Measuring the Role of Policy Diffusion in American Cities' Climate Mitigation Actions

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Abstract

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As international institutions have failed to take sufficient action to mitigate climate change, cities have emerged as leaders in tackling this challenge. Policy commitments on climate mitigation lack concrete benefits for cities, as the actions of one city does not reduce future impacts of climate change for that city in particular. Policy diffusion, the established patterns through which policies spread across municipalities, is often cited as an explanation for policy adoptions, but the collective action feature of climate policies, and the inability to determine short term success, interfere with conventional ideas of diffusion. This study seeks to answer the question of whether policy diffusion can explain adoptions of climate mitigation policies in American cities. Event History Analysis is used to measure the influence of diffusion on adoptions of climate action plans, chief sustainability officers, and green building policies. The results indicate that conventional learning and imitation are not occurring in the spread of these policies. This research gives insight into the sequencing of different climate policy adoptions among cities of varying sizes and locations in the U.S., and the motivations of these cities to adopt those policies.

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I. Introduction

In 2019 at the twenty-fifth Conference of the Parties to the United Nations Framework Convention on Climate Change, the international body tasked with addressing climate change failed to come to any conclusions on their agenda items to implement stated commitments to emissions reduction from the Paris Agreement. While disappointing, this outcome was unsurprising. As experts continue to reiterate that opportunities to limit warming to 1.5 or 2 degrees are fleeting, international bodies consistently fail to take sufficient action. Amidst a lack of action from our highest institutions, the world has begun to look to subnational governments for climate solutions.

Cities have earned a prominent spot in the conversation about climate change in the 21st century. Although cities only occupy two percent of landmass, they are responsible for 70 percent of Global CO_2 emissions (C40, Why Cities?). While cities are responsible for significant global emissions, they are disproportionately burdened by the impacts of climate change. Cities have been some of the first to experience impacts of warming and sea level rise, with 70 percent of global cities already dealing with such effects of climate change.

Today, more than half (55%) of the world's population lives in cities and that number is expected to grow to two-thirds (68%) by 2050 (United Nations, 2019). With concentration of population comes a concentration of economic activity, built environment, and emissions. Because of the density of the built environment, temperature rise is exaggerated in urban areas through the urban heat island. Additionally, cities are also often situated on major bodies of water, lending them to increased risk of flooding from sea level rise. Increased risk and high population density mean that cities are visible epicenters where the human effects of climate change are on display.

Amidst the visible effects of climate change that cities have faced, many city governments have risen to the challenge and have become some of the most active policy innovators for climate solutions. The prominence of cities as both contributors to and recipients of climate change effects has caused the world to turn to urban centers for answers on the path forward. Cities have significant decision-making power that positions them well to address climate change. Their governments typically control transportation, land use, and building policy and are less susceptible to the partisan gridlock that frequently occurs on a national and international scale. Some cities have stepped up to the plate and become leaders in sustainability while others have lagged behind. Some cities, such as the Hague, Netherlands or Miami, Florida, have already experienced severe flooding due to rising sea levels, and have been forced to begin adaptation planning and implementation. Climate nonprofits, such as 100 Resilient cities, support those cities that are coping with new climate stresses that affect social and physical attributes of a city, from unemployment to the deterioration of infrastructure. The environmental challenges of cities are very location specific, so they may be best addressed at the municipal level. In the contemporary era, cities are continually searching for ways to adapt to our changing world as their citizens begin to feel effects of climate change.

Policy commitments on mitigation of climate change lack concrete benefits for cities. One city's emission reduction, while contributing in part to global mitigation of climate change, does not necessarily reduce the risks of climate change for that city in particular, and may not even have measurable effects on national emissions reduction if surrounding municipalities do not act in unison (Zahran et. al., 2008). This dynamic creates a global collective action problem around climate change: The responsibility for our changing climate is shared between emitting governments and companies all over the world. The actions needed to reduce future emissions require money and motivation, and don't provide measurable benefits for any one actor. Ideally, nations would altruistically act in unison on this global problem. In the US, and in most countries globally, this is not the reality. There is an imperative for subnational governments such as cities to step up to overcome the collective action problem of climate change where their national governments fail to do so.

