional and social networks have on the diffusion of policy (Mintrom and Vergari 1998). McNeal et al. (2003) found that state officials' involvement in professional networks was an indicator of e-government innovation. The model uses the city’s participation in the Public Technology Institute (PTI) to measure its professional network participation.

3: RESEARCH DESIGN AND HYPOTHESIS

The dissertation has argued about technology's role and how it affects how humans govern, the change over time from NPM to a technology-driven DEG model. Using a time series approach is a well-documented way of studying diffusion. Berry and Berry (1990) first used event history analysis (EHA) in their paper examining state lottery adoptions. The unit of analysis is state-year. The outcome variable coded as 1 if a state adopted the policy in a given year and 0 otherwise. States that adopt the policy drop out of the data in years after it is adopted. The analysis can estimate parameters on state-level and time-varying covariates. Boehmke (2009) notes that the standard approach to modeling policy innovation at the state level for over a decade is the use of EHA.

EHA has proved to be a fruitful way to study the diffusion of a single policy over time, however, this analysis examines multiple technologies and the impact that a range of independent variables have on that adoption. Like the work of Boehmke et al. (2020), this research attempts to move beyond empirical analyses of single policies to analyze a more comprehensive set of technologies adoptions and their inferred diffusion networks. Mallison (2020) describes the importance of pushing diffusion research towards larger-N studies and using new methods to extend testing diffusion boundaries. He notes that these methods are pushing diffusion research in a new direction. Mallison (2020) examined over 500 papers dealing with diffusion models and found that none of the models represented local governments and technology policy. He also offers a critique of the research to date in that a large number of the studies examined "recycle Berry and Berry's original lottery model" (p. 13). The work of Maggetti and Gilardi (2016) stresses a similar approach in stressing the need to create "original, innovative research designs instead of the replication of widely used templates" (p. 104). The intent here is that this research represents just that, an original and innovative approach to studying technology diffusion over time.

The dissertation has outlined the literature to date. The following section takes this literature and conceptualizes it into a testable empirical model regarding some of the governments' critical characteristics that affect adoption of electronic government technologies. This dissertation argues that this analysis does look at multiple technologies over a broad time frame across multiple geographies. It also addresses shortcomings that Mallinson (2020) found in that it pushes diffusion research towards analysis with larger-N values offering new means to testing diffusion dynamics. This chapter consists of hypothesis development, an overview of the variables used, and the research design methods.

3.1 Hypothesis Development

Technology has become an essential part of everyday life for a majority of citizens. The application of new information and communication technologies in the form of the Internet, automation tools, and mobile devices within the public sector has brought substantial advantages. Three main research questions emerge: *How are specific technologies adopted, how does their implementation spread over time, and what are the impacts of external versus internal determinants on implementation?*

This research is interested in how digital governance at the local level has spread governments over time. While there has been research on the spread of single applications of digital governance over time, such as the use of government websites or social media, there has not been a comprehensive look at the spread of multiple technologies across an extended period. Three types of interactions between citizens and their government emerge that influence technology adoption over time. These are primarily one-way interactions in wave 1.0 and opportunities for two-way interactions in government 2.0 and co-production in open government. It is these that influence the dissertation's research questions.

Early on, governments focused on technologies that improved the transparency of government operations (posting meeting minutes online), ways to contact the government (email), and other self-service options (find property information using an online web map). They then moved to make paying bills more accessible and more efficient (online bill pay). Generally, these technologies facilitated one-way interactions. However, technologies like email and online bill pay are initiated by citizens and facilitate two-way communication between citizen and their government. As a result, these technologies would evolve, and new ways to interact with governments emerged. These technologies, typically referred to as social media technologies, focused on the potential for providing increased two-way communication between government and citizens. Again this evolved into more sophisticated technologies like open data and data portals for citizens to access, consume, and analyze government data directly. Open-data initiatives make government data open and machine-readable to empower citizens to make their own decisions and conclusions about government operations. It also intersects with the literature on co-production as citizens use this information to build their applications and find uses for the information to improve government services.

Diffusion theory is used as a theoretical framework to examine the spread of multiple digital government applications of technology over time and space (Rogers 2003, Eyestone 1977). This dissertation examines internal and external determinants of adoption (Berry and Berry 2018) and operationalizes these determinants using social, political, economic, and geographic variables. These variables are then examined over three periods (2005, 2010, and 2015) to see how digital governance has spread within governments in the United States. Data was mined regarding electronic government technology from the front pages of 231 government websites during each of these periods. The 231 governments are chosen based on their population. The cities represented the largest cities in the United States in 2015 by population.

The dissertation's research uses nine hypotheses to test the diffusion of electronic government technology innovation over time. The conceptual framework and review of the literature are the basis for the study's hypothesis. The hypothesis tests the diffusion of digital governance over time based on their nine sub-factors. The prior research informs how these sub-factors fall within larger factors and impact electronic government diffusion.

Advances in methodological sophistication of event history analysis have allowed for external and internal determinants of policy choices to be examined simultaneously (Berry and Berry 1990). However, Shipan and Voldan (2012) find that the literature on diffusion forces too often a simple count of the number of states bordering a particular state that has adopted a specific policy. Berry and Berry (2018) updated their modeling. Still, they found that diffusion is a function of the motivations of key political actors within government, the amount of resources available to the units for overcoming obstacles to adoption, the interaction with other policies already adopted by the units, and external influences (Mallison 2020). The dissertation has built the empirical model around this concept of internal and external determinants. Like Berry and Berry's (2018) Unified Model of Policy Diffusion, this dissertation unifies the city's internal characteristics and external influences.[3]

The model includes two external determinants, participation in the collaborative technology network as well as geographic proximity. Internal are demographic, economic, and political.

[3] Berry and Berry (2018) examined external and internal at the state level this dissertation adapts this based on the city level work Ho (2002), Mossberger et al. (2013), Zavattaro et al. (2015), Grimmelikhuijsen and Feeney (2017) and Young (2020) to name a few that look at technology and diffusion at the city level.

These characteristics, which are internal to the city, examine educational attainment, race, median age, population size, and the number of individuals employed by a given area's technology sector. The model also examines the role that government revenue (slack resources), median income, and the form of government have on policy diffusion. The digital governance and diffusion literature inform the internal and external determinants. The following table summarizes each factor, sub-factor determinant, and how they are tested and provides several examples from the literature.

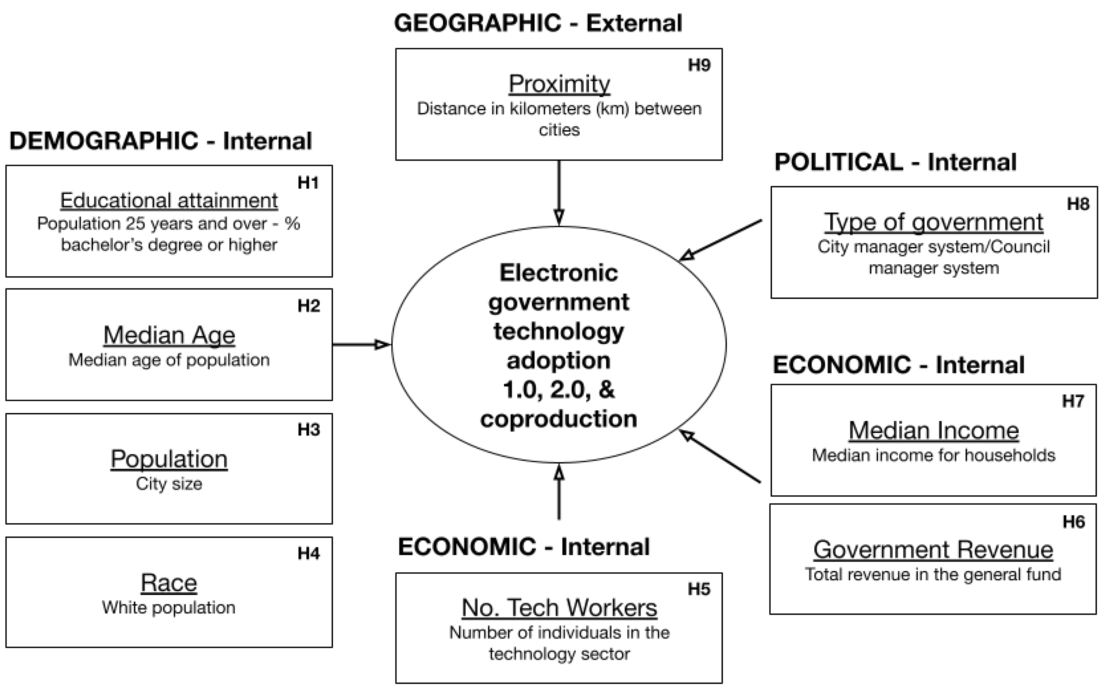
Table 1 Hypotheses on Factors, and Sub-factors of Technology Adoption

Factor	Sub-Factor	Determinant	Hypothesis	Examples
DEMOGRAPHIC	Educational attainment	Internal	H1: Higher levels of education of residents will lead to the adoption of technologies over time by the government.	Reddick (2005), Chatfield and Reddick (2017), Jaeger (2003), Norris and Reddick (2013), West (2004), Walker (1969), Tolbert et al. (2008), Young (2020)
	Median age	Internal	H2: Lower median age of residents will lead to the adoption of technologies over time by the government.	Bonsón et al. (2012), Dawes (2008)
	Population	Internal	H3: Cities with larger populations will be more likely to adopt electronic government technologies.	Thorsby et al. (2017), Chatfield and Reddick (2017), Young (2020)
	Employment in the technology sector	Internal	H4: Larger number of individuals employed in the computer and mathematical occupations will lead to the adoption of technologies over time by the government.	Brown (2005)
	Race	Internal	H4: Cities with larger white populations will be more likely to adopt electronic government technologies.	Norris (2001), Mossberger, Tolbert, and Stansbury (2003), Ho (2002)
ECONOMIC	Government revenue	Internal	H5: Higher government revenue (annual budget) will lead to the adoption of technologies over time by the government.	Ganapati and Reddick (2012), Jun and Weare (2011)
	Median income	Internal	H6: Higher median income of residents will lead to the adoption of technologies over time by the government.	Tolbert et al. (2008), Walker (1969), Tummers and Rocco (2015), Norris and Reddick (2013), Young (2020)
POLITICAL	Form of government	Internal	H7: Governments with council-manager form will be adopters of technologies over time by the government.	Moon (2002), Jun and Weare (2011), Grupp and Richards (1975)
GEOGRAPHY	Proximity	External	H8: Being closer to a city adopting electronic government technologies will likely adopt the same technologies.	Lev-On and Steinfield (2015), Shadbolt et al. (2012), Lutz (1986), Berry and Berry (1990)

The primary research questions of interest are how internal and external forces influence electronic government technology adoption. Of interest are what technologies are present in 2005, 2010 and 2015. Which governments are early adopters (have x technology in 2005 versus 2015)? How quickly do governments adopt over the ten years? The research arrives at the following testable hypotheses based on the conceptual framework and existing literature on why they influence adoption.

In turn, these factors, sub-factors, and determinant type (internal or external) constitute the conceptual framework, which informs the dissertation's empirical model. The goal is to use this framework to provide insight into electronic government technology adoption over time. The following is the conceptual framework for the research:

Figure 2 Conceptual Framework



The framework provides an overview of the analytical setting that the dissertation discusses in the subsequent chapters. From the literature, the dissertation develops the following nine hypotheses to test using a mixed-methods approach:

H1: Higher levels of education of residents will lead to the adoption of technologies over time by the government.

H2: Lower median age of residents will lead to the adoption of technologies over time by the government.

H3: Cities with larger populations will be more likely to adopt electronic government technologies.

H4: Cities with larger white populations will be more likely to adopt electronic government technologies.

H5: Larger number of individuals employed in the computer and mathematical occupations will lead to the adoption of technologies over time by the government.

H6: Higher government revenue (annual budget) will lead to the adoption of technologies over time by the government.

H7: Higher median income of residents will lead to the adoption of technologies over time by the government.

H8: Governments with council-manager form will be adopters of technologies over time by the government.

H9: Being closer to a city adopting electronic government technologies will likely adopt the same technologies.

The hypothesis addresses four key factors: demographic, economic, political, and geography. These are traced back to the foundational work of innovation by Walker (1969) in examining the determinants of social, political, and economic variables. The research uses demographics in the role of social. Further, these factors contain sub-factors that flesh out the nine hypotheses. The nine sub-factors get separated into determinant categories (external and internal). The role of internal and external determinants is a primary contribution to the diffusion literature by Berry and Berry (1990) on how policy innovations occur. This dissertation and its empirical modeling have moved past discretely studying internal and external predictors of policy adoption and have outlined an integrated unified approach to test digital governance diffusion across numerous electronic government technologies. These determinates should be important factors in understanding and predicting digital governance as measured by technology policy adoption based on these foundational works.

3.2 Data Sources

The phase of digital governance and its associated technologies make up the dependent variable in the model. The independent variables represent internal and external determinants informed by the diffusion literature. The data of these variables are from a range of different sources. The revenue (slack resources) data is from The Government Finance Database from Willamette University. The database contains all of the census data from 1967 to the present. The Fiscal Policy Space (FPS) is the source for the form of government. The FPS is sourced from the University of Illinois at Chicago's College of Urban Planning and Public Affairs. The dataset aggregates a range of sources from 100 of the largest cities in the U.S. The form of government is also updated through data mining of existing websites to update the data to 2015.[4] The analysis then combines this with data from the US Census and the Bureau of Labor Statistics, as indicated in Table 2.

The model's primary dependent variables are the number of technologies each government has adopted over the three examined periods by the technology grouping (1.0, 2.0, and 311 and open data portals) and the sum of all technologies across groupings adopted by a government in a given period (total). The explanatory variables used are related to the government's socio-demographic variables (population size, race, median age, educational attainment, median income, and the number of individuals employed in the technology sector). In addition to these, the study also examines the role that geographic proximity has. The analysis examines the distance between governments for the three technology groupings at each of the three periods.

The table below outlines the complete list of variables and their data sources. This table represents how the model operationalizes the variables.

[4] The FPS data can be downloaded here: http://www.srl.uic.edu/fiscalpolicyspace

Table 2 Variables and Data Sources

Independent variables		
Measure	Variables	Data source
Geographic proximity	Distance between governments with electronic government 1.0 technologies	Self-generated
	Distance between governments with electronic government 2.0 technologies	
	Distance between governments with electronic government co-production technologies	
Community characteristics	Median age	US Census
	Population (logarithm)	US Census
	Educational attainment	US Census
	Median income (logarithm)	US Census
	Percent white	US Census
	Revenue per capita	Government Finance Database
	Form of government	Government Finance Database
	Number of employees in the technology sector	Bureau of Labor and Statistics

Dependent variables		
Measure	Variables	Data source
Electronic government 1.0	Online bill pay link, Meeting minutes' link, Email link, GIS/Interactive map	Data mining
Electronic government 2.0	RSS link, Twitter link. YouTube link. Facebook link	Data mining
Electronic government 311/Open Data Portal	Open data portal, 311	Data mining

3.3 Methods and Research Design

This analysis breaks the electronic government technologies into three broad categories (1.0, 2.0, and 311 and open data portal), each of these categories then consists of ten technologies that predominate government technology offerings to capture the multiple phases of technology adoption's differing types. These technologies represent trends in more substantial technology innovations. Governments adopt technologies at different points in time. Adoption can be for various factors, whether political, economic, or social (Berry and Berry 2018).

Data for eleven variables across three periods, 2005, 2010, and 2015 for the 231 largest urban governments in the United States, was collected. The 231 governments represented the largest urban areas in 2005 based on population. Most of the research to date has analyzed electronic government initiatives at the state level (West 2004, Welch and Pandey 2006, Ganapati and Reddick 2012) or the national level (Moon 2002, Wang 2001, Yang and Kathe 2005, Bonsón et al. 2012, Oliveira and Welch 2013, Lev-On and Steinfeld 2015). The work of Mossberger et al. (2013) is the most like this dissertation's research design. In that study, they selected the 75 largest cities in the United States and examined them between 2009 and 2011. That analysis explicitly focused on interactive tools utilized. Mossberger et al. (2013), Moon (2002), Wang (2001), and Ho (2002) have all used the city population to determine their samples. Ho (2002) and Moon (2002) also find that it is more probable that larger cities are first adopters of electronic government initiatives and often have more sophisticated websites than smaller governments. Researchers also find those larger cities more likely to use technology to engage their citizens (Yang and Kathe 2005).

The Wayback Machine (http://archive.org/web/) is used to collect data for these three periods. The Wayback Machine is a digital archive of the internet. The machine allows users to see saved versions of a website on specific dates and years. The Wayback Machine has archived web pages since 1996. The website archives a website image approximately every two weeks or, in some instances, months; each time, it takes a snapshot of the code at that time. The Wayback Machine captures and archives content that would otherwise be lost whenever a website is revised or removed. The goal of the machine was to archive the internet in its entirety. The Wayback Machine is used to collect historical information from government websites. The dataset is built by gathering cached web pages for each of the three periods and then tabulating the technologies present.

The dissertation classifies electronic government technologies into three categories. Each technology requires differing levels of technical sophistication and political and financial capital to adopt. For example, Twitter or Facebook have low technology sophistication thresholds and relatively low financial cost, but getting political buy-in may be more difficult. The sophistication of creating and implementing a data portal for serving and providing access to government-collected data to encourage co-production between citizens and government has a higher threshold than 2.0 technologies. Open government data portals require higher technological sophistication to implement and support and higher financial and political costs. The thought is that quick to adopt technologies, like Twitter and Facebook, require less political and financial investment than a 311 system or an open government data portal.