Some cities have overcome this collective action problem successfully, implementing emissions reduction policies that even national governments can look to as models. Others have failed to make these commitments to climate change, and remain free riders. I seek to answer the question of why some cities invest and commit to mitigation measures while others fail to make these commitments and investments. In other policy areas, variation in adaptation can be attributed to established processes of policy diffusion, but these policy areas do not feature the collective action problem of climate mitigation policy. Do climate mitigation policies follow these same patterns of policy diffusion, or does the decision to act on climate break this mold and depend more strongly on other factors?

II. Diffusion of Policy Innovation – Review of Literature

One of the benefits of the multilevel governing system in the United States (U.S.) is the opportunity for subnational governments to act as "Laboratories of Democracy," meaning that state and city governments can develop policy solutions to emerging societal problems and learn from each other (Karch, 2014). As laboratories of democracy, subnational governments borrow ideas from each other in a process that is summarily called policy diffusion. Walker (1969) was the first researcher to identify the concept of policy diffusion in his article *The Diffusion of Innovations among the American States*. Walker defined diffusion as a state adopting for the first time a policy that had been adopted previously by other states. Walker found that larger, wealthier states with representative legislatures were more likely to be early adopters of new programs and that diffusion occurs when policymakers mimic the actions of other states that face similar problems to their own. These findings laid the groundwork for the study of policy diffusion.

Since Walker's inaugural definition of diffusion, the literature on this topic has expanded immensely (Graham et. al., 2008). In a review of the policy diffusion literature across the subfields of American politics, comparative politics and international relations, Graham, Shipan, and Volden (2008, p. 3) define diffusion broadly as "when one government's decision about whether to adopt a policy innovation is influenced by previous choices by other governments. Put another way, policy adoptions can be interdependent, where a country or state observes what other countries or states have done and conditions its own policy decisions on these observations." Summarily, policy diffusion is the movement of policy across jurisdictional boundaries in a process that has been defined by several distinct mechanisms.

In an attempt to explain why policy diffusion occurs, scholars have generated a number of theories, termed "mechanisms", of why certain governments are more likely to adopt the policies of other governments. Policy diffusion research has coalesced around four main mechanisms of diffusion: learning, economic competition, imitation and coercion.

A. Learning

Learning is the ideal version of diffusion and most resembles the metaphor of "Laboratories of democracy (Karch, 2014)." Learning occurs when policymakers observe the effects of a policy in another city and deduce how that policy would translate to the context of their own city to come to an informed decision about adoption. If a policy has been successful at tackling a certain goal, another city with the same goal may choose to adopt that policy with the hope it will be similarly successful.

The theory of Learning assumes that if a policy is deemed to be successful, a city is more likely to adopt. It also theorizes that diffusion is more likely to occur when a higher number of cities have already adopted a policy, because there is more information to determine success (Shipan & Volden, 2006).

In climate policy, cities may learn from others about what policies are cost effective, implementable, or effective in reducing greenhouse gas emissions. Climate mitigation is a relatively new area of policy and policymakers have much to learn about implementing effective policies. Transnational Municipal networks are meant to facilitate learning in the climate policy sphere. The Summary for Urban Policymakers on the Intergovernmental Panel on Climate Change (IPCC) 1.5°C report states that "The effects of a city's actions are not limited to its own borders or region, and, likewise, lessons learned in some cities and urban areas can serve as inspiration and resources for solutions in other urban areas. (IPCC, 2018, p.6)" For precisely this reason, policy learning is an essential component of these networks as they enable leaders to forge connections and draw lessons from other members' policy actions (Lee & Meene, 2011). For a challenge as wide reaching as climate change, multi-level governance structures are necessary, and effective city climate governance is one key component of said structure (Homsy & Warner, 2015).

B. Economic Competition

Economic Competition is when policymakers are motivated by the market effects of a policy. This mechanism is driven by competition for resources between municipalities. A government may adopt a policy to gain a competitive advantage over their neighbor, or to avoid losing business, tax revenue or tourism (Baybeck et. Al., 2011; Graham et. al., 2013). An example of economic competition at work is that states are less likely to adopt generous welfare policies if their neighbors don't have them, because they fear being a magnet for citizens seeking public assistance, and thus incurring greater financial obligations. This mechanism often leads to diffusion of policies that generate economic spillovers over jurisdictional borders (Shipan & Volden, 2006). This mechanism generally affects jurisdictions that are geographically adjacent, and therefore is less applicable to city action on climate change.

C. Imitation

A third mechanism of diffusion is called imitation. This same mechanism is sometimes referred to as emulation, but in this paper the term imitation will be used. Imitation is when policymakers look to other jurisdictions and replicate their policies. Imitation is distinct from learning because it places the significance on *who* adopted the policy rather than what they did and whether it was successful. In other words, imitation is more of a blind mimicking of another city than an informed decision based on the results of a policy. As Shipan and Volden (2006, p. 843) put it, learning focusses on the action while imitation focusses on the actor. Imitation often occurs when policymakers want their city to appear as favorably viewed as early innovator cities (Karch, 2014). In imitation, innovation leaders are usually larger, wealthier and more cosmopolitan cities that smaller "laggard" cities aspire to be like. Imitation could be prominent in environmental policy because it's hard to definitively measure the effectiveness of environmental policies, which makes true learning difficult. Based on imitation, one would expect that policy adoption is more likely when a city's larger peers have already adopted that policy.

D. Coercion

The fourth mechanism of policy diffusion is coercion in which an actor or set of actors imposes their policy solution on other governments (Graham et. al., 2013). Coercion most conventionally occurs between a higher-level government and a lower level government, such as international bodies and nations, or federal and subnational governments. For cities, coercion is most applicable when a federal or state government issues a mandate or incentive for the implementation of a policy in local governments.

Horizontal coercion is also possible in contexts where one government applies normative pressure to another government of the same level. This may occur when more powerful governments impose norms and preferences on other governments (Graham et. al., 2013) but is much more probable in the international context. While it is possible for more powerful cities to coerce smaller cities, it is unclear how this process is measurably different from imitation.

There are no federal incentives or requirements for sustainability in the U.S., so federal coercion does not occur. There is, however, potential for coercion to occur from states to cities. For example, there is a demonstrated vertical relationship between green building policies enacted at the state and city levels. Green Building policies appear more among cities located in states with incentives for energy efficient buildings or renewable energy systems (Kontokosta, 2011). Though there is evidence for state to city coercion in certain circumstances, these circumstances are uncommon in the U.S. and research has shown that the state incentives that do exist lack enforcement power (Krause, 2011).

Since federal incentives do not exist and research suggests that state characteristics do not have a widespread impact on city environmental action, vertical coercion is not a likely diffusion mechanism to occurring in climate policy.

E. Environmental policy diffusion

Environmental policies often complicate the question of policy diffusion. Often, they are specific to the location that they are being implemented. For example, a conservation policy or a policy to preserve water quality must be tailored to the specific environmental conditions of that city. For climate mitigation policies, the details of a city's energy profile, infrastructure, and electricity sources will inform the specificities of their mitigation efforts.

The goal of climate mitigation policy is to minimize the future effects of climate change. Since this is a long-term goal, it is nearly impossible to determine "success" of a policy of this kind, which interferes with the process of learning. Still, scholars have studied the adoption and diffusion of a variety of environmental policies in an attempt to observe whether policy diffusion is occurring despite these challenges. While the conceptualization of policy adoption and diffusion have crucial distinctions, they are closely intertwined and much of the research on environmental policies blurs the line between these two areas of study. In reality, municipalities are influenced by external (i.e. diffusion) and internal (i.e. demographics, finances, political characteristics) factors, so it is important to review the relevant literature on both.