This dissertation's research builds a model for electronic government 1.0, 2.0, and co-production using data collected at the government level. The model separates this analysis from the previous ones in that it examines government at the local level (versus nation or state) and within the United States. Previously, Walker (1969), Gray (1973), and Berry and Berry (1990) used the American states as the social system in which to apply their diffusion models. The dissertation examines it at a more micro-level during multiple periods. The hope is that this will provide an understanding of this evolution across time and space and is a unique contribution to the public administration literature.

The approach is similar to the approach taken by Millard (2018) in their classification of technology evolution. In their research, they identified the stages as E-government, T-government, I-government, and O-government. E-government deals with the application of ICT to existing government systems. This dissertation is classifying it as 1.0. T-government or transformative government is where ICTs are used to transform the government system. 2.0 technologies are indicative of this stage. For example, online bill pay translates into arguable leaner, more efficient government or, as Millard classifies, I-government where ICTs enable the government to do more with less. The final wave in Millard's research is an O-government or open government where ICTs, like open data portals, are used to open up governments to collaborate.

The approach builds on the work of Millard. It also provides explanatory power to understanding the parts (1.0, 2.0, and 311 and open data portals) and their prevalence to provide insight into electronic government diffusion patterns. It is also a reaffirmation of the geographically driven diffusion theory forwarded by Berry and Berry (1990). Finally, the dissertation has noted applying this technique in practice to other government entities (school districts, county government, local police departments, for example).

Figure 3 Urban Areas Studied[5]

The dissertation selects urban places in America based on population. Studies by Norris and Moon (2005) and West (2004) have found that local governments generally lag behind other government levels regarding information technology implementation. However, there is evidence that large urban places have been leaders in technology adoption (Moon 2002, Ho 2002, Jun and Weare 2011, Mossberger et al. 2012). In addition, these studies have pointed out that the nation's largest cities are more likely to reveal innovative practices surrounding technology adoption and civic engagement than their counterparts.

Based on the literature, the dissertation groups electronic government technologies into three phases: 1.0, 2.0, and 311[6]/Open Data Portal. Older technologies like online bill pay, the posting of meeting minutes and agenda of government meetings online, providing ways to contact the

[5] A comprehensive list of all the urban areas included is found in Appendix E: List of Urban Areas Studied.

[6] 311 is a dedicated phone number used in many cities in the United States and Canada. The number unlike 911 provides access to non-emergency services.

government with concerns, and providing online interactive maps for looking at property information represent 1.0 technologies. These are technologies that inform residents but do not offer much in the way of interaction. Cities use these technologies typically to provide citizens information. Phase two outlined as electronic government 2.0 technologies are more sophisticated and represent the next phase of government adoption technologies. The presence of an RSS (rich site summary) link[7], Twitter link, YouTube link, or Facebook link on the government website's front page represents 2.0 technologies. Their presence illustrates that the city, at a minimum, offers these technologies. The presence does not give a sense of interaction with just a simple link on the level of engagement or how built out these technologies are, but it does indicate if the city uses them at some fundamental level. The technologies show that these cities are looking to increase interaction and back and forth communication with citizens. Finally, the dissertation examines 311 and Open Data Portal technologies, typified by increasing complexity and sophistication compared to 1.0 and 2.0. Like with 2.0, this research does not know the level of interaction. In the case of open data portals, the measure of presence shows that they exist, however, it does not measure how much data is in them. Here the presence is just noting that the government has an open data platform. It is the same for 311 systems, the data gathering shows that they have a way for citizens to report problems but does not inventory the number of issues reported or cleared, the type of problems, or if they respond to them. Both of these technologies also offer the prospect of co-production, where citizens take an active role in improving government efficiency or reporting issues, however, this is also not captured in the data collection and does not measure if this is happening. The method captures these platforms' presence in the city’s website, but it does not measure co-production activity.

[7] RSS or Rich Site Summary utilizes standard web feed formats to create a feed that typically includes: blogs, news headlines from web sites, along with audio and video as well. The RSS output is typically referred to as a “feed” and summarizes these sources as a text based output.

In addition to the technologies, this research maps each urban area over time to get a spatial understanding of how electronic government technologies diffuse over time. GIS is heavily used in geography, environmental science, and engineering but is less so in the social sciences. The mapping will lend unique explanatory power in understanding how electronic government technologies diffuse over time. This diffusion will provide insights into how and why governments adopt these technologies.

This dissertation examines these technologies across multiple periods to operationalize electronic government technologies that are diffusing. A summary of these variables is in the following table, which indicates the grouping of the ten electronic variables collected:

Table 3 Electronic Government Technologies and Phases in Cities (2005 – Present)

Variable Name	**Phase**
Online bill pay link	1.0
Meeting minutes' link	
Email link	
GIS/Interactive map	
RSS link	2.0
Twitter link	
YouTube link	
Facebook link	
Open Data Portal	311/Open Data Portal
311	

Since each city uses a slightly different vocabulary when referring to the electronic government technologies on its landing page, the research captures commonly used phrases as part of a data dictionary of electronic government technology synonyms. The "contact us" variable (email address) or social media technologies (Facebook, Twitter, YouTube) is used uniformly across all the cities. A technology was marked present during the corresponding year if one of these words was present. Variables are collected through mining the HTML[8] of each landing page for

[8] HyperText Markup Language (HTML) is the standard markup language for creating web pages and web applications.

231 governments for the three years and searched for the key terms. The analysis searches on these key terms and listed in the table below on the HTML versions of the web pages that allowed for predictability and standardization across the different years for the government landing pages.

Table 4 Data Dictionary Used for Content Analysis

Variable	**Synonym**
Online bill pay link	Make Payments, Pay, ePay, Bill, Online Payments
Meeting minutes' link	Agenda, Minutes, Meeting, Report
Email link	Contact us, Provide feedback
GIS/Interactive map	GIS, Geographic Information Systems, Maps Online, Map
RSS link	xml, .rss, RSS
Twitter link	Twitter
YouTube link	YouTube
Facebook link	Facebook
Open Data Portal	Open Data, Open [City Name], Open Government
311	Report an Issue, Report, Request help with, Report a problem, Fix it, Engage [City Name], See Click Fix, Citizen Service Request, Request for Service, Report a Concern

When transformed to panel data, the dataset has 693 observations of 19 variables, the most extensive electronic government analysis to date, in addition to these mined variables, the analysis uses United States Census data related to socio-demographics. The inclusion of socio-demographic variables is to understand if income or educational attainment predicts electronic government adoption, or if the social and economic composition of a city is a determinant in electronic government technology adoption.

The analysis collects historical archived websites for 2005 and 2010 using the Wayback Machine, a digital archive of the World Wide Web, and other information on the Internet created by the Internet Archive, a nonprofit organization, to assess the state of the landing pages. For 2015 the existing website at the time is logged as the government's landing page. Each of the ten mined variables collected was coded 0 = no or 1 = yes as nominal level variables.

The analysis uses fixed-effects regression for modeling the impact community characteristics have on predicting technologies adopted by governments over time. The fixed-effects model is a regression model in which groups (in this instance, urban area) are fixed (non-random). Fixed-effects modeling is common in economic analysis, however, it is used here to correlate the instance of DEG policy adoption using panel data to compare how a change in time (year) has on adoption rates.

Panel data allows us to control for variables that change over time. The research is interested in accounting for differences across the urban areas in the analysis. The analysis groups them according to observed electronic government technologies or socio-demographic variables by year. A benefit of this approach is how it addresses heterogeneity within the sample.

This method addresses heterogeneity by deriving estimates for predictors, controlling for other predictors, by comparing the presences of a specific phase of technology adoption (i.e., 1.0). The model will take individual years for each urban area and compare the various phases with the predictors. For example, it takes Chicago in 2005 and looks at the number of 1.0 technologies and compares it to independent variables like median income. The model analyzes three time periods as well as all 231 urban areas. To accomplish the fixed-effects modeling, the analysis uses the "plm" package in R. The package allows for both random and fixed effects estimates of static linear panel data models.

Fixed-effects (FE) is a statistical method used to analyze the impact of variables that vary over time. FE examines the relationship between the predictor and outcome variables within an entity (city). Each city has characteristics that may or may not influence the predictor variable (electronic government technology 1.0, 2.0, co-production). When using FE, the assumption is that something within the city may impact or bias the predictor or outcome variable, and the analysis needs to control for this. The control is the rationale behind the assumption of the correlation between the city's error term and predictor variables. FE removes the effect of those time-invariant characteristics making it so the analysis can assess the predictors' net effect on the outcome variable. In addition to this the model also factors the year of adoption. The next chapter outlines the findings of the empirical modeling and testing and discusses the results.

4: RESULTS AND DISCUSSION

This chapter examines the effects that community characteristics have on electronic government technology and DEG within the context of diffusion theory and the prospect for co-production of technology between citizens and government at the city level.

4.1 Descriptive and Exploratory Analysis

Table 5 Change in Number of Governments with Given Technology (2005-2015)

Variable	# in 2005	# in 2010	# in 2015	Increase (n)	% change 2005-15	% adoption 2015
Online bill pay link	138	201	229	91	65.9%	99.1%
Meeting minutes' link	189	215	230	41	21.7%	99.6%
Email link	191	212	229	38	19.9%	99.1%
GIS/Interactive map	130	182	217	87	66.9%	93.9%
RSS link	8	87	145	137	1712.5%	62.8%
Twitter link	0	102	211	211	N/A	91.3%
YouTube link	2	64	179	177	8850.0%	77.5%
Facebook link	3	96	215	212	7066.7%	93.1%
311	116	170	218	102	87.9%	94.4%
Open Data Portal	10	14	78	68	680.0%	33.8%

Most of the cities by 2015 have online bill pay (229), meeting minutes (230), and email feedback (229). Interestingly RSS subscription opportunities lag (145). By 2015, Social media is nearly uniformly adopted, Twitter (211), and Facebook (215). 1.0 technologies grew slower but that was often the case because they were present in 2005 where many of the 2.0 technologies were not. Social media technologies for instance expanded rapidly, at 8,850% for YouTube and 7,066% for Facebook. Feedback opportunities using 311 systems are similar and 218 cities adopted the technology in 2015. Predictably the more recent and more challenging to implement open data portal technology has the least amount of adoption with only 78 cities in 2015.

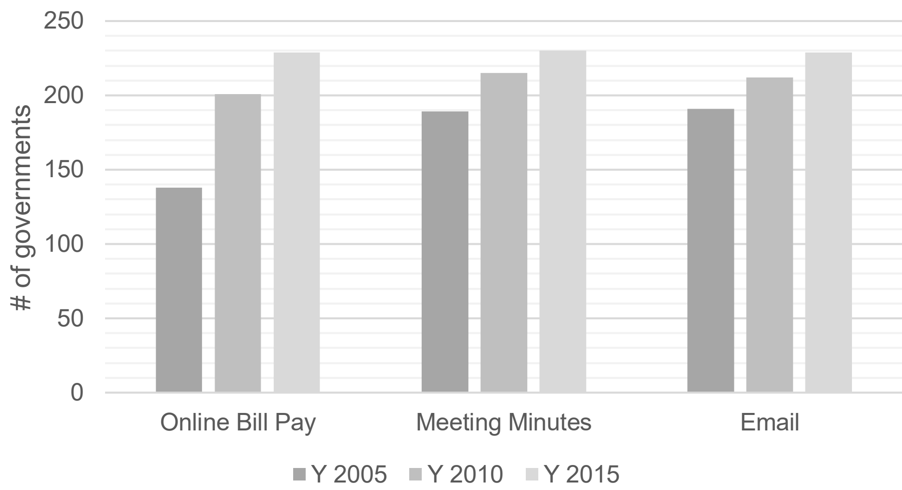
An examination of the electronic government data collected for this study shows that technology is indeed changing over time and, in many cases, rapidly. In some instances, it was rare for governments to have a specific technology on their front page in 2005, and 10 years later, it has near-universal adoption. The table 6 outlines the change in the model's 11 independent variables.

There has been a dramatic change in social media use from 2005-2015. Facebook and Twitter each rose by over 90% in their prevalence in America's largest city governments.[9] Some of the latest technologies like 311 and Open Data Portal platforms have also shown a marked increase of adoption (311 at 94%).

While not all governments examined adopted electronic government technologies, the analysis finds that nearly all (93-99%) of governments had adopted electronic government 1.0 technologies, again, the most significant gains came in using social media technologies (Twitter, YouTube, and Facebook). The figures 4-6 show just how quickly the adoption of electronic government technologies was occurring. Within ten years, there was rapid growth and especially within social media technologies (Twitter, YouTube, and Facebook).

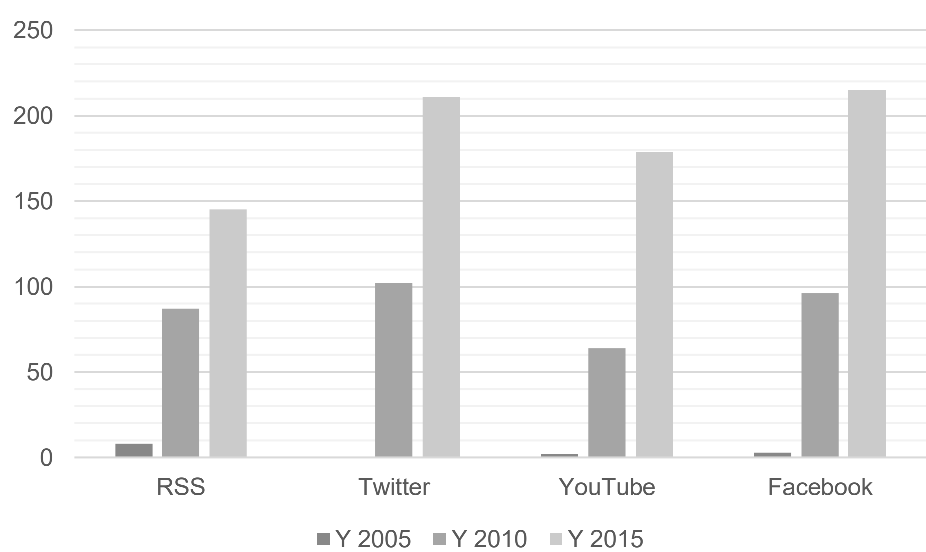
[9] Twitter was launched on 4/5/2006 and Facebook on 2/4/2004.

Figure 4 Change in Electronic Government 1.0 Technologies (2005-2015)



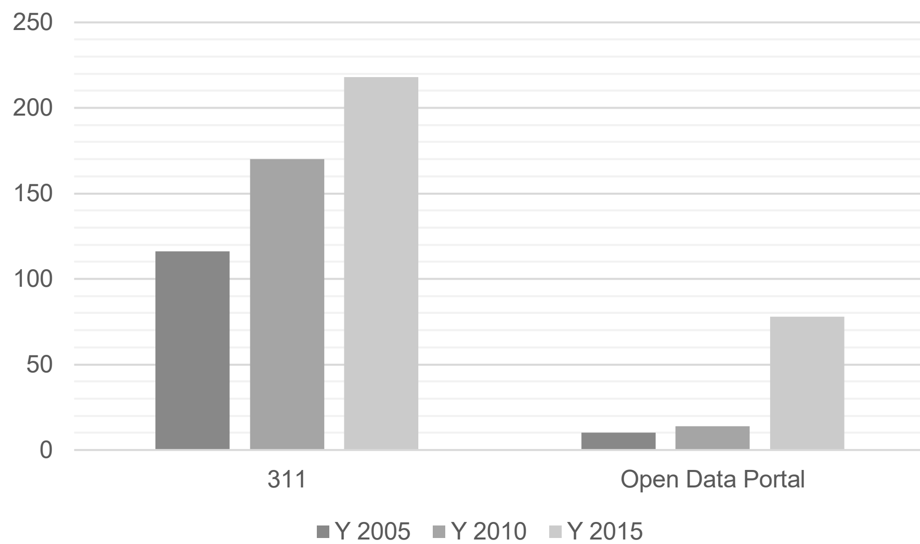
All of the electronic government 1.0 technologies increased in prevalence over time. None of the technologies is 100% implemented in the cities, according to the data. Still, the study found that electronic government 1.0 had the highest adoption rates, ranging from 93-99% of the largest governments.

Figure 5 Change in Electronic Government 2.0 Technologies (2005-2015)



One of the starkest changes is the use of social media technologies. These 2.0 technologies have seen a dramatic increase between 2005 and 2015. Notably, the use of Twitter and Facebook has increased by 90.5 and 92.5%, respectively.

Figure 6 Change in Electronic Government 311/Open Data Portal Technologies (2005-2015)



311 and Open Data Portal platforms are present in each of the three-time periods. Even the more technologically sophisticated open data portal was present in 2005 in a small number of cities (10), albeit not in the same state as implementations in 2015. Both 311/report issue systems and open data portals increased in prevalence from 2005 to 2015. 311 and open data portals require the most technological sophistication to set up. Regardless of this investment, it is evident that cities are investing the resources in these technologies. 311/report issue systems were present in nearly every government in the sample population by 2015 (93.5%), illustrating this technology's impact. While open data portals made a dramatic increase from only 4.5% of governments in 2005 to 34.5% in 2015. 1.0, 2.0, and Co-production technologies are diffusing over time based on an initial examination of the data collected in this study. Next, the paper

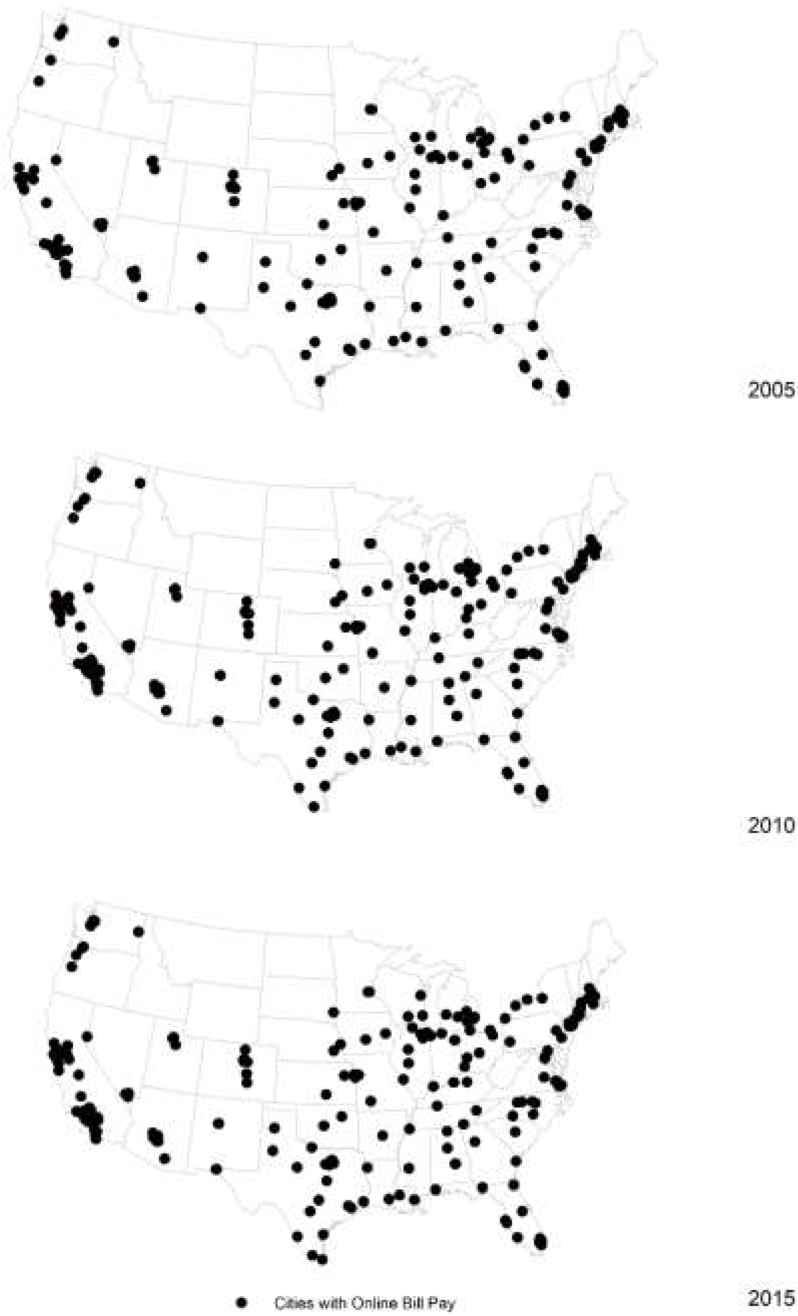
turns to a more in-depth analysis using geospatial analysis or GIS to better understand the spatial dimension of electronic government technology adoption.

4.2 Role of Geographic Proximity in Select Places

Before performing some geostatistical analysis on clustering and dispersion, the analysis visually sees how electronic government technologies have changed over time. The following series of geospatial maps show these technologies over time and space. The maps were created using the tabular data and then mapping them in geographic space for the entire United States.

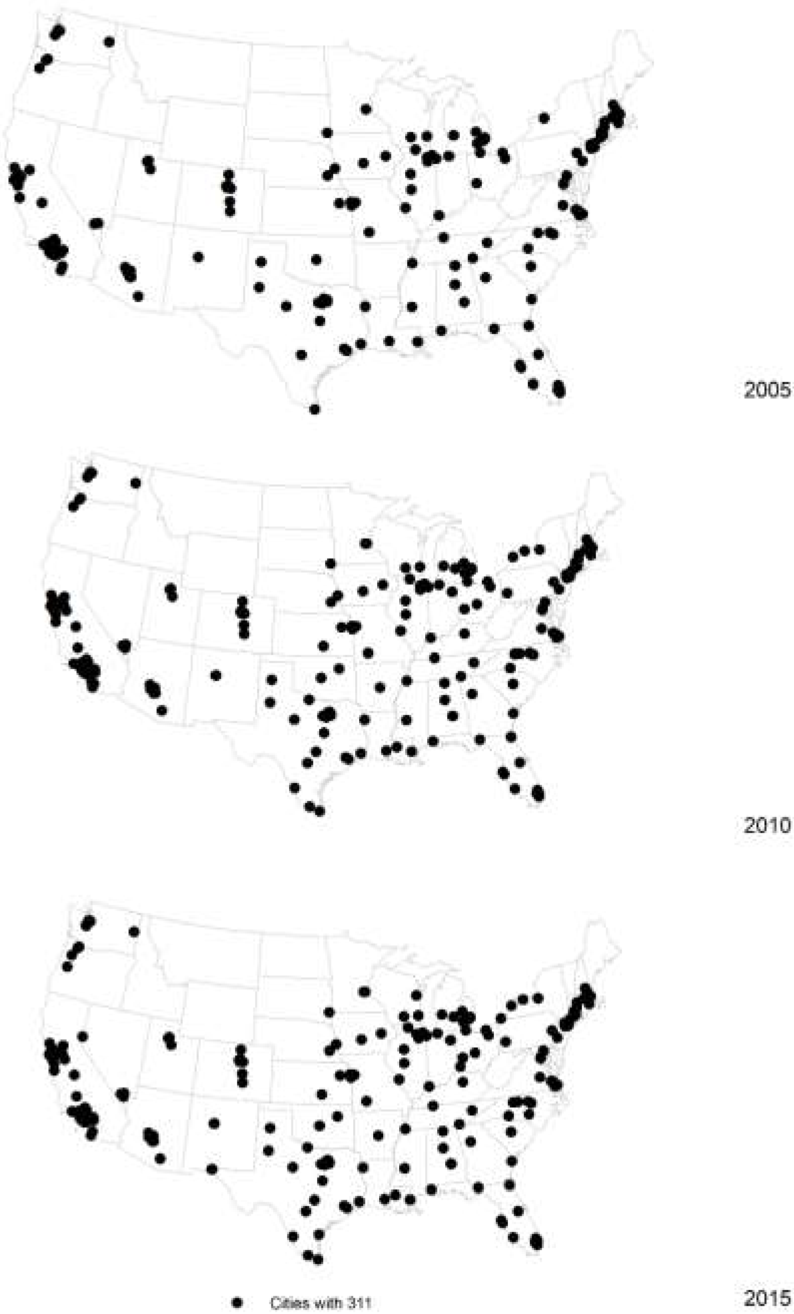
A geographic information system (GIS) is a system that utilizes geography to collect, index, analyze and present spatial information and data. While the electronic government data was collected as a table using GIS, the analysis can link those attributes to a geographic location. By linking the electronic government data to a geographic location, the dissertation examines different spatial measures to look for patterns. Near analysis and nearest neighbor analysis, as well as a simple spatial distribution of technology, provides insights into how electronic government technology might diffuse. The following maps show the change of certain technologies over time. The first map shows that particular technology in 2005, followed by that technology in 2010, and the final map shows it in 2015.

Figure 7 Online Bill Pay 2005 to 2015



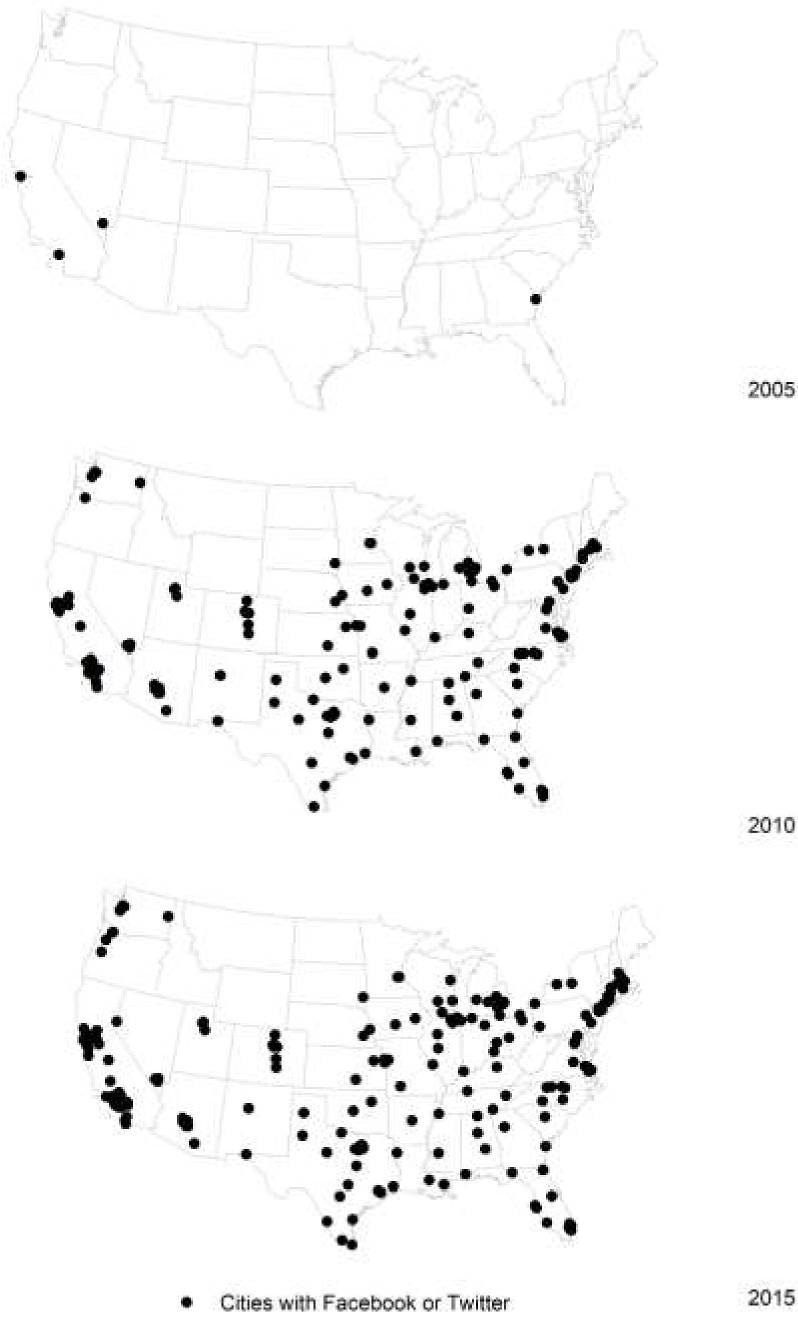
Online bill pay is an electronic government technology that was adopted early on — primarily motivated by the opportunity to make it easier for citizens to pay bills for government services (parking passes, water bills, for example) and increase government revenues. The analysis shows an increase in the number of governments deploying online bill pay from 2005 to 2015.

Figure 8 Use of 311 Systems 2005 to 2015



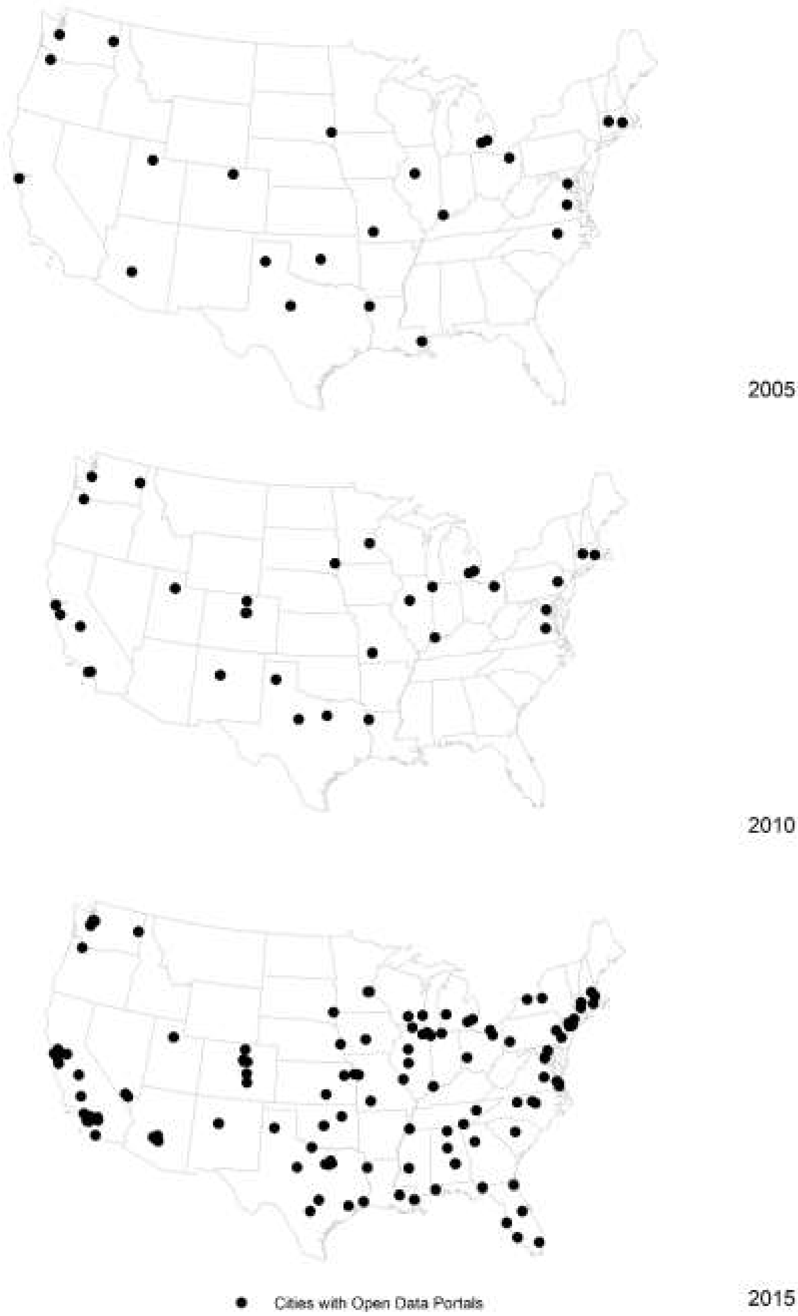
Like online bill pay, 311 report issue systems were adopted early by governments. This technology allows citizens to report non-emergency issues like graffiti, an out streetlight, or a pothole. Like online bill pay, there is an economic incentive for governments, allowing citizens to do some of the reporting and monitoring of the community to generate increased efficiencies.

Figure 9 Use of Facebook and Twitter 2005 to 2015



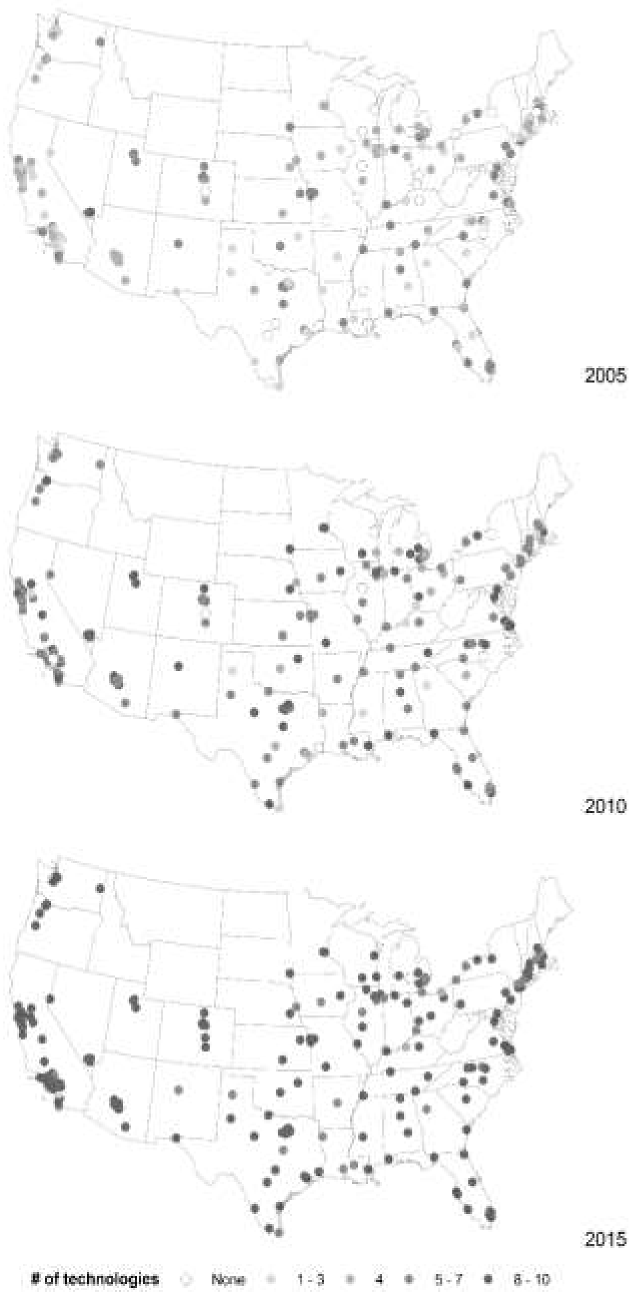
The geographical analysis looks at the combination of two commercial tools, Facebook and Twitter. These technologies exhibited rapid growth going from being only in 4 cities in 2005 to 239 in 2015. These technologies allow citizens to interact directly with their government about a range of issues.