Feiock and West (1993) studied the adoption of curbside recycling programs in cities around the country. Their research is one of the earliest studies to look at environmental policy adoption at the city level. At the time, there was a national effort to increase the proportion of garbage that came from recycling and this study sought to investigate why some cities made the substantial investment to implement recycling programs while others did not. They found that a city's shortage of landfill space, support from state government, and financial means are the strongest predictors of adoption. Their findings suggested that the decision to adopt this policy came out of a combination of need, capacity and influence of higher governments.

In more recent research on variation in environmental action among cities, transnational municipal networks have been frequently studied, as they are a useful proxy for a city's commitment to climate change. Transnational Municipal Networks (TMN) are groups of subnational municipalities, in which member cities make some form of climate commitment, and in return often receive support and resources from the network. These networks are meant to encourage global cooperation among cities around the common goal of climate governance. Membership in TMNs can both signal an existing commitment to climate policy and be a cause for further action from a member city. They are also often included in research about policy diffusion as they are thought to encourage learning between member cities. In a network analysis of the C40 Cities Climate Leadership Group, Lee and Meene (2012) found that information seeking does occur in climate governance between cities as a key part of the learning process. Their study concluded that learning occurs when cities share a regional context, which indicates that future studies may look to cities in the same regions to observe learning. This study also used climate action plans and green building policies as examples of policy areas where learning occurs, which is relevant to the policy choices of the present research.

In a study of over 900 U.S. cities' adoptions of climate protection initiatives, indicated by a dummy variable of membership in the Mayor's Climate Protection Initiative, Krause (2011) found that state-level demographic characteristics have little effect on the likelihood of cities adopting climate protection policies. Demographic characteristics such as population size, median income, and political leaning on the city level were significant determinants of membership in the Mayors Climate Protection Initiative. The adoption of climate plans or greenhouse gas targets at the state level did not influence policy adoption of similar measures at the city level and states generally lacked enforcement power over municipalities. This contrasts Feiock and West's (1993) earlier finding that state level actions including mandates, financial assistance and trash reduction targets do influence city level adoptions of such programs. This collection of research leaves some disagreement over whether state environmental policy actions are significant in predicting city level environmental policies.

Another study examined the determinants of adoption of green building policies and the diffusion of such policies (Kontokosta, 2011). Cities with higher per capita carbon emissions were more likely to adopt mandatory policies, which appears to be a rational response to the problem that these cities face. Regarding policy diffusion, Kontokosta identifies "innovative" cities, which he defines as cities with more patents per capita, as more likely to adopt green building policies. This study supports the notion that policy diffusion takes place over time and across geographies, as the number of cities with green building policies has expanded over time, and expansion was spurred after high profile policy adoptions in New York and Washington DC. While diffusion appears to be occurring in green building policy adoption, this paper theorizes that green building policy adoption is more likely to occur through imitation or economic competition, rather than through learning.

The diffusion of environmental policies is an evolving topic in the policy diffusion literature. Researchers acknowledge the specificities of environmental policy that complicate the diffusion process. This paper will further explore the possibility of diffusion of climate policy, which is a crucial piece of our understanding of why cities adopt emissions reduction policies.

Climate Risk Amongst the research on the qualities of cities that may cause them to be innovators of climate policy, one understudied relationship is that of a cities' own anticipated risk from climate change and the effect of that risk on a city's climate policy decisions. Mohr's (1969) model of policy adoptions suggests that policy decisions are impacted by the strength of a government's motivation to implement a policy. Under this model, impending negative impacts of climate change could certainly be a motivator for cities to enact policy to combat climate change. As previously mentioned, the impacts of climate mitigation efforts are not localized so there is a false causal relationship between a city reducing GHG emissions and saving themselves from future climate change impacts and costs. That being said, impending climate change effects could provide selective incentives to overcome the collective action problem of climate mitigation (Sharp et. al., 2011).