Figure 10 Use of Open Data Portals 2005 to 2015



The ability to download and access public data started relatively modestly in 2005 but has become more sophisticated (web services, direct connections, searchable databases) and widespread. These tools often require technical expertise and commitment by governments to offer data in an accessible and readable format for their citizens to use. Given this investment, 68 of the governments currently have an open data portal available to their citizens.

Figure 11 Overall Technologies 2005 to 2015



The maps above give us a better understanding of adoption over time. Visually the intensity of governments using more and more of the electronic technologies examined increases from 2005 to 2015. The mean number of technologies in 2005 was 3.95, in 2015, it is 8.84. The number of technologies in 2015 intensifies, particularly in the governments on the west coast.

The discussion of these maps and the geographic distribution of electronic government technologies has mainly been qualitative up to this point. They serve as a similar function as descriptive statistics to give us a basic understanding of what is happening spatially. Next, the dissertation gets into more depth using quantitative measures, specifically some geospatial analysis, initially looking at the distance between governments that have adopted a particular level of technology. The geographic analysis is done using the near function. The near function computes the distance from each point to the nearest point. In this analysis, the centers of the 231 cities represent the points.

Table 6 Distance between Electronic Government Technologies (2005-2015)

Electronic government technology phase	**2005**		**2010**		**2015**		**Δ 2005-2015**
	km	N	km	N	km	N	km
1.0 technologies	65.9	196	65.5	215	64.6	215	-1.3
2.0 technologies	38.0	9	86.8	137	65.7	210	27.7[10]
311/Open Data Portal	86.6	117	69.7	170	67.4	205	-19.2

The above table shows the average distance between large city governments with one or more specific technology in a given period. This analysis removes Alaska and Hawaii, given the long distance from the other urban areas in the sample. The analysis shows, for 1.0 technologies, modest decreases in the distance over time from 0.4 kilometers from 2005 to 2010 and 0.9 kilometers from 2010 to 2015. A total decrease of 1.3 kilometers between cities with more than one electronic government technology provides evidence that they have become more concentrated and diffusing.

The nature of the 2.0 technologies makes it more nuanced when supporting a case for diffusion. The small sample cities in 2005 are densely clustered, with only an average distance of 38.0 kilometers. This distance jumps to 86.8 kilometers in 2010 as the number of cities with 2.0

[10] Across the study the analysis sees 2.0 technologies being adopted later. If the model use this methodology and apply it to 2010 (versus 2005) there is a decrease in distance, -21.1 which is consistent with other technologies (distance decreases over time).

technologies increases to 137. Perhaps a more accurate way of examining diffusion for 2.0 technologies is to compare similar samples. 2010 and 2015 arguably provide a more accurate picture with their larger sample sizes. It also may be illustrative that this is when most governments are adopting it. They might not be neighbors, but the analysis shows the filling of the map overall. Also, the decrease in distance between these periods is significant. There is a drop from 86.8 kilometers to 65.7 kilometers or an average of 21.1 kilometers between 2010 and 2015. The drop in the distance shows significant diffusion in 2.0 technologies from 2010 to 2015 in large American urban areas.

Examining co-production technologies provides similar support for the technology diffusion hypothesis. There is a drop in the mean distance in each of the years studied in the cities examined. Overall there is a decrease in the mean distance between 2005 and 2015 for large American urban cities implementing co-production technologies by an average of 19.2 kilometers. Like in each other instance, the analysis indicates that technologies are diffusing over time over the 10-year study period.

The dissertation runs an additional average nearest neighbor analysis on the data to provide a more in-depth examination of proximity and geography distribution. Clark and Evans (1954) developed the nearest neighbor analysis to analyze the spatial distribution. The method compares the observed average distance between points and their nearest neighbor with the distance expected between nearest neighbors randomly. Simply, the average nearest neighbor calculates the index using the average distance from one feature to its closest neighboring feature. Anchorage, Alaska, and Honolulu, Hawaii, are removed from the sample for the analysis, given its sizeable geographic distance from the rest of the cities in the contiguous United States. The notion is that technologies are dispersed initially and then begin to cluster over time. At first, only several governments were employing certain technologies, but there is higher clustering as more adopt. The Nearest Neighbor Index is the proportion of the Observed to the Expected. The expected distance is the mean distance between neighbors in a theoretical random distribution. An index less than 1 indicates that the pattern exhibits clustering. An index greater than 1 shows that it is trending toward dispersion. The following table is the result of this analysis.

Table 7 Average Nearest Neighbor Analysis Results (distance in kilometers (km))

Technology	**2005**	**2010**	**2015**	**Δ 2005-2015**
All technology				
Observed mean distance	65.63	65.51	65.12	-0.51
Expected mean distance	113.66	108.80	105.89	-7.77
Nearest neighbor ratio	0.58	0.60	0.62	0.04
1.0				
Observed mean distance	66.44	64.54	64.63	-1.81
Expected mean distance	113.38	108.80	105.42	-7.96
Nearest neighbor ratio	0.59	0.59	0.61	0.02
2.0				
Observed mean distance	380.75	86.87	65.61	-315.14
Expected mean distance	389.01	134.87	107.07	-281.94
Nearest neighbor ratio	0.98	0.64	0.61	-0.37
311/Open Data Portal				
Observed mean distance	85.99	69.50	67.54	-18.45
Expected mean distance	146.28	122.00	108.05	-38.23
Nearest neighbor ratio	0.59	0.57	0.63	0.04

The nearest neighbor ratio analysis supports the notion that there is increased clustering over time. There is a decrease in both the observed and expected mean distance in all three technology phases. There is also a decrease over the ten years of 0.51 and 7.77 kilometers for all technology. 1.0 technology use shows a similar clustering pattern with the distance between cities decreasing in both observed and expected by 1.81 and 7.96 kilometers, respectively. The most considerable change observed is that in 2.0 technologies. In 2005 the distance between cities with 2.0 technologies was nearly 400 kilometers apart. Ten years later, the analysis shows distances of 65.61 and 107.07 kilometers in 2015, a change of 315.14 in observed mean and 281.94 in the expected mean distance. The distance between cities with co-production technologies decreased as well. The observed distance decreased by 18.45 kilometers and the expected distance declined by 38.23 kilometers. While interesting and descriptive, the observed or expected mean distance decreases are not convincing because it is the nearest neighbor ratio that matters most in this analysis.

The critical output in this geospatial analysis is the nearest neighbor ratio. Again, if the result is less than 1 there is an indication of clustering; if it is greater than 1 it exhibits diffusion characteristics. The values indicate clustering with a slight move toward becoming more disperse, albeit very small for all technologies. The ratio for 1.0 technologies is similar to a minor change of 0.02. 2.0 technologies show the most considerable change in the ratio with a decrease in the ratio of 0.37. Changing from 0.98 in 2005, a value near 1, which indicates a trend toward dispersion to a value of 0.61 in 2015, shows a clustering of 2.0 technologies (more governments adding 2.0 technologies). Like all and 1.0 technology provisions, 311 and Open Data Portal platforms have similar results, indicating clusters and a slight change toward dispersion; again, the change is minimal (0.04).

The mapping illustrates that technologies adopted by these governments are increasing over time. Ideally, the nearest neighbor ratios under one initially should move towards values over one as adoption becomes dispersed. It is possible, though the nearest ratios decrease as the adoption across the urban areas becomes more widespread. There is a possibility that a larger sample can improve the results, rather than picking governments based on size, the dataset is not a truly random distribution. However, the analysis does reinforce the comparison of the distance between technologies. The analysis also illustrates that the governments are adopting a particular technology phase over time.

The spatial mapping and the comparison in the distance between urban areas with a certain technology clearly show the diffusion of technologies over time. The analysis shows the shortening of distance and the change in observed and expected distances, all decreasing, illustrating a change from dispersed to clustering. However, there are limitations. For the nearest neighbors to increase its explanatory power, increasing the sample size from 231 urban areas would improve the analysis. Nearest neighbor calculates the average nearest neighbor distance index based on the assumption that the points can fall anywhere within the study geography, meaning there are no barriers, and the location of features is independent of each other.

Increasing the sample size has the opportunity to increase the explanatory power of nearest neighbor analysis. The previous literature uses geographic proximity and neighbor status, however, geographic analysis and, specifically, the nearest neighbor is new to the diffusion literature. Mapping the technologies clearly illustrates changes in the adoption of technologies over time and provides a potential technique when examining policy and decision making in other areas – not just electronic government.

4.3 Linear Regression Analysis

The following table lists the descriptive statistics of the independent variables included in the linear regression as well as the fixed effects regression models.

Table 8 Descriptive Statistics, 2005-2015 for Independent Variables

Variable	Median	Mean	Std. Dev.	Min	Max	N
Percent with bachelor's degree (%)	19	19.45	4.64	9	34	693
Median income	54,102	55,607.48	12,104.93	30,034	96,310	693
Median age	35.50	35.47	2.94	23.20	47.10	693
Percent of technology sector employees (%)	1	1.82	4.38	0	78	693
Revenue per capita	54	138	300	0	3199	693
Population	792,313	1,692,227	2,386,437	95,786	10,038,388	693
Form of government	0.00	0.49	0.50	0.00	1.00	693
Percent of white (%)	72	70.54	14.04	28	95	693
Distance between 1.0 technologies	26,458.40	64,028.60	74,212.43	5,481.81	364,393.59	592
Distance between 2.0 technologies	29,511.68	79,540.02	102,391.76	5,481.81	671,030.95	328
Distance between 311/Open Data Portal technologies	28,328.39	71,632.26	83,524.24	5,481.81	471,518.98	463

The above table illustrates the differences between the urban areas over the study period. Overland Park, Kansas has the highest percent of individuals with bachelor's degrees with 34% in 2015. Two cities have instances of the low at 9%, Brownsville, Texas and Baskerville, California. In 2015 Sunnyvale, Santa Clara and San Jose, California all have the highest median income, they are all located geographically next to each other. Brownsville, Texas is the lowest in 2005 with a median income of $30,034. The youngest population is Provo, Utah at 23.2 years of age in 2005. The oldest is 47.10 years in St. Petersburg, Florida, in 2015. Salinas, California has 78% of its population working in the technology sector in 2015, the highest. 294 cities across the time period have 0% of their populations in the technology sector according to the Bureau of Labor and Statistics. Mobile, Alabama had the highest revenue per capita in 2015 at 3,199. There were 129 instances of 0 or years and cities that were missing data. Norfolk, Virginia in 2010 is the smallest urban area in the study. The largest is Burbank, California at 10,038,388. Springfield, Missouri in 2005 and Lubbock, Texas in 2015 had the highest percentage of white individuals at 95%. Jackson, Mississippi in 2005 had the lowest percentage at 28% in 2015.

Before running the fixed-effects regression models, the dissertation runs some simple linear regressions to look for potential patterns between the variables and their ability to predict electronic government adoption of the various stages. Regression analysis is a statistical method that allows us to determine relationships between different types of variables. Variables unaffected by other variables are independent variables (IV) or predictor or explanatory variables. The ones that are affected are known as dependent variables (DV) or response variables. Linear regression predicts the value of a response variable based on one or more of the predictor variables. In this instance, the analysis uses linear regression, predicting a response variable's value on a single explanatory variable.

The full results of the analysis are in

Appendix B: Linear Regression Results. The results of each of the linear models show little significance across the different dependent variables across the three time periods (2005, 2010, 2015). For 2005 there is significance for geographic distance for the number of all and 1.0 technologies. Technology collaboration has some significance when it comes to 1.0 technologies as well. City revenue per capita shows significance when it comes to 311 and open data portal adoption in 2005. The level of education attainment and median income are significant in 2005 when examining 1.0 technologies. All significance values do not exceed 5 percent level and most are not significant.

Examining technology adoption in 2010 is a bit more promising. Education attainment and median age are significant at the 10 percent level for predicting total technologies. These two variables are also significant at the 5 percent level for 2.0 technologies. Education attainment is also significant for 311 and open data portals at the 5 percent level. Percent white is significant at the 5 percent for all technologies. Geographic distance is significant at 5 percent level as well for 1.0 technologies. Education attainment, geographic distance, percent white and revenue per capita all have some significance in adopting 311 systems and open data portals.

Many of the independent variables are not significant when examining technologies in 2015. Education attainment is significant for predicting total technologies and open data portals. Median income is significant at the 10 percent level when examining the adoption of 311 and open data portals. Overall all though most are not significant predictors for 2015.

While the value added by this regression analysis offers some evidence of significance, each of the years is isolated within a specific period and does not account for change over time. An important component of analyzing policy diffusion is to illustrate how these independent variables have more explanatory value when compared over time. The lack of strong significance and consistent pattern across the technologies leads to the running of a fixed-effects regression model to examine the impact of each independent variable.

Table 9 Results from Linear Regression Modeling

	Dependent variables – Technology adoption											
	2005				2010				2015			
Independent variables	**All**	**1.0**	**2.0**	**311/ ODP**	**All**	**1.0**	**2.0**	**311/ ODP**	**All**	**1.0**	**2.0**	**311/ ODP**
Median income (log)	0.0534•	0.1755	0.280	0.8673	0.5589	0.3431	0.1380	0.5824	0.3511	0.5242	0.990	0.0699•
Percent with BA	0.0251*	0.1091	0.755	0.6917	0.0568•	0.5258	0.0209 *	0.0354*	0.0542•	0.4606	0.213	0.0449*
Median age	0.3113	0.1860	0.868	0.6084	0.0621•	0.8547	0.0436 *	0.5294	0.1606	0.3207	0.136	0.9071
Percent technology workers	0.7613	0.3898	0.329	0.7837	0.5597	0.4022	0.5971	0.1595	0.2082	0.5497	0.178	0.7096
Population (log)	0.6325	0.2032	0.326	0.8630	0.3474	0.6618	0.7591	0.4917	0.9690	0.3431	0.846	0.7403
Geographic distance	0.0320*	0.0507•	0.720	0.3251	0.2272	0.0227 *	0.4267	0.0566•	0.3729	0.2591	0.502	0.7118
Percent white	0.1514	0.2966	0.890	0.1100	0.0346 *	0.3149	0.3170	0.0369*	0.7549	0.5627	0.619	0.6744
Manager	0.4407	0.2004	0.553	0.5898	0.5499	0.5231	0.4865	0.7475	0.7976	0.6237	0.354	0.4157
Mayor	0.165	0.1936	0.359	0.2202	0.4298	0.4680	0.3602	0.6476	0.9619	0.4768	0.549	0.3983
City revenue / population	0.1210	0.4471	0.686	0.0232 *	0.9362	0.7851	0.4731	0.0990•	0.5541	0.5669	0.882	0.3468
Technology collaboration	0.7504	0.0746•	0.551	0.3990	0.4865	0.0314*	0.2822	0.2874	0.9651	0.2590	0.696	0.8482

• = p < 0.1, * p<0.05, ** p<0.01, *** p<0.001

4.4 Fixed-effects Regression Results

The descriptive statistics illustrate that governments are increasingly adopting electronic government technologies across the three types and study years. The next test is to understand *why* adoption is taking place. The model uses panel data across three time periods, allowing us to use a fixed-effects model. Here, the fixed-effects model refers to a regression model in which a group means is fixed (non-random) compared to the random effects model in which group means are a random sample from a population. Fixed effects regression modeling is an effective estimation technique when used with panel data. It allows for one to control for time-invariant unobserved individual characteristics correlated with the observed independent variables. The benefit of this approach is that fixed-effects models allow unobservable variables to have whatever associations with the observed variables.

Using the plm package in R, the analysis runs a series of fixed effects regressions for total technology (across all phases), the number of technologies for 1.0, 2.0, and 311 and Open Data Portal (four models in total). Appendix C: Fixed-effects Regression has all the results. The fixed-effects results indicate that some socio-demographic variables are coming into play over the years that influence technology adoption. The following table summarizes the findings from running the models.

Table 10 Results from Fixed-effects Modeling[11]

	Dependent variables – Technology adoption			
Independent variables	**All**	**1.0**	**2.0**	**311/Open Data Portal**
Median income (log)	0.9465	0.1778	0.9722	0.6002013
Percent with BA	0.4212	0.6630	0.6231	0.2235216
Median age	0.2453	0.1726	0.3580	0.6747214
Percent technology workers	0.9936	0.4693	0.1130	0.6324205
Population (log)	0.2643	0.8519	0.4050	0.4692189
Percent white	0.3039	6.658e-05 ***	0.5971	0.2571638
City revenue / population	0.7709	0.3365	0.6531	0.3883442
Factor (year) 10	<2e-16 ***	1.545e-10 ***	<2e-16 ***	0.9940370
Factor (year) 15	<2e-16 ***	7.851e-12 ***	<2e-16 ***	0.0005081 ***

• = $p < 0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

When we account for years many of the independent variables are insignificant. The analysis finds year dummy variables to be the most significant predictors of technology adoption in total, 1.0 and 2.0 technologies and 311 and open data portals. These are all highly significant at the 1 percent level. This makes sense as more cities adopt technologies as time passes. While this provides strong evidence that these technologies are indeed diffusing over time, there is no clear sense of what is causing the diffusion. Overall, the internal and external variables prove not to be significant when we include the time fixed effects in the model.

Of note is the role that percent white of the city plays when predicting 1.0 technologies. It has a positive effect when predicting 1.0 technology adoption and is worthy of further analysis and discussion regarding equality, access, and issues surrounding the digital divide. Are cities that are predominately white adopt technology quicker than others? Percent white is not a significant predictor for total technologies, 2.0 technologies, or the more recent 311 and open data portal adoptions, however, it is significant at the 1 percent level for 1.0 technologies and this is something to note and an opportunity for future research.

[11] Note in the fixed effects regression that the variables for manager, mayor, technology collaboration and distance drop out due to the fact there is no change because they remain constant between the three study periods. All three also proved to be non-significant in the linear regression modeling.

The fixed effects modeling reinforces the lack of trends in the predictors in the linear regression models. There was no significant independent variable that consistently appeared across technologies in each of the three study periods. For example, median income was significant at the 10 percent level in 2005 for predicting all technologies but had no significance in 2010 or 2015. In 2015 median income again had slight significance in predicting 311 and open data portal adoption but was not the case in 2005 or 2010. Similar trends occurred for education attainment, median age, geographic distance, percent white, revenue per capita, and technology collaboration, yet there was no consistent significance for an independent variable across 2005, 2010, and 2015. The best predictor was education with a significance of 5 percent for 4 of the 12 regressions and two at 5 percent level.

The only true pattern the analysis reveals is that more technologies are adopted as time passes. The geographic analysis also reinforces this. Of course, it is possible that a different approach, such as using multilevel models, can account for within and between effects or use of EHA or survival analysis done by other researchers. Nevertheless, both the fixed effects, linear regression, and geographic analysis suggests that there is no better predictor than time when predicting technology adoption.

Another component that the dissertation examines when looking at distance and collaboration is if cities nearby adopt at different rates than dispersed urban areas. The analysis breaks the largest urban areas into groups by geography. The following section outlines this analysis.

4.5 The Role of Collaboration and Competition

The methodology creates five groupings of cities. Their proximity to each other and their being in the same core-based statistical area (CBSA) as defined by the United States Census determined these groupings. The following table outlines the groupings:

Table 11 Urban Places Examined: Government Competition

CBSA	Included Governments	Total population (2010)	Grouping
Los Angeles-Long Beach-Anaheim, CA	(19) Anaheim, Burbank, Downey, El Monte, Fullerton, Garden Grove, Huntington Beach, Inglewood, Irvine, Lancaster, Long Beach, Los Angeles, Norwalk, Orange, Palmdale, Pasadena, Pomona, Santa Ana, Santa Clarita	7,076,190	1
New York-Newark-Jersey City, NY-NJ-PA	(5) Elizabeth, Jersey City, Newark, New York, Yonkers	9,020,815	2
San Francisco-Oakland-Hayward, CA	(8) Berkeley, Concord, Daly City, Fremont, Hayward, Oakland, Richmond, San Francisco	3,441,784	3
Dallas-Fort Worth-Arlington, TX	(8) Arlington, Dallas, Fort Worth, Garland, Grand Prairie, Irving, Mesquite, Plano	1,993,705	4
Virginia Beach-Norfolk-Newport News, NC	(6) Chesapeake, Hampton, Newport News, Norfolk, Portsmouth, Virginia Beach	1,316,696	5

The figure 13 shows the geographic distribution of the five groupings in the United States. These groupings are selected because they cover multiple urban areas in the study. A white circle and blackout line represent the grouped urban areas, and grey points indicate all the rest of the urban areas. The mapping allows us to test geographic proximity and the neighbor relationship to determine any difference between clustered and non-clustered cities.

Figure 12 Collaboration/Competition Groups and Other Urban Areas

One measure of potential competition and collaboration is to examine if urban places near each other have a higher level of adoption and a faster adoption rate than those that are not close to each other. The following table shows the results of this analysis. The dataset has five clusters spread across the United States. Then all the other urban areas in the study are placed into the "rest" grouping to see if geographic proximity affects the adoption rate of technologies. The groupings' purpose is to see if there are collaborative networks between cities that are similar and share geographic proximity. Do urban areas like Los Angeles and surrounding urban neighbors behave similarly? Are urban neighbors more likely to adopt same technology solutions? The distance between them is measured using the average distance (km) of the cities in those groupings. The analysis examines if the clusters adopt at rates faster than non-neighboring urban areas. N represents the number of urban areas in that group with a certain type of technology.

The expectation is that the number of technologies to be higher in clustered cities because of either competition or collaboration. The analysis also includes kilometers (km) as a distance measure for the geographic distribution of technologies within the clusters and the rest grouping.

Table 12 Distance and Adoption Rate for Clustered Cities (2005-2015)

	2005			**2010**			**2015**			**Δ 2005-2015**		
	km	N	%[12]	km	N	%	km	N	%	% change # technologies	Change in distance (km)[13]	% change in distance (km)
Group 1: CA LA Area												
1.0 technologies	13.05	19	100	13.03	19	100	11.93	19	100	0	-1.12	-8.58%
2.0 technologies	0	0	0	18.22	8	42	11.93	19	100	+100	-6.29	-34.52%
311/Open Data Portal	15.25	13	68	14.82	15	79	14.09	17	89	+21	-1.16	-7.61%
Group 2: NY-NJ-PA											0	
1.0 technologies	14	5	100	14	5	100	13.23	3	60	-40	-0.77	-5.50%
2.0 technologies	0	0	0	26.56	2	40	12.18	3	60	+60	-14.38	-54.14%
311/Open Data Portal	0	1	20	26.82	2	40	24.01	3	60	+40	-2.81*	-10.48%
Group 3: CA SF Area											0	
1.0 technologies	13.4	8	100	13.4	8	100	13.4	8	100	0	0	0.00%
2.0 technologies	0	1	13	12.81	5	63	13.4	8	100	+88	0.59	4.61%
311/Open Data Portal	16.14	5	63	14.05	7	88	13.4	8	100	+38	-2.74	-16.98%
Group 4: TX											0	
1.0 technologies	13.02	8	100	13.02	8	100	13.02	8	100	0	0	0.00%
2.0 technologies	0	1	13	15.77	7	88	13.02	8	100	+88	-2.75	-17.44%
311/Open Data Portal	20.2	4	50	166.12	5	63	13.02	8	100	+50	-7.18	-35.54%
Group 5: NC											0	
1.0 technologies	16.51	4	50	14.65	5	63	14.65	5	63	+13	-1.86	-11.27%
2.0 technologies	0	0	0	20.15	4	50	14.65	5	63	+63	-5.5	-33.31%
311/Open Data Portal	16.36	4	50	14.65	5	63	14.65	5	63	+13	-1.71	-10.45%
Rest[14]												
1.0 technologies	81.03	152	83	78.78	152	83	77.25	152	83	0	-3.78	-4.66%
2.0 technologies	372.75	7	4	98.9	100	55	78.46	150	82	+78	-294.29	-78.95%
311/Open Data Portal	105.95	91	50	82.77	123	67	79.68	147	80	+31	-26.27	-24.79%

[12] Indicated the percentage of that particular group that has adopted that technology.
[13] When distance between is zero the following year is used (i.e. 2010-2015).
[14] Anchorage and Honolulu not included in the distance measures.

Examining the distance and rate of adoption over time reinforces the linear regression results for distance and membership in collaborative technology networks that collaboration does not increase the chances of technology adoption. The San Francisco and Dallas area saw the most significant percent growth as measured by the average change in all technologies (42 and 46%, respectively). North Carolina and the New York-New Jersey area saw a slower growth rate than the non-grouped urban areas in the study (30 and 33%, respectively). The analysis shows for percent change overall for grouped urban areas, an average percent change at 38.[15] Clustered areas are similar to non-clustered urban areas with a percent change of 36. Based on this analysis, technology adoption is happening at similar rates for clustered and non-clustered urban areas.

The next measure was to examine the change in the average distance between the clusters and non-clusters. The analysis would expect to decrease the distance at a higher rate in the clustered group areas than in non-clustered urban areas. The analysis finds that the non-clustered urban area's distance decreased from 2005 to 2015 by 36%. The decrease in clustered groups is smaller, at 16%.[16] Of note is that clustered and non-clustered urban areas in the study had decreased in distance. Thus, the geographic distances do not prove that being near other government adopters predicts greater adoption of electronic government technology.

The clustered urban areas changed, on average, 2.6% in the adoption of 1.0 technologies. The result shows many of them already fully adopted the technology in 2005. The rapid growth is evident when looking at the average change of 2.0 technologies for the clustered urban areas.

[15] Percent change for clustered urban areas is the average of all five of the groups selected for study across all three areas (1.0, 2.0 and co-production) for 2005 and 2010. In the event 2005 was not present, some technologies had not yet been created, 2010 was used. The change for un clustered urban areas is the rest of the urban areas that do not fall within the five groups.

[16] Average distance change for the adoption of all three technologies for 2005 and 2015. Clustered is those that are not in the five groups. The clustered is an average of the percent change in adoption from 2005 to 2015 for the clustered groups.

From 2005-2010 these areas increased by 79% in their adoption of 2.0 technologies. Co-production technologies during this period, for clustered urban areas, saw an increase of 32%. For non-clustered, the change in adoption rate was similar, 0% for 1.0, 79% for 2.0 and 30% for co-production technologies.

The analysis shows no actual trends that differentiate the average percentage change of technologies adopted and the average percent change in the distance between urban areas for clustered and non-clustered urban areas. The analysis shows an overall adoption of the various technologies at similar rates for both clustered and non-clustered urban areas, it also shows decreases in the distance between them. An increase in adoption and a decrease in the distance for all urban areas support the hypothesis that technologies are diffusing over time. While collaborative and competitive actions contribute to this analysis, it would be difficult to make that case. One potential area for more in-depth investigation is the role of 2.0 technology adoption. For non-clustered urban areas, the distance between cities decreased by 79% whereas for the clustered cities, the decrease was only 27%.

5: CONCLUSION

5.1 Summary of Research

This research introduces a new way of understanding digital governance diffusion by testing electronic government technologies over time. The research offers a new means for collecting historical data in regard to adopted technology. It is also comprehensive in scope, collecting thousands of data points for cities across the United States for over ten years. The research builds on diffusion theory (Rogers 2003, Eyestone 1977, Walker 1969, Berry and Berry 1990), applied to digital governance. The dissertation also tests diffusion theory in a large N-study and applies it to technology policy at the city level – a gap in the diffusion literature (Mallinson 2020). The dissertation builds an empirical model that tests diffusion theory in novel ways further to understand digital governance adoption in large American cities. The dissertation research contributes to the understanding of the complexities of adopting electronic government technologies. The research asks the following question(s): *How are specific technologies adopted, how does their implementation spread over time, and what are the impacts of external versus internal determinants on adoption?*

The dissertation has grouped DEG policy adoption into three phases. The first phase of electronic policy adoption is 1.0. These technologies focus on establishing an online presence to create opportunities for citizens to consume information about their city. 1.0 technologies focus on information dissemination (posting of meeting minutes, interactive map of services), two-way communication (email), and offering service and financial transactions (online bill pay). They are early examples of creating client-focused structures that directly allow citizens to contact and interact with their governments. The model operationalizes these as online bill pay, meeting minutes/agendas, email link/address, or “contact us” link. The second phase, or 2.0, begins around 2010, these technologies account for the social web's advent through social media technologies. 2.0 technologies cover social networking sites, video sharing sites, blogs, and wikis. Web 2.0 focuses on technologies that deal with interaction, the ability to upload citizen documents or comment on online content. The final phase deals with collaborative technologies such as the 311 systems and open data portals. 2.0 technologies are more recent developments than 1.0, and they carry the prospect of a new level of engagement with citizens.

The dissertation uses this framework to examine the diffusion of electronic government overtime in the largest urban areas in the United States. The analysis looking at three points in time can understand better what is driving electronic government technology adoption. This long-term view across policy areas provides a better view of how innovation is communicated between entities over time among the social system participants (Rogers 2003). The work of Berry and Berry (1990) provides additional clarification of the predictors of diffusion by classifying external and internal determinants. By integrating these theories into one concise theoretical framework for empirical research, the analysis can describe the adoption of different technologies and examine their relationship with organizational, socio-demographic, and political characteristics.

Next, the analysis uses a mixed-methods approach, which is more comprehensive than prior diffusion models at the city level. The dissertation uses a variety of quantitative methods. Descriptive statistics, linear regression, and fixed effects regression, along with geospatial analysis using near distance. The examination through descriptive statistics shows that the rate of technology adoption is increasing over time. The geographic distance analysis shows a decrease in the distance between governments with specific technologies, reinforced as a decrease in the distance between cities using the three phases of technology.

The analysis uses linear regression to examine significance of some independent variables to predict specific electronic government technology adoption within a specific year. Phase 1.0

technologies show the significance of geographic distance in both 2005 and 2010. Technology collaboration also shows significance for 1.0 technologies in 2005 and 2010. For phase 2.0, there is no significant predictors in 2005 or 2015, however, education attainment and median age have significance in 2010. Similar to phase 1.0, there is no consistent trend across the three-time periods. When examining 311 and open data portals, city revenue per capita is significant in 2005 and 2010, this would be consistent with the notion that these systems require a large amount of resources to set up and implement. There is also significance for education attainment and geographic distance in 2010. Education attainment and median income are also significant in 2015, again indicating that expertise (education) and resources (income) have a role in 311 and open data portal technology adoption. Distance and median income were significant in 2005 and median age in 2010. Arguably one of the most consistent trends present in the regression analysis is that education attainment is significant for overall technology adoption in 2005, 2010, and 2015.

The fixed-effects regression intends to offer insights into how governments adopt certain technologies over time. When the model controls for years the analysis reveals that only time variables show significance. The year dummies are highly significant at the 1 percent level for total technology adoption, phase 1.0, 2.0, and one out of the two years for 311 and open data portal. There is an instance of high significance for phase 1.0 when it related to percent white variable. This is the only instance of significance outside of years, and has relation to themes of equity and inclusion and the digital divide overall when it comes to access to government services. The analysis reveals positive relationships across all the dependent variables, however, as noted, little significance outside of the time variables. The regression concludes that more cities adopt a greater number of technologies over time, which is true overwhelmingly for all phases. The fixed effects regression confirms that as internal factors of median income, education attainment, median age, the percent of technology workers, population, percent white, and city revenue per capita, so do the total number of DEG technologies – yet with few instances of significance.

The linear regression reveals some patterns. The fixed effects regression, when controlling for years, accounts for most of the variation. At the same time, it does validate that over time cities adopt more technologies and are diffusing over time. In several instances, the analysis examines the role of collaborative networks or geographic proximity on adopting the technology. The research looks at the technology organization participation of cities and if they were within the same core-based statistical area (CBSA). The research hypothesizes that this would provide insight into either competition between neighboring urban areas or governments' cooperation to adopt electronic government technology. As noted, the geographic proximity and being a part of a collaborative technology organization is slightly significant in specific years in the linear regression. However, the fixed effects regression does not find either participation or distance to be significant in this study. As Mallinson (2020) illustrated in his examination of 30 years of diffusion literature, the role of geographical proximity in this analysis is mixed, as he predicted. Shipan and Voldan (2012) had found similar issues with looking at solely geographic clustering as a measure of diffusion.

Overall, the analysis expects that educational attainment, population, government revenue, employees in the technology sector, percent white, median income, and close geographic proximity to another large city would positively affect the rate and number of technologies adopted over time. In addition, the research hypothesizes based on the literature that a younger population would demand higher levels of technology adoption by their government with an expected negative correlation.

Table 13 Summary of Hypotheses for Technology Diffusion Adoption

Hypothesis	Sub-Factor	Determinant	Expected	Actual
H1	Educational attainment	Internal	+	+
H2	Median age	Internal	-	+
H3	Population	Internal	+	+
H4	Percent white	Internal	+	+
H5	Employed in the technology sector	Internal	+	+
H6	Government revenue	Internal	+	+
H6	Median income	Internal	+	+
H7	Form of government	Internal	+	+
H8	Proximity	External	-	-

The mixed methods help answer the first research question the dissertation asks back in chapter two: How are specific technologies adopted, and how do their adoption spreads over time? Time as noted, is the most significant predictor of technology adoption. Moreover, while other measures do not have significance they are positive. The fixed-effects regression model indicates that large American urban areas with older populations and higher education attainment have a higher probability of adopting electronic government technologies. The finding of median age is contrary to the hypothesis that urban areas with younger, more "technology savvy" citizens would demand that their governments provide various technologies. The adoption rate of digital governance increased during the period for all measures, also, the geographic analysis finds that the geographic distance decreased over time. Simply meaning that as time progressed, more electronic government technologies were being adopted and, in turn, decreasing the distance between the study areas. The proximity distance does not prove significant in the fixed effects regression analysis, but it finds some interesting patterns when the dissertation looks at the measure using other spatial techniques.

The analysis supplements the linear regression and fixed effects with spatial analysis using simple distance and nearest neighbor to get a more in-depth understanding of geographic proximity. The nearest neighbor ratio analysis supports the notion of increased clustering over time. In all three of the examples explored, the results show a decrease in the geographic distance between the communities adopting technologies, in some cases, drastically when the threshold to adoption is low (social media). The nearest neighbor ratio supports a similar conclusion: all technologies decrease the mean distance between cities and related technologies. Parsing out the urban areas into regions and looking at a collaboration measure, the analysis does not observe competition or collaboration as significant factors in predicting technology adoption.

The second question the dissertation poses: What are the impacts of external versus internal determinants on technology adoption? The analysis finds that internal measures of education attainment, median age, population size, employees in the technology sector, government revenue, and the median income of the citizens all positively influence technology adoption, albeit non-significant in the fixed effects regression. The percent of white individuals has high significance when it comes to phase 1.0 technology adoption. The external determinant of geography is significant when examining years individually in the linear regression for some technologies. The geographic analysis also shows evidence of external determinants. The analysis finds no evidence that factors such as government type predict the implementation of electronic government technologies.