Some studies have investigated this relationship. In looking at the diffusion of green building policies in US cities, Kontokosta (2011) found that climate zones, which measure the number of very hot or very cold days in a year, are not significant in predicting policy adoption and diffusion. They found an exception in one climate zone, which has a temperate climate, where cities were less likely to implement these policies. Climate zones only measure the historical climate of a city, not the anticipated changes that a location will experience, or the costs that climate change may impose. Lee and Hughes (2017) found that adoption of adaptation measures is influenced by a city's expected climate hazards. For mitigation actions, the effects of climate hazards was less clear in this study. There is a demonstrated relationship between citizens' belief that climate change will threaten their well-being and the willingness of governments to pursue costly climate change policies (Zahran et. al., 2006). Two studies in 2008 looked at the influence of climate risk on cities' decisions to join the Cities for Climate Protection (CCP) program and found conflicting results. One (Zahran et. al.,2008) found that cities most at risk of the adverse effects of climate change are not the same cities adopting significant policy reforms, while the other (Brody et. al.,2008) found that measures of climate risk including coastal proximity and extreme weather are both strong predictors of a city's membership in CCP, indicating commitment to climate protection.

I hypothesize that cities with greater risks of adverse climate change effects are more likely to adopt climate mitigation policies. Though these types of policies impact global processes rather than localized climate conditions, an acute awareness of the negative threats of climate change may be sufficiently powerful for a city's policymakers to override incentives to free ride voluntary climate mitigation measures. Empirical research on the relationship between a city's risk of climate change effects and the adoption of climate change mitigation strategies thus far has been inconclusive. The studies that have directly tackled this question were conducted over a decade ago, at a time when the potential risks of climate change were not as widely understood among the general public, and when cities were not leaders in climate policy to the extent they are now. It is plausible that in the past decade as awareness of climate risks has grown and as our ability to measure them has increased, the anticipation of these risks has bolstered the causal relationship between climate risk and climate policy.

The policy adoption and diffusion literature does not offer unanimous evidence on how climate risk impacts a city's decision to implement forward-thinking climate mitigation policies. Further, more contemporary research is needed to answer this question. In an attempt to do so, this study includes a control variable that represents the predicted climate effects on a city. I hope that this research, by tracing climate policies at a variety of commitment levels, will offer a more definitive answer on the impact of climate hazard on climate action.

III. Research Design

A. Analytic framework

The key question examined in this study is whether the adoption of climate mitigation policies by American cities follows established patterns of policy diffusion despite an inability to measure success of these policies, an apparent roadblock to the standard process of policy diffusion. To answer this question, adoption of three policies that represent climate mitigation action are examined across 67 cities in the United States. Policy adoptions were examined during the years 2000-2019, which is a time period when climate change ascended in the public consciousness (Capstick et. al., 2015) and local policy adoptions in the U.S. seem to parallel this trend. My unit of analysis is the city-year, meaning the action of a specific city in a given year. The key independent variables in this study represent the policy diffusion mechanisms of learning and imitation. The key dependent variables in this study are whether a city adopts a climate mitigation policy.

The policies tracked are adoption of Climate Action Plan, the creation of a chief sustainability officer (or equivalent role), and the creation of a Green Building Policy. These actions all indicate a commitment to Greenhouse gas (GHG) emissions reduction, but vary in magnitude and scope. Looking at multiple policies that indicate different levels of commitment will allow for a more comprehensive understanding of where policy diffusion is and is not occurring. Research has shown that governments are more likely to reach for "low hanging fruit" policies (Sharp et. al., 2011; Wang, 2013) or policies that require lower commitment and are easier to implement. Observing the diffusion patterns of multiple policies of varying magnitude should identify differences between the cities that implement higher/lower commitment level policies.

B. Defining policy choices

A climate action plan is the first policy included in this research, and indicates the highest level of commitment to climate action of the three policies included. Such plans are comprehensive and establish an array of local actions that are meant to achieve emissions reduction targets (Millard-Ball, 2012). The process of developing an emissions reduction plan demands time, financial and personnel investment and requires policymakers to consider the specific actions that are applicable to the local context of their city. Cities whose rationale for climate protection rests in achieving financial co-benefits are less likely to undertake community-wide emissions reduction planning (Krause, 2013), so I theorize that implementation of climate action plans will tend towards cities with authentic goals of climate protection.