While none of the nine hypotheses proves to have significance in the fixed effects analysis, there is strong significance and reaffirmation that cities adopted more technologies over time. In addition to the hypothesis testing, the research finds that professional networks in some instances has slight significance as a predictor of digital governance adoption. The empirical model incorporates both external and internal determinants, as has been suggested as a sound strategy for diffusion modeling (Berry and Berry 1990, Box-Steffensmeier and Jones 1997, Shipan and Voldan 2012). However, overwhelmingly the determinants are internal, and in future research, incorporating more external determinants would provide additional insights. In addition to the modeling, the depth and scope of the data collected contribute to the literature, as Mallinson has noted, few researchers have addressed diffusion policy on a large scale (large N value). Also, the process of mining historic websites can be adapted to other policy areas as well and can serve as a contribution in and of itself.

5.2 Policy Implications

From a policy perspective, the research provides several insights on digital governance adoption in America's largest cities. It is impactful to think about how and why governments adopt technology and how that evolves and diffuses over time. Overall, every city adopted more technology over time and more of each type of technology. The role of technology and digital governance will continue to grow in an always-connected world. The dissertation concludes by examining some of the research's policy implications.

The research indicates an almost complete adoption of 1.0 and 2.0 technologies by 2015. 1.0 technologies like online bill pay options, posting meeting minutes, and email links to contact the government are adopted at 99% and above. 2.0 technologies have similar high adoption rates with Twitter (91.3%) and Facebook (93.1%). They are relatively easy technologies to roll out and require little investment. YouTube is lesser, with 77.5% yet still high, and has grown by 8850% since 2005. RSS is the only 2.0 technology without that high adoption rate (62.8%), but one possibility is a lack of understanding of the technology and its benefits. That said, featuring RSS links increased by 1712.5% since 2005. There should not be much need to invest in policies outlining their rollout given the adoption rate, however, cities will need to consider issues of tampering and privacy. Another is the reliance on private for-profit companies to provide these platforms, which requires future study of their policies. Another potential policy implication is that the role of 2.0 technologies was not impacted heavily by population size, indicating that medium-small governments could implement these technologies as potentially beneficial strategies.

Throughout the research, the area of growth and continued development is the use of 311 systems to report problems and the implementation of open data systems for sharing primary data. These platforms promise to create co-production opportunities when done well, and expressly examining these digital governance tools and how they encourage service production is an important area of research. 311 systems were adopted earlier and have seen greater implementation, with nearly all (94.4%) of cities utilizing some platform to report problems in need of government response. These systems are often complex and what is and is not possible to report and track is an area that requires continued analysis. Transparency of which problems are fixed and which are not is also of continued interest. The policy can benefit by examining potential gaps on issues that citizens are reporting and how the government is responding. Also, examining the cost and benefit of these systems increases participation and information availability to citizens. Open data portals are similar. Merely putting up data as discussed does not achieve its objective of increasing transparency, improving decision-making, increasing accountability, or engaging citizens in the decision-making process. The analysis of government websites noted that these platforms exist, but a deeper dive through surveys or case studies would inform the depth and usefulness of these systems. It was not until recently that researchers have begun to ask questions regarding the impact that open data has caused (Worthy 2015, Janssen et al. 2012). The next generation of open data portals offers better user interfaces, instructions, and context on how they are used (Young 2020). These new platforms allow cities and citizens to make decisions based on data, evidence, and insights.

One area of interest for policymaking is the role that age of population plays in digital governance. The assumption and prior literature pointed to the notion that younger populations might demand more technology services from their government. This is not the case in this analysis, as urban areas with older populations had higher rates of electronic government technology adoption. One potential explanation for this is that while young people use technology more, they might not interact with governments. Also, they do not need government services as much, this is consistent with political participation and civic engagement, both increase with age. The use of government technology by young people is an area that needs more future research, and it is also something that governments should focus on if they desire to engage and interact with younger citizens in their communities. Examining how and why younger populations use technologies and then leveraging that to create opportunities for governments to involve them in the decision-making process is crucial in building a diverse and informed citizenry.

One particular concern is the positive and, in one case, significant effect that percent of the white population had on technology adoption. It is critical when thinking about digital governance and how it can improve the lives of citizens that it is not only serving one particular type of citizen. Factoring in equity, justice, and inclusion in DEG is critical. The digital divide literature has brought attention to this issue. It is critical moving forward that DEG policy initiatives are being implemented with the consideration of all residents regardless of their education level, income, and race.

5.3 Limitations and Future Research

A key component underlying any democracy is access to information. (Harrison and Sayogo 2014). This study has illustrated how initially cities implemented 1.0 technologies, moved to more interactive forms, 2.0, and recently begun implementing citizen reporting systems (311) and open data portals. The research provides a historical account of digital governance diffusion in American urban areas and outlines several adoption determinants. Future research is required to understand these determinants in-depth as well. Expanding the data collection past 2015 could also lend more explanatory power as some of the social media technologies examined here were in their early stages in 2005-2015.

Also, the analysis identifies which governments have social media technologies, but it does not show the depth of usage. Having a Twitter account and using one are two different things. The analysis shows that a city has a Twitter or Facebook account or a GIS or 311 system. Some cities use social media to broadcast (1.0), while others use it to engage (2.0). Future research can move past the measure of just having something and moving towards a measure of effective use of technology. Twitter requires a lot of money and time investment by the government to make it work, just like a GIS system. The dissertation does not account for how these cities respond to feedback on their social media accounts. Alternatively, how many issues are being reported and responded to in their 311 systems? From this analysis, there is no sense of the level of interaction of these technologies. A more in-depth look at social media technologies in these cities is an area of future research.

The examination of technologies that have emerged post-2015 is also of interest. New technologies like Instagram have grown in popularity. SMS (short message service) text messaging to push out information to citizens is another technology not included in the dissertation's empirical model. They, too, just like Twitter or Facebook before have the potential for government-citizen communication. Expansion of the scope could also provide further evidence on the emergence of co-production in large urban areas. Specifically, the analysis found the rapid growth of co-production technologies, open data portals 680% change from 2010 to 2015. It would contribute to the electronic government literature if the rapid expansion continued despite the significant government investment in time and money required to implement these portals. Another additional benefit of the expanded scope is to see if any large urban governments have curbed their use of social media, specifically Facebook, in light of data breaches, privacy concerns, and misinformation that have happened in recent years.

The role and importance of information and technology's ability to disseminate it will continue to be crucial for an informed citizenry and a well-functioning government. Co-production and its associated technologies provide opportunities for new engagement levels, and open data platforms promote transparency and the opportunity for citizens to participate in the decision-making process related to policymaking and solving public problems. Another aspect the dissertation did not look at but could benefit from further study is how these initiatives stimulate innovation, economic growth and impact government service delivery. It is also crucial for future studies to examine the impact these technological innovations have had on social and racial equity. Have they been adopted at the same rate in poorer or more or less diverse urban areas? What are the impacts that economics and race have on adopting different technologies and the opportunities for citizens to use them to engage their governments in the decision-making process actively? Future research needs to focus on digital governance’s equity implications. The gap between those skilled with using technology and data and those that are not continues to grow; it will be critical for policy and academics to find opportunities for disadvantaged citizens to gain these crucial skills. There is the opportunity to reduce disparity as opposed to increasing it through the realization of these opportunities.

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Education

PhD ABD	University of Illinois, Chicago, Public Administration
MA	Western Washington University, Political Science, 2006
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Employment

2019 - 2020	Northwestern University, Data Services Faculty Librarian, University Libraries * Lead the Geospatial and Data Services Team
2014 - 2019	Northwestern University, Geospatial and Data Analyst, University Libraries
2015 - Present	Northwestern University, Lecturer, McCormick School of Engineering

Articles

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Analytic and Computer Graphics (Introduction to GIS), McCormick School of Engineering, 2015-Present

Presentations

“The World is Round and Maps are Flat: Charting Geography’s New Course,” Northwestern University Libraries Board of Govenors Meeting, Evanston, IL, May 2019.

APPENDICES

Appendix A: Metadata for Electronic Government Database

Variable	Description	Variable (continued)	Description (continued)
CITY	Unique city name	DEM_15	% of people that vote democrat 2015
NAME	Simple city name	REV_05	Revenue 2005
ST	State	REV_10	Revenue 2010
PLACEFIPS	Place Fipscode	REV_15	Revenue 2015
Group_	City grouping by geography	REVPOP_05	Revenue/population 2005
MEDAGE_05	Median age 2005	REVPOP_10	Revenue/population 2010
POP_05	Population 2005	REVPOP_15	Revenue/population 2015
LOGPOP_05	Log of population 2005	CI_05	City innovation score 2005
WHITE_05	Number of white individuals 2005	CI_10	City innovation score 2010
EDATT_05	Educational attainment 2005	CI_15	City innovation score 2015
MEDINC_05	Median income 2005	SRL_ME	SRL name
LOGMEDINC_05	Log of median income 2005	SRL	In SRL yes/no
MEDAGE_10	Mediage age 2010	Total_05	Total # of tech 2005
POP_10	Population 2010	Total_10	Total # of tech 2010
LOGPOP_10	Log of population 2010	Total_15	Total # of tech 2015
WHITE_10	Number of white individuals 2010	One_05	# of 1.0 technologies 2005
MEDINC_10	Educational attainment 2010	Two_05	# of 2.0 technologies 2005
LOGMEDINC_10	Median income 2010	Co_05	# of Co-production technologies 2005
MEDAGE_15	Log of median income 2010	One_10	# of 1.0 technologies 2010
POP_15	Population 2015	Two_10	# of 2.0 technologies 2010
LOGPOP_15	Log of population 2015	Co_10	# of Co-production technologies 2010
WHITE_15	Number of white individuals 2015	One_15	# of 1.0 technologies 2015
EDATT_15	Educational attainment 2015	Two_15	# of 2.0 technologies 2015
MEDINC_15	Median income 2015	Co_15	# of Co-production technologies 2015
LOGMEDINC_15	Log of median income 2015	eGov_avg	The average number of egov technologies
ONBP_05	Online bill pay 2005	FIPS_code	State FIPS code
MMIN_05	Meeting minutes 2005	State	State name full
EMAIL_05	Email information 2005	State_abbreviation	State name abbreviated
RSS_05	RSS subscribed listed 2005	MSA_code	Metropolitan statistical area code
TW_05	Twitter link 2005	MSA_join	Metropolitan statistical area join id
YT_05	YouTube link 2005	Complete	Complete record yes/no
FB_05	Facebook link 2005	oesm_05	# employed in technology sector 2005
F311_05	311/Report an issue 2005	oesm_10	# employed in technology sector 2010
MAP_05	GIS/Map 2005	oesm_15	# employed in technology sector 2015
OD_05	Open data portal/open data 2005	oesmden_05	# employed in technology sector/population 2005
ONBP_10	Online bill pay 2010	oesmden_10	# employed in technology sector/population 2010
MMIN_10	Meeting minutes 2010	oesmden_15	# employed in technology sector/population 2015
EMAIL_10	Email information 2010	FIPSJOIN	FIPS field for joining
RSS_10	RSS subscribed listed 2010	NEAR_FID	FID of nearest City to that city
TW_10	Twitter link 2010	DIST_05	Distance to nearest city 2005
YT_10	YouTube link 2010	DIST_10	Distance to nearest city 2010
FB_10	Facebook link 2010	DIST_15	Distance to nearest city 2015
OD_10	Open data portal/open data 2010	pti_12	Public technology institute participation 2012
ONBP_15	Online bill pay 2005	Count_1_05	# of 1.0 technologies in MSA in 2005
MMIN_15	Meeting minutes 2005	Count_1_10	# of 1.0 technologies in MSA in 2010
EMAIL_15	Email information 2005	Count_1_15	# of 1.0 technologies in MSA in 2015
RSS_15	RSS subscribed listed 2005	Count_2_05	# of 2.0 technologies in MSA in 2005
TW_15	Twitter link 2005	Count_2_10	# of 2.0 technologies in MSA in 2010
YT_15	YouTube link 2005	Count_2_15	# of 2.0 technologies in MSA in 2015

Variable	Description	Variable (continued)	Description (continued)
FB_15	Facebook link 2005	Count_Co_05	# of Co-production technologies in MSA in 2005
F311_15	311/Report an issue 2005	Count_Co_10	# of Co-production technologies in MSA in 2010
MAP_15	GIS/Map 2005	Count_Co_15	# of Co-production technologies in MSA in 215
OD_15	Open data portal/open data 2005	Tech_One_05_Dist	Distance to nearest city w/ 1.0 technology 2005
MNG_05	Manager form government 2005	Tech_One_10_Dist	Distance to nearest city w/ 1.0 technology 2010
MNG_10	Manager form government 2010	Tech_One_15_Dist	Distance to nearest city w/ 1.0 technology 2015
MNG_15	Manager form government 2015	Tech_Two_05_Dist	Distance to nearest city w/ 1.0 technology 2005
MAY_05	Mayor form government 2005	Tech_Two_10_Dist	Distance to nearest city w/ 2.0 technology 2005
MAY_10	Mayor form government 2010	Tech_Two_15_Dist	Distance to nearest city w/ 2.0 technology 2010
MAY_15	Mayor form government 2015	Tech_Co_05_Dist	Distance to nearest city w/ CoProd tech 2005
DEM_05	% of people that vote democrat 2005	Tech_Co_10_Dist	Distance to nearest city w/ CoProd tech 2010-
DEM_10	% of people that vote democrat 2010	Tech_Co_15_Dist	Distance to nearest city w/ CoProd tech 2015

Appendix B: Linear Regression Results

```
> #Run linear regression models for 2005
> total_lr_05 <- lm(Total_05~LOGMEDINC_05+BAED_05+MEDAGE_05+techw_05+LOGPOP_05+DIST_05+WP
OP_05+MNG_05+MAY_05+REVPOP_05+pti_12, data=data.wide)
> summary(total_lr_05)

Call:
lm(formula = Total_05 ~ LOGMEDINC_05 + BAED_05 + MEDAGE_05 +
    techw_05 + LOGPOP_05 + DIST_05 + WPOP_05 + MNG_05 + MAY_05 +
    REVPOP_05 + pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max
-3.6980 -0.7378  0.0915  0.8221  4.2702

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.491e+01  5.941e+00   2.510   0.0129 *
LOGMEDINC_05 -2.668e+00  1.373e+00  -1.944   0.0534 .
BAED_05       5.409e-02  2.396e-02   2.257   0.0251 *
MEDAGE_05     3.085e-02  3.039e-02   1.015   0.3113
techw_05      7.798e-03  2.563e-02   0.304   0.7613
LOGPOP_05    -1.013e-01  2.115e-01  -0.479   0.6325
DIST_05      -1.070e-06  4.953e-07  -2.161   0.0320 *
WPOP_05       9.520e-03  6.609e-03   1.440   0.1514
MNG_05       -3.800e-01  4.918e-01  -0.773   0.4407
MAY_05       -6.841e-01  4.909e-01  -1.394   0.1651
REVPOP_05     4.512e-02  2.896e-02   1.558   0.1210
pti_12       -6.649e-02  2.087e-01  -0.319   0.7504
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.152 on 186 degrees of freedom
  (33 observations deleted due to missingness)
Multiple R-squared:  0.104,	Adjusted R-squared:  0.05097
F-statistic: 1.962 on 11 and 186 DF,  p-value: 0.03438

> one_lr_05 <- lm(One_05~LOGMEDINC_05+BAED_05+MEDAGE_05+techw_05+LOGPOP_05+DIST_05+WPO
P_05+MNG_05+MAY_05+REVPOP_05+pti_12, data=data.wide)
> summary(one_lr_05)

Call:
lm(formula = One_05 ~ LOGMEDINC_05 + BAED_05 + MEDAGE_05 + techw_05 +
    LOGPOP_05 + DIST_05 + WPOP_05 + MNG_05 + MAY_05 + REVPOP_05 +
    pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max
-3.3684 -0.4955  0.2884  1.0269  1.8152

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   8.154e+00  6.163e+00   1.323   0.1872
LOGMEDINC_05 -1.969e+00  1.449e+00  -1.359   0.1755
BAED_05       4.169e-02  2.592e-02   1.609   0.1091
MEDAGE_05     4.389e-02  3.308e-02   1.327   0.1860
techw_05      2.519e-02  2.923e-02   0.862   0.3898
LOGPOP_05     2.946e-01  2.308e-01   1.276   0.2032
DIST_05      -6.063e-07  3.086e-07  -1.965   0.0507 .
WPOP_05       7.255e-03  6.935e-03   1.046   0.2966
```

```
MNG_05       -7.338e-01  5.713e-01  -1.284   0.2004
MAY_05       -7.432e-01  5.699e-01  -1.304   0.1936
REVPOP_05     2.522e-02  3.312e-02   0.762   0.4471
pti_12        4.160e-01  2.322e-01   1.792   0.0746 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.345 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.08457,    Adjusted R-squared:  0.03838
F-statistic: 1.831 on 11 and 218 DF,  p-value: 0.05029

> two_lr_05 <- lm(Two_05~LOGMEDINC_05+BAED_05+MEDAGE_05+techw_05+LOGPOP_05+DIST_05+WPO
P_05+MNG_05+MAY_05+REVPOP_05+pti_12, data=data.wide)
> summary(two_lr_05)

Call:
lm(formula = Two_05 ~ LOGMEDINC_05 + BAED_05 + MEDAGE_05 + techw_05 +
    LOGPOP_05 + DIST_05 + WPOP_05 + MNG_05 + MAY_05 + REVPOP_05 +
    pti_12, data = data.wide)

Residuals:
     Min       1Q   Median       3Q      Max
-0.18770 -0.08554 -0.04650 -0.02011  2.90521

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.300e+00  1.511e+00  -0.861    0.390
LOGMEDINC_05  3.845e-01  3.550e-01   1.083    0.280
BAED_05      -1.989e-03  6.353e-03  -0.313    0.755
MEDAGE_05     1.354e-03  8.108e-03   0.167    0.868
techw_05     -7.010e-03  7.166e-03  -0.978    0.329
LOGPOP_05    -5.568e-02  5.657e-02  -0.984    0.326
DIST_05      -2.713e-08  7.563e-08  -0.359    0.720
WPOP_05      -2.350e-04  1.700e-03  -0.138    0.890
MNG_05       -8.326e-02  1.400e-01  -0.595    0.553
MAY_05       -1.284e-01  1.397e-01  -0.920    0.359
REVPOP_05    -3.283e-03  8.118e-03  -0.404    0.686
pti_12       -3.400e-02  5.691e-02  -0.597    0.551

Residual standard error: 0.3297 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.02363,    Adjusted R-squared:  -0.02564
F-statistic: 0.4796 on 11 and 218 DF,  p-value: 0.9147

> co_lr_05 <- lm(Co_05~LOGMEDINC_05+BAED_05+MEDAGE_05+techw_05+LOGPOP_05+DIST_05+WPOP_
05+MNG_05+MAY_05+REVPOP_05+pti_12, data=data.wide)
> summary(co_lr_05)

Call:
lm(formula = Co_05 ~ LOGMEDINC_05 + BAED_05 + MEDAGE_05 + techw_05 +
    LOGPOP_05 + DIST_05 + WPOP_05 + MNG_05 + MAY_05 + REVPOP_05 +
    pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max
-1.0364 -0.5267  0.1933  0.4572  1.4944

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   4.550e-01  2.561e+00   0.178   0.8591
LOGMEDINC_05 -1.007e-01  6.019e-01  -0.167   0.8673
```

```
BAED_05       4.276e-03  1.077e-02   0.397   0.6917
MEDAGE_05     7.053e-03  1.375e-02   0.513   0.6084
techw_05      3.339e-03  1.215e-02   0.275   0.7837
LOGPOP_05     1.656e-02  9.589e-02   0.173   0.8630
DIST_05      -1.264e-07  1.282e-07  -0.986   0.3251
WPOP_05       4.624e-03  2.881e-03   1.605   0.1100
MNG_05       -1.282e-01  2.374e-01  -0.540   0.5898
MAY_05       -2.911e-01  2.368e-01  -1.230   0.2202
REVPOP_05     3.146e-02  1.376e-02   2.286   0.0232 *
pti_12       -8.153e-02  9.647e-02  -0.845   0.3990
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5588 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.06706,    Adjusted R-squared:  0.01998
F-statistic: 1.424 on 11 and 218 DF,  p-value: 0.1632

> #Run linear regression models for 2010
> total_lr_10 <- lm(Total_10~LOGMEDINC_10+BAED_10+MEDAGE_10+techw_10+LOGPOP_10+DIST_10+WP
OP_10+MNG_10+MAY_10+REVPOP_10+pti_12, data=data.wide)
> summary(total_lr_10)

Call:
lm(formula = Total_10 ~ LOGMEDINC_10 + BAED_10 + MEDAGE_10 +
    techw_10 + LOGPOP_10 + DIST_10 + WPOP_10 + MNG_10 + MAY_10 +
    REVPOP_10 + pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max
-4.3740 -1.1714 -0.2454  1.5906  3.5082

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.354e+01  9.181e+00   1.475   0.1419
LOGMEDINC_10 -1.235e+00  2.109e+00  -0.585   0.5589
BAED_10       7.083e-02  3.697e-02   1.916   0.0568 .
MEDAGE_10    -8.524e-02  4.544e-02  -1.876   0.0621 .
techw_10      1.813e-02  3.103e-02   0.584   0.5597
LOGPOP_10    -3.126e-01  3.319e-01  -0.942   0.3474
DIST_10      -9.597e-07  7.924e-07  -1.211   0.2272
WPOP_10       2.100e-02  9.868e-03   2.128   0.0346 *
MNG_10        4.751e-01  7.933e-01   0.599   0.5499
MAY_10        6.292e-01  7.953e-01   0.791   0.4298
REVPOP_10    -4.135e-03  5.161e-02  -0.080   0.9362
pti_12        2.240e-01  3.213e-01   0.697   0.4865
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.853 on 203 degrees of freedom
  (16 observations deleted due to missingness)
Multiple R-squared:  0.07885,    Adjusted R-squared:  0.02894
F-statistic:  1.58 on 11 and 203 DF,  p-value: 0.1067

> one_lr_10 <- lm(One_10~LOGMEDINC_10+BAED_10+MEDAGE_10+techw_10+LOGPOP_10+DIST_10+WPO
P_10+MNG_10+MAY_10+REVPOP_10+pti_12, data=data.wide)
> summary(one_lr_10)

Call:
lm(formula = One_10 ~ LOGMEDINC_10 + BAED_10 + MEDAGE_10 + techw_10 +
    LOGPOP_10 + DIST_10 + WPOP_10 + MNG_10 + MAY_10 + REVPOP_10 +
    pti_12, data = data.wide)
```

```
Residuals:
    Min      1Q  Median      3Q     Max 
-3.5422 -0.3238  0.4306  0.5719  1.9510 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)   7.940e+00  4.955e+00   1.602   0.1105  
LOGMEDINC_10 -1.085e+00  1.142e+00  -0.950   0.3431  
BAED_10       1.295e-02  2.038e-02   0.636   0.5258  
MEDAGE_10    -4.550e-03  2.481e-02  -0.183   0.8547  
techw_10      1.445e-02  1.722e-02   0.839   0.4022  
LOGPOP_10     7.739e-02  1.767e-01   0.438   0.6618  
DIST_10      -5.453e-07  2.376e-07  -2.295   0.0227 *
WPOP_10       5.381e-03  5.342e-03   1.007   0.3149  
MNG_10       -2.826e-01  4.418e-01  -0.640   0.5231  
MAY_10       -3.212e-01  4.418e-01  -0.727   0.4680  
REVPOP_10     7.813e-03  2.861e-02   0.273   0.7851  
pti_12        3.853e-01  1.779e-01   2.166   0.0314 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.034 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.07274,    Adjusted R-squared:  0.02595 
F-statistic: 1.555 on 11 and 218 DF,  p-value: 0.114

> two_lr_10 <- lm(Two_10~LOGMEDINC_10+BAED_10+MEDAGE_10+techw_10+LOGPOP_10+DIST_10+WPO
P_10+MNG_10+MAY_10+REVPOP_10+pti_12, data=data.wide)
> summary(two_lr_10)

Call:
lm(formula = Two_10 ~ LOGMEDINC_10 + BAED_10 + MEDAGE_10 + techw_10 + 
    LOGPOP_10 + DIST_10 + WPOP_10 + MNG_10 + MAY_10 + REVPOP_10 + 
    pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.5824 -1.2315 -0.2673  1.3427  2.8853 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)   1.393e+01  7.234e+00   1.925   0.0555 .
LOGMEDINC_10 -2.481e+00  1.667e+00  -1.489   0.1380  
BAED_10       6.923e-02  2.975e-02   2.327   0.0209 *
MEDAGE_10    -7.353e-02  3.622e-02  -2.030   0.0436 *
techw_10      1.330e-02  2.513e-02   0.529   0.5971  
LOGPOP_10    -7.917e-02  2.579e-01  -0.307   0.7591  
DIST_10      -2.762e-07  3.468e-07  -0.796   0.4267  
WPOP_10       7.821e-03  7.798e-03   1.003   0.3170  
MNG_10        4.495e-01  6.449e-01   0.697   0.4865  
MAY_10        5.914e-01  6.449e-01   0.917   0.3602  
REVPOP_10    -3.002e-02  4.177e-02  -0.719   0.4731  
pti_12        2.800e-01  2.597e-01   1.078   0.2822  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.51 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.07535,    Adjusted R-squared:  0.02869 
F-statistic: 1.615 on 11 and 218 DF,  p-value: 0.09588
```

```
> co_lr_10 <- lm(Co_10~LOGMEDINC_10+BAED_10+MEDAGE_10+techw_10+LOGPOP_10+DIST_10+WPOP_
10+MNG_10+MAY_10+REVPOP_10+pti_12, data=data.wide)
> summary(co_lr_10)

Call:
lm(formula = Co_10 ~ LOGMEDINC_10 + BAED_10 + MEDAGE_10 + techw_10 +
    LOGPOP_10 + DIST_10 + WPOP_10 + MNG_10 + MAY_10 + REVPOP_10 +
    pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max
-1.0285 -0.3852  0.1535  0.2792  1.3492

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.159e+00  2.438e+00   0.885   0.3770
LOGMEDINC_10 -3.093e-01  5.618e-01  -0.551   0.5824
BAED_10       2.122e-02  1.003e-02   2.117   0.0354 *
MEDAGE_10    -7.691e-03  1.221e-02  -0.630   0.5294
techw_10      1.196e-02  8.472e-03   1.412   0.1595
LOGPOP_10    -5.987e-02  8.693e-02  -0.689   0.4917
DIST_10      -2.240e-07  1.169e-07  -1.916   0.0566 .
WPOP_10       5.518e-03  2.629e-03   2.099   0.0369 *
MNG_10       -7.007e-02  2.174e-01  -0.322   0.7475
MAY_10       -9.952e-02  2.174e-01  -0.458   0.6476
REVPOP_10     2.333e-02  1.408e-02   1.657   0.0990 .
pti_12       -9.337e-02  8.754e-02  -1.067   0.2874
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.509 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.1008,     Adjusted R-squared:  0.05545
F-statistic: 2.222 on 11 and 218 DF,  p-value: 0.01435

> #Run linear regression models for 2015
> total_lr_15 <- lm(Total_15~LOGMEDINC_15+BAED_15+MEDAGE_15+techw_15+LOGPOP_15+DIST_15+WP
OP_15+MNG_15+MAY_15+REVPOP_15+pti_12, data=data.wide)
> summary(total_lr_15)

Call:
lm(formula = Total_15 ~ LOGMEDINC_15 + BAED_15 + MEDAGE_15 +
    techw_15 + LOGPOP_15 + DIST_15 + WPOP_15 + MNG_15 + MAY_15 +
    REVPOP_15 + pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max
-6.0761 -0.4849  0.3826  0.7338  2.1136

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.524e+01  6.427e+00   2.371   0.0186 *
LOGMEDINC_15 -1.372e+00  1.468e+00  -0.935   0.3511
BAED_15       5.352e-02  2.765e-02   1.936   0.0542 .
MEDAGE_15    -4.606e-02  3.271e-02  -1.408   0.1606
techw_15      2.096e-02  1.660e-02   1.262   0.2082
LOGPOP_15     8.992e-03  2.309e-01   0.039   0.9690
DIST_15      -2.800e-07  3.136e-07  -0.893   0.3729
WPOP_15       2.179e-03  6.970e-03   0.313   0.7549
MNG_15        1.494e-01  5.817e-01   0.257   0.7976
MAY_15       -2.786e-02  5.821e-01  -0.048   0.9619
REVPOP_15     1.776e-02  2.998e-02   0.593   0.5541
```

```
pti_12       -1.029e-02  2.347e-01  -0.044   0.9651
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.363 on 216 degrees of freedom
  (3 observations deleted due to missingness)
Multiple R-squared:  0.04548,    Adjusted R-squared:  -0.003127
F-statistic: 0.9357 on 11 and 216 DF,  p-value: 0.507

> one_lr_15 <- lm(One_15~LOGMEDINC_15+BAED_15+MEDAGE_15+techw_15+LOGPOP_15+DIST_15+WPO
P_15+MNG_15+MAY_15+REVPOP_15+pti_12, data=data.wide)
> summary(one_lr_15)

Call:
lm(formula = One_15 ~ LOGMEDINC_15 + BAED_15 + MEDAGE_15 + techw_15 +
    LOGPOP_15 + DIST_15 + WPOP_15 + MNG_15 + MAY_15 + REVPOP_15 +
    pti_12, data = data.wide)

Residuals:
     Min       1Q   Median       3Q      Max
-1.83378  0.03195  0.07986  0.11091  0.45244

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   4.751e+00  1.376e+00   3.452 0.000669 ***
LOGMEDINC_15 -2.008e-01  3.148e-01  -0.638 0.524254
BAED_15       4.385e-03  5.933e-03   0.739 0.460661
MEDAGE_15    -6.957e-03  6.990e-03  -0.995 0.320764
techw_15      2.138e-03  3.568e-03   0.599 0.549724
LOGPOP_15     4.671e-02  4.917e-02   0.950 0.343145
DIST_15      -7.621e-08  6.737e-08  -1.131 0.259191
WPOP_15       8.673e-04  1.496e-03   0.580 0.562773
MNG_15       -6.140e-02  1.250e-01  -0.491 0.623788
MAY_15       -8.913e-02  1.251e-01  -0.713 0.476893
REVPOP_15     3.686e-03  6.429e-03   0.573 0.566962
pti_12        5.693e-02  5.031e-02   1.132 0.259084
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.293 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.03685,    Adjusted R-squared:  -0.01175
F-statistic: 0.7582 on 11 and 218 DF,  p-value: 0.6815

> two_lr_15 <- lm(Two_15~LOGMEDINC_15+BAED_15+MEDAGE_15+techw_15+LOGPOP_15+DIST_15+WPO
P_15+MNG_15+MAY_15+REVPOP_15+pti_12, data=data.wide)
> summary(two_lr_15)

Call:
lm(formula = Two_15 ~ LOGMEDINC_15 + BAED_15 + MEDAGE_15 + techw_15 +
    LOGPOP_15 + DIST_15 + WPOP_15 + MNG_15 + MAY_15 + REVPOP_15 +
    pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max
-3.4519 -0.3327  0.3054  0.7307  1.1724

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.646e+00  4.695e+00   0.776    0.438
LOGMEDINC_15  1.373e-02  1.074e+00   0.013    0.990
BAED_15       2.526e-02  2.024e-02   1.248    0.213
```

```
MEDAGE_15    -3.569e-02  2.385e-02  -1.497    0.136
techw_15      1.644e-02  1.217e-02   1.350    0.178
LOGPOP_15    -3.257e-02  1.677e-01  -0.194    0.846
DIST_15      -1.547e-07  2.298e-07  -0.673    0.502
WPOP_15       2.546e-03  5.105e-03   0.499    0.619
MNG_15        3.959e-01  4.264e-01   0.928    0.354
MAY_15        2.560e-01  4.267e-01   0.600    0.549
REVPOP_15     3.253e-03  2.193e-02   0.148    0.882
pti_12       -6.709e-02  1.716e-01  -0.391    0.696

Residual standard error: 0.9995 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.04209,	Adjusted R-squared:  -0.006242 
F-statistic: 0.8709 on 11 and 218 DF,  p-value: 0.5697

> co_lr_15 <- lm(Co_15~LOGMEDINC_15+BAED_15+MEDAGE_15+techw_15+LOGPOP_15+DIST_15+WPOP_
15+MNG_15+MAY_15+REVPOP_15+pti_12, data=data.wide)
> summary(co_lr_15)

Call:
lm(formula = Co_15 ~ LOGMEDINC_15 + BAED_15 + MEDAGE_15 + techw_15 + 
    LOGPOP_15 + DIST_15 + WPOP_15 + MNG_15 + MAY_15 + REVPOP_15 + 
    pti_12, data = data.wide)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.3612 -0.2968 -0.2033  0.6158  0.9199 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)  
(Intercept)   6.425e+00  2.582e+00   2.488   0.0136 *
LOGMEDINC_15 -1.076e+00  5.905e-01  -1.822   0.0699 .
BAED_15       2.245e-02  1.113e-02   2.017   0.0449 *
MEDAGE_15    -1.531e-03  1.311e-02  -0.117   0.9071  
techw_15      2.496e-03  6.693e-03   0.373   0.7096  
LOGPOP_15    -3.061e-02  9.224e-02  -0.332   0.7403  
DIST_15      -4.675e-08  1.264e-07  -0.370   0.7118  
WPOP_15      -1.181e-03  2.807e-03  -0.421   0.6744  
MNG_15       -1.912e-01  2.345e-01  -0.815   0.4157  
MAY_15       -1.986e-01  2.347e-01  -0.846   0.3983  
REVPOP_15     1.137e-02  1.206e-02   0.943   0.3468  
pti_12        1.809e-02  9.438e-02   0.192   0.8482  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5496 on 218 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.04035,	Adjusted R-squared:  -0.008068 
F-statistic: 0.8334 on 11 and 218 DF,  p-value: 0.6068
```