New York City implemented one of the earliest and most comprehensive Climate Action Plans in the U.S., titled PlaNYC. This plan was spearheaded by Mayor Michael Bloomberg in 2006 when the city initiated public consultation and strategic planning to meet the long-term goal of reducing New York City's greenhouse gas (GHG) emissions 30 percent below 2005 levels by 2030. PlaNYC utilized a wide array of mechanisms to reduce GHG emissions across the city. The city regulated building codes to improve energy efficiency, set standards for building operations, and banned the use of heavy polluting heating oils in buildings. The plan also enabled changes to the city's energy supply by working with ConEdison to improve efficiency of electricity generation in the city's power plants, and expanded renewable energy mainly through solar power investment (Hughes, 2019). PlaNYC also included provisions to address Brownfield restoration, air and water quality, and public transportation. This far reaching climate action plan is an example of an action from a city that demonstrates high commitment to emissions reduction and is often considered the gold standard for cities.

An alternative example of a climate action plan is the Austin Community Climate Plan. This plan was adopted in 2015 after the city council set the target of reaching net-zero GHG emissions by 2050. This plan focusses on three sectors: Electricity and Natural Gas, Transportation and Land Use, and Materials and Waste Management and contains 130 actions for city departments and the community to reduce their greenhouse gas emissions (City of Austin, 2015). Some examples involve financing mechanisms for improving energy efficiency, bolstering trip reduction programs for large employers and implementing methane gas capture at city owned landfills. Austin has successfully implemented many of the actions that are under the direct purview of city departments and has successfully reduced its carbon emissions since the plan's adoption. Compared to PlaNYC, the aspects of Austin's Climate Plan that are not directly controlled by the government are less enforceable. Many of the components of Austin's climate action plan are exploratory or suggestions, rather than codified and enforceable requirements. Though this plan is not as far reaching as PlaNYC, Austin's climate action plan still has been successful in targeting some of the highest sources of emission in Austin and is promising for reducing emissions.

The second policy examined is city government's creation of a Chief Sustainability officer, or like position. This position takes on a variety of titles in different cities, including Sustainability Manager, Sustainability Director, or Sustainability Coordinator, but for the sake of simplicity this paper will use "Chief Sustainability officer" to refer to these positions categorically. By hiring a city officer who is dedicated to pursuing sustainability, a city is demonstrating some level of prioritization of sustainability. From one view, creating a paid position requires dedication of personnel and resources to the goal of sustainability. On the other hand, simply hiring someone and giving them a title of "sustainability officer" could be simply a symbolic action. While the choice to create a position of chief sustainability officer doesn't require the critical thinking, and context specific planning of an emissions reduction plan, the willingness to dedicate a position entirely to the issue indicates a level of commitment to sustainability.

In some cases, this position takes form as the head of a city department, such as a department of Environment, or office of sustainability. For example, in Washington D.C. the Department of Energy was created in 2005, and a director was appointed, marking the creation of a CSO position. When created, this department was charged with protecting the environment and promoting energy efficiency issues (Washington D.C., 2006). Since its creation, the department has championed new climate policies, including Washington DC's climate action plan and a plastic bag fee. The present director of this department has over 300 environmental professionals working under him on a variety of issues.

In contrast, the first sustainability coordinator of Madison, Wisconsin, was hired in 2018 and is part of the Engineering Division (City of Madison, 2018). She also oversees Madison's climate action plan, but is not part of a larger department that does so. This role involves coordinating a variety of sustainability efforts across city departments, which is very different from a director of a department devoted to the environment. Though these positions are different, both are designated solely to environmentalism in that city, making them a marker of sustainability commitment.

The third policy examined is Green Building Policies, or policies that incentivize or mandate some level of energy efficiency of buildings. Much of the innovation in green building regulations is occurring at the city level, since city government typically has authority over building and zoning codes (Kontokosta, 2011). Within green building policies, there is variation in the intensity of the policy. Some policies are incentives while others are requirements, and some policies apply to only public buildings while others cover private buildings as well. For example, Los Angeles's green building policy, which was adopted in 2008, requires all developments of 50,000 square feet or greater to earn LEED Certification. Additionally, this policy offers an incentive in the form of expedited reviewing for projects seeking the higher level of LEED Silver. This plan is relatively comprehensive and encompasses much of the city's construction. In contrast, the City of Cambridge, Massachusetts, adopted a green building policy in 2002 requiring that any construction or renovation of municipal buildings, including schools, follow LEED guidelines. This policy is less comprehensive as it only applies to municipal buildings. Green building policies tend to be lower commitment than a climate action plan or chief sustainability officer, but constitute a specific and substantive action that might follow from a climate action plan. Though this policy doesn't always indicate high commitment, it is more technical and not as publicly visible as the two other policies.

C. Defining Diffusion

In this study, the learning and imitation mechanisms of policy diffusion are examined. These two mechanisms are often conceptualized as opposing versions of a similar process. Both involve cities adopting a policy based on the actions of peer cities, rather than through coercion or for threats of economic competition. Learning and imitation are contrasted in that learning occurs because of a city's interest in the policy and its effects, while imitation occurs out of an interest in aligning with another city that has adopted the policy which is being imitated. Examining learning and imitation side by side will illuminate the difference between policy adopted out of genuine concern for climate change, and policies adopted for the sake of appearance.

The diffusion mechanisms of Economic Competition and Coercion are excluded from this study. Because my sample consists of 67 cities that are spread across the U.S. and are not always geographically proximate, modeling economic competition becomes much more difficult. Studies of economic competition among subnational governments have often looked at states that share borders, meaning their models are not applicable to a study with geographically dispersed cities. While there are feasible ways in which economic competition may occur in urban climate policy, modeling those applications are not within the scope of the present research. Coercion is also excluded from this analysis. Coercion from the federal level is not occurring in cities in the US. Coercion from the state to city level is possible, but these coercive policies on the state level are uncommon and lack enforcement power. Scenarios in which coercion would play a significant and distinct role in policy diffusion in American cities adopting climate policies are uncommon, so the mechanism of coercion is not included in this analysis.

To measure learning, the proportion of similar cities that have already adopted a policy is used. Learning is more likely to occur between "similar" cities, where policymakers can reasonably assume that a successful policy is transferable to the context of their own city. "Similarity" between cities is conceptualized on two dimensions: geographic region and population size. The proportions of cities within regions and size categories that adopted a policy are measured. If a large proportion of cities in a given region has already adopted a policy, a city in that same region should be more likely to adopt it as well.

To measure imitation, a similar strategy was employed, but the proportion of cities in the size category larger than the city of interest was used, rather than the proportion in the same size category. When imitation occurs, a city is looking to emulate a larger or more acclaimed city. If imitation is occurring, a city will be more likely to adopt a policy if a higher proportion of larger cities have adopted that policy.

D. Key Hypotheses

Learning Hypotheses:

i. A city will be more likely to adopt a policy if a higher proportion of cities in the same region have already adopted that policy.

ii. A city will be more likely to adopt a policy if a higher proportion of cities of a similar size have already adopted that policy.

Imitation Hypotheses:

i. A city will be more likely to adopt a policy when a higher proportion of cities larger than them has already adopted that policy.

Climate Risk Hypothesis

i. Cities with a higher risk of experiencing negative climate change impacts are more likely to implement higher commitment climate mitigation actions like climate action plans.

IV. Data and Measurements

The coming section will cover the specific methodology of this research. It will detail the data sources used in this analysis, the operationalization of all variables, and methods of analysis used.