Appendix C: Fixed-effects Regression Results

```
Call:
plm(formula = Total ~ BAED + MEDAGE + LOGMEDINC + techw + LOGPOP +
   WPOP + MNG + MAY + DIST + REVPOP + factor(year), data = data.long,
   model = "within", index = c("CITY"))

Unbalanced Panel: n = 230, T = 1-3, N = 641

Residuals:
   Min.  1st Qu.  Median  3rd Qu.     Max.
-3.90295 -0.64689  0.00000  0.66634  3.13428

Coefficients:
                 Estimate  Std. Error t-value Pr(>|t|)
BAED           -0.09494164  0.11791824 -0.8051   0.4212
MEDAGE          0.20941604  0.17999263  1.1635   0.2453
LOGMEDINC      -0.42499555  6.32483913 -0.0672   0.9465
techw           0.00034903  0.04363471  0.0080   0.9936
LOGPOP          6.95164971  6.21890521  1.1178   0.2643
WPOP            0.03976004  0.03862234  1.0295   0.3039
REVPOP         -0.01925332  0.06607205 -0.2914   0.7709
factor(year)10  2.09219670  0.21244829  9.8480   <2e-16 ***
factor(year)15  4.28884215  0.32895885 13.0376   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    2739
Residual Sum of Squares: 613.15
R-Squared:      0.77614
Adj. R-Squared: 0.64361
F-statistic: 154.864 on 9 and 402 DF, p-value: < 2.22e-16
> fixed.od <- plm(OD~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+REVP
OP+factor(year), index = c("CITY"), model = "within", data=data.long)
> summary(fixed.od)
Oneway (individual) effect Within Model

Call:
plm(formula = OD ~ BAED + MEDAGE + LOGMEDINC + techw + LOGPOP +
   WPOP + MNG + MAY + DIST + REVPOP + factor(year), data = data.long,
   model = "within", index = c("CITY"))

Unbalanced Panel: n = 230, T = 1-3, N = 645

Residuals:
    Min.   1st Qu.   Median   3rd Qu.      Max.
-0.861783 -0.200129  0.067864  0.108563  0.530704

Coefficients:
                 Estimate  Std. Error t-value  Pr(>|t|)
BAED            0.03232053  0.02651223  1.2191 0.2235216
MEDAGE         -0.01717895  0.04090410 -0.4200 0.6747214
LOGMEDINC       0.75383906  1.43719068  0.5245 0.6002013
techw          -0.00420288  0.00878006 -0.4787 0.6324205
LOGPOP          1.02421696  1.41382403  0.7244 0.4692189
WPOP           -0.00996354  0.00878065 -1.1347 0.2571638
REVPOP         -0.01297885  0.01502963 -0.8636 0.3883442
factor(year)10 -0.00036109  0.04828555 -0.0075 0.9940370
factor(year)15  0.26138670  0.07458250  3.5047 0.0005081 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Total Sum of Squares:    44.667
Residual Sum of Squares: 32.079
R-Squared:      0.28181
Adj. R-Squared: -0.1392
F-statistic: 17.7011 on 9 and 406 DF, p-value: < 2.22e-16
> fixed.Co <- plm(Co~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+REVPOP+factor(year), index = c("CITY"), model = "within", data=data.long)
> summary(fixed.Co)
Oneway (individual) effect Within Model

Call:
plm(formula = Co ~ BAED + MEDAGE + LOGMEDINC + techw + LOGPOP +
    WPOP + MNG + MAY + DIST + REVPOP + factor(year), data = data.long,
    model = "within", index = c("CITY"))

Balanced Panel: n = 230, T = 3, N = 690

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.097199 -0.274133  0.043389  0.278245  1.009920

Coefficients:
                Estimate Std. Error t-value  Pr(>|t|)
BAED          -0.0060448  0.0395160 -0.1530   0.87849
MEDAGE        -0.1036033  0.0574336 -1.8039   0.07192 .
LOGMEDINC     -0.2468687  2.1218206 -0.1163   0.90743
techw         -0.0095681  0.0135100 -0.7082   0.47917
LOGPOP         2.6010626  2.0530652  1.2669   0.20584
WPOP           0.0054301  0.0116760  0.4651   0.64211
REVPOP        -0.0072019  0.0229709 -0.3135   0.75403
factor(year)10  0.3066680  0.0685140  4.4760 9.644e-06 ***
factor(year)15  0.8158565  0.1046881  7.7932 4.548e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    152.67
Residual Sum of Squares: 87.308
R-Squared:      0.42812
Adj. R-Squared: 0.12632
F-statistic: 37.5136 on 9 and 451 DF, p-value: < 2.22e-16
> fixed.One <- plm(One~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+REVPOP+factor(year), index = c("CITY"), model = "within", data=data.long)
> summary(fixed.One)
Oneway (individual) effect Within Model

Call:
plm(formula = One ~ BAED + MEDAGE + LOGMEDINC + techw + LOGPOP +
    WPOP + MNG + MAY + DIST + REVPOP + factor(year), data = data.long,
    model = "within", index = c("CITY"))

Balanced Panel: n = 230, T = 3, N = 690

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.505252 -0.381934 -0.048913  0.393264  2.327117

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
BAED          -0.032335   0.074151 -0.4361    0.6630
MEDAGE        -0.147230   0.107773 -1.3661    0.1726
LOGMEDINC     -5.373660   3.981544 -1.3496    0.1778
```

```
techw          0.018360   0.025351  0.7242    0.4693
LOGPOP        -0.719638   3.852526 -0.1868    0.8519
WPOP           0.088206   0.021910  4.0259 6.658e-05 ***
REVPOP         0.041471   0.043104  0.9621    0.3365
factor(year)10  0.842462   0.128565  6.5528 1.545e-10 ***
factor(year)15  1.380354   0.196445  7.0267 7.851e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    467.33
Residual Sum of Squares: 307.42
R-Squared:      0.34217
Adj. R-Squared: -0.0049703
F-statistic: 26.0658 on 9 and 451 DF, p-value: < 2.22e-16
> fixed.Two <- plm(Two~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+RE
VPOP+factor(year), index = c("CITY"), model = "within", data=data.long)
> summary(fixed.Two)
Oneway (individual) effect Within Model

Call:
plm(formula = Two ~ BAED + MEDAGE + LOGMEDINC + techw + LOGPOP +
    WPOP + MNG + MAY + DIST + REVPOP + factor(year), data = data.long,
    model = "within", index = c("CITY"))

Balanced Panel: n = 230, T = 3, N = 690

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.652138 -0.586139  0.038952  0.534725  2.118269

Coefficients:
                Estimate Std. Error t-value Pr(>|t|)
BAED           -0.043050   0.087535 -0.4918   0.6231
MEDAGE          0.117059   0.127226  0.9201   0.3580
LOGMEDINC      -0.163914   4.700238 -0.0349   0.9722
techw           0.047527   0.029927  1.5881   0.1130
LOGPOP          3.790342   4.547931  0.8334   0.4050
WPOP            0.013680   0.025864  0.5289   0.5971
REVPOP         -0.022888   0.050885 -0.4498   0.6531
factor(year)10  1.318195   0.151772  8.6854   <2e-16 ***
factor(year)15  2.974618   0.231904 12.8269   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1610.7
Residual Sum of Squares: 428.42
R-Squared:      0.73401
Adj. R-Squared: 0.59364
F-statistic: 138.282 on 9 and 451 DF, p-value: < 2.22e-16
```

Appendix D: R Code

```
#Install required packages
install.packages("dplyr")
install.packages("tidyselect")
install.packages("tidyr")
install.packages("plm")
install.packages("stringr")

#Run linear regression models for 2005
total_lr_05 <-
lm(Total_05~LOGMEDINC_05+BAED_05+MEDAGE_05+techw_05+LOGPOP_05+DIST_05+WPOP_05+M
NG_05+MAY_05+REVPOP_05+pti_12, data=data.wide)
summary(total_lr_05)

one_lr_05 <-
lm(One_05~LOGMEDINC_05+BAED_05+MEDAGE_05+techw_05+LOGPOP_05+DIST_05+WPOP_05+M
NG_05+MAY_05+REVPOP_05+pti_12, data=data.wide)
summary(one_lr_05)

two_lr_05 <-
lm(Two_05~LOGMEDINC_05+BAED_05+MEDAGE_05+techw_05+LOGPOP_05+DIST_05+WPOP_05+M
NG_05+MAY_05+REVPOP_05+pti_12, data=data.wide)
summary(two_lr_05)

co_lr_05 <-
lm(Co_05~LOGMEDINC_05+BAED_05+MEDAGE_05+techw_05+LOGPOP_05+DIST_05+WPOP_05+MN
G_05+MAY_05+REVPOP_05+pti_12, data=data.wide)
summary(co_lr_05)

#Run linear regression models for 2010
total_lr_10 <-
lm(Total_10~LOGMEDINC_10+BAED_10+MEDAGE_10+techw_10+LOGPOP_10+DIST_10+WPOP_10+M
NG_10+MAY_10+REVPOP_10+pti_12, data=data.wide)
summary(total_lr_10)

one_lr_10 <-
lm(One_10~LOGMEDINC_10+BAED_10+MEDAGE_10+techw_10+LOGPOP_10+DIST_10+WPOP_10+M
NG_10+MAY_10+REVPOP_10+pti_12, data=data.wide)
summary(one_lr_10)

two_lr_10 <-
lm(Two_10~LOGMEDINC_10+BAED_10+MEDAGE_10+techw_10+LOGPOP_10+DIST_10+WPOP_10+M
NG_10+MAY_10+REVPOP_10+pti_12, data=data.wide)
summary(two_lr_10)

co_lr_10 <-
lm(Co_10~LOGMEDINC_10+BAED_10+MEDAGE_10+techw_10+LOGPOP_10+DIST_10+WPOP_10+MN
G_10+MAY_10+REVPOP_10+pti_12, data=data.wide)
summary(co_lr_10)

#Run linear regression models for 2015
total_lr_15 <-
lm(Total_15~LOGMEDINC_15+BAED_15+MEDAGE_15+techw_15+LOGPOP_15+DIST_15+WPOP_15+M
NG_15+MAY_15+REVPOP_15+pti_12, data=data.wide)
summary(total_lr_15)

one_lr_15 <-
lm(One_15~LOGMEDINC_15+BAED_15+MEDAGE_15+techw_15+LOGPOP_15+DIST_15+WPOP_15+M
NG_15+MAY_15+REVPOP_15+pti_12, data=data.wide)
summary(one_lr_15)
```

```
two_lr_15 <-
lm(Two_15~LOGMEDINC_15+BAED_15+MEDAGE_15+techw_15+LOGPOP_15+DIST_15+WPOP_15+M
NG_15+MAY_15+REVPOP_15+pti_12, data=data.wide)
summary(two_lr_15)

co_lr_15 <-
lm(Co_15~LOGMEDINC_15+BAED_15+MEDAGE_15+techw_15+LOGPOP_15+DIST_15+WPOP_15+MN
G_15+MAY_15+REVPOP_15+pti_12, data=data.wide)
summary(co_lr_15)

#Data prep for fixEd effect regression modeling

#Load packages
library(tidyselect)
library(dplyr)
library(tidyr)
library(stringr)
library(plm)

#Separating the variables and year
data.long <- data.wide %>%
  select(CITY, starts_with("LOGMEDINC_"), starts_with("MEDAGE_"), starts_with("BAED_"),
starts_with("WPOP_"),
        starts_with("LOGPOP_"), starts_with("techw_"), starts_with("TOTAL_"), starts_with("MNG_"),
starts_with("MAY_"), starts_with("DEM_"),
        starts_with("REVPOP_"), starts_with("CI_"), starts_with("OD_"), starts_with("One_"),
        starts_with("Two_"), starts_with("Co_"), starts_with("DIST_")) %>% # get rid of uneeded columns
  gather(var, value, starts_with("LOGMEDINC_"), starts_with("MEDAGE_"), starts_with("WPOP_"),
starts_with("BAED_"),
        starts_with("LOGPOP_"), starts_with("techw_"), starts_with("TOTAL_"), starts_with("MNG_"),
starts_with("MAY_"), starts_with("DEM_"),
        starts_with("REVPOP_"), starts_with("CI_"), starts_with("OD_"), starts_with("One_"),
        starts_with("Two_"), starts_with("Co_"), starts_with("DIST_")) %>%
  mutate(year=as.integer(str_extract(var, "\\d+")),
        var=str_replace(var, "_\\d+", "")) %>%
  spread(var, value)

#Run fixed effect model
fixed.total <-
plm(Total~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+REVPOP+factor(y
ear), index = c("CITY"), model = "within",data=data.long)
summary(fixed.total)

fixed.od <-
plm(OD~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+REVPOP+factor(ye
ar), index = c("CITY"), model = "within", data=data.long)
summary(fixed.od)

fixed.Co <-
plm(Co~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+REVPOP+factor(ye
ar), index = c("CITY"), model = "within", data=data.long)
summary(fixed.Co)

fixed.One <-
plm(One~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+REVPOP+factor(y
ear), index = c("CITY"), model = "within", data=data.long)
summary(fixed.One)

fixed.Two <-
plm(Two~BAED+MEDAGE+LOGMEDINC+techw+LOGPOP+WPOP+MNG+MAY+DIST+REVPOP+factor(y
ear), index = c("CITY"), model = "within", data=data.long)
summary(fixed.Two)
```

Appendix E: List of Urban Areas Studied

Anchorage, AK
Birmingham, AL
Huntsville, AL
Mobile, AL
Montgomery, AL
Little Rock, AR
Chandler, AZ
Gilbert, AZ
Glendale, AZ
Mesa, AZ
Peoria, AZ
Phoenix, AZ
Scottsdale, AZ
Tempe, AZ
Tucson, AZ
Anaheim, CA
Bakersfield, CA
Berkeley, CA
Burbank, CA
Chula Vista, CA
Concord, CA
Corona, CA
Costa Mesa, CA
Daly City, CA
Downey, CA
El Monte, CA
Escondido, CA
Fontana, CA
Fremont, CA
Fresno, CA
Fullerton, CA
Garden Grove, CA
Glendale, CA
Hayward, CA
Huntington Beach, CA
Inglewood, CA
Irvine, CA
Lancaster, CA
Long Beach, CA
Los Angeles, CA
Modesto, CA
Moreno Valley, CA
Norwalk, CA
Oakland, CA
Oceanside, CA
Ontario, CA
Orange, CA
Oxnard, CA
Palmdale, CA
Pasadena, CA
Pomona, CA
Rancho Cucamonga, CA
Richmond, CA
Riverside, CA
Sacramento, CA
Salinas, CA
San Bernardino, CA
San Diego, CA
San Francisco, CA
San Jose, CA
Santa Ana, CA
Santa Clara, CA
Santa Clarita, CA
Santa Rosa, CA
Simi Valley, CA
Stockton, CA
Sunnyvale, CA
Thousand Oaks, CA
Torrance, CA
Vallejo, CA
West Covina, CA
Arvada, CO
Aurora, CO
Colorado Springs, CO
Denver, CO
Fort Collins, CO
Lakewood, CO
Pueblo, CO
Westminster, CO
Bridgeport, CT
Hartford, CT
New Haven, CT
Stamford, CT
Waterbury, CT
Washington, DC
Cape Coral, FL
Clearwater, FL
Coral Springs, FL
Fort Lauderdale, FL
Hialeah, FL
Hollywood, FL
Jacksonville, FL
Miami, FL
Orlando, FL
Pembroke Pines, FL
St. Petersburg, FL
Tallahassee, FL
Atlanta, GA
Savannah, GA
Honolulu, HI
Cedar Rapids, IA
Des Moines, IA
Aurora, IL
Chicago, IL
Joliet, IL
Naperville, IL
Peoria, IL
Rockford, IL
Springfield, IL
Evansville, IN
Fort Wayne, IN
Gary, IN
South Bend, IN
Kansas City, KS
Overland Park, KS
Topeka, KS
Wichita, KS
Lexington, KY
Louisville, KY
Baton Rouge, LA
Lafayette, LA
New Orleans, LA
Shreveport, LA
Boston, MA
Lowell, MA
Springfield, MA
Worcester, MA
Baltimore, MD
Ann Arbor, MI
Detroit, MI
Flint, MI
Grand Rapids, MI
Lansing, MI
Livonia, MI
Sterling Heights, MI
Warren, MI
Minneapolis, MN
St. Paul, MN
Independence, MO
Kansas City, MO
St. Louis, MO
Springfield, MO
Jackson, MS
Charlotte, NC
Durham, NC
Fayetteville, NC
Greensboro, NC
Raleigh, NC
Winston-Salem, NC
Lincoln, NE
Omaha, NE
Manchester, NH
Elizabeth, NJ
Jersey City, NJ
Newark, NJ
Paterson, NJ
Albuquerque, NM
Henderson, NV
Las Vegas, NV
North Las Vegas, NV
Reno, NV
Buffalo, NY
New York, NY
Rochester, NY
Syracuse, NY
Yonkers, NY
Akron, OH
Cincinnati, OH
Cleveland, OH
Columbus, OH
Dayton, OH
Toledo, OH
Oklahoma City, OK
Tulsa, OK
Eugene, OR
Portland, OR
Salem, OR
Allentown, PA
Erie, PA

Philadelphia, PA
Pittsburgh, PA
Providence, RI
Columbia, SC
Sioux Falls, SD
Chattanooga, TN
Clarksville, TN
Knoxville, TN
Memphis, TN
Abilene, TX
Amarillo, TX
Arlington, TX
Austin, TX
Beaumont, TX
Brownsville, TX
Carrollton, TX
Corpus Christi, TX
Dallas, TX
El Paso, TX
Fort Worth, TX
Garland, TX
Grand Prairie, TX
Houston, TX
Irving, TX
Laredo, TX
Lubbock, TX
McAllen, TX
Mesquite, TX
Pasadena, TX
Plano, TX
San Antonio, TX
Waco, TX
Wichita Falls, TX
Provo, UT
Salt Lake City, UT
West Valley City, UT
Alexandria, VA
Chesapeake, VA
Hampton, VA
Newport News, VA
Norfolk, VA
Portsmouth, VA
Richmond, VA
Virginia Beach, VA
Bellevue, WA
Seattle, WA
Spokane, WA
Tacoma, WA
Vancouver, WA
Green Bay, WI
Madison, WI
Milwaukee, WI