A. Construction of Sample

Given the challenges of data availability due to the lack of a centralized information source about environmental policies across local governments, using a random sample of cities was not a possibility. Instead, an inductive approach was used in constructing the sample of cities in this study. After selecting the policies that would be analyzed and identifying data sources for each of those policies along with the other variables of interest, I looked at the data that were available and chose cities with consistent data across all of my measures. Any city that had implemented all three policies of interest and was included in the other relevant data sets was included in the sample. I also included cities that were present in all data sets but had implemented two or fewer of the policies of interest. With this method of sampling there is inherent bias. The cities I've selected are ones that have available data, so they are also more likely to have taken action on climate change. In future studies, selecting a random sample of cities would allow for more accurate results, and a more comprehensive data source for local environmental policies would make a study like this possible.

B. Data Collection

The primary data collection was gathering the years of adoption for the three policies examined in this study in a variety of cities. The years of adoption served as the dependent variable and were also used to construct the independent variable. The independent variables are measures of policy diffusion, represented by the proportions of cities that have adopted a specific policy prior to a given year. The equations to calculate these proportions used only the adoption years and identifying information of the cities like their location and population size.

Climate Action Plan. Data on climate action plan adoption came from CDP (Carbon Disclosure Project), which is a nonprofit that encourages cities to disclose environmental data. Cities can opt into disclosing of emissions, climate adaptation and mitigation actions, governing structures and more. CDP also scores cities on their environmental performance to incentivize disclosure and environmental leadership. Data from cities is collected through an annual survey to participating cities, which asks a variety of questions about emissions reduction targets and actions. CDP makes the data they collect from cities available online, which was utilized to identify cities' emissions reduction plans.

In CDP's Open Data Portal, I looked at responses to the Cities 2019 Questionnaire and narrowed the results to cities in the United States who had identified an emissions reduction plan. In 2019, 181 cities in the United States reported to CDP (2019 Cities disclosing to CDP dataset). This is a large enough sample of cities to give us a broad representation of the climate actions of cities in the US. Specifically, the question of interest was question 5.5, asking "Does your city have a climate change mitigation or energy access plan for reducing city-wide GHG emissions?" This question leads to several other related questions, prompting the respondent city to answer about the title and contents of the plan along with the year of adoption, which was used for measuring diffusion[1]. Cities are also asked whether they participated in a stakeholder

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[1] Several data substitutions were made of climate action plan years of adoption from the original data obtained from CDP. Substitutions were based on information in the Portney (2013) book which discussed climate action plans implemented in large cities, the dates of which precede those reported in the CDP data. The following cities' climate action plan years of adoption were substituted: New York City, Philadelphia, Los Angeles, Denver, and Washington D.C.

engagement process to develop their climate action plan. This is another variable of interest, since stakeholder engagement may indicate learning (Wang et. al., 2012). A dichotomous variable was created to capture stakeholder engagement. If a city did stakeholder engagement, it was coded as "1"; if it did not engage in stakeholder engagement or did not answer that question in the survey, it was coded as "0."

Chief Sustainability Officer. To identify the hiring of Chief Sustainability Officers, I started with the Urban Sustainability Directors Network (USDN), a nonprofit that connects sustainability officers in local governments around the United States and Canada. USDN publishes the cities from which they have members on their website, though they do not disclose the names or titles of those members. From their website, I identified the cities that have a member in USDN. I assume that those cities have a Chief Sustainability Officer, or someone of a similar position. The position titles varied but the most common titles were Chief Sustainability Officer, Sustainability Manager, Sustainability Director and Sustainability Coordinator. From a list of common titles for officers of this position, I began to search for documentation of the inaugural hiring of a sustainability officer in each city with a member in USDN. First, I searched on Google for a city government press release or official notice that announced the hiring of the city's first sustainability officer. If an official press release was unavailable, I used Access World News to search for media coverage of the first sustainability officer for a city. I used the Advanced Search feature to narrow the search to publications that were local to the city of interest and used search terms of "City" and "First" with "Sustainability Director," "Sustainability Officer," "Sustainability Manager" or other similar terms. For most cities I was able to locate a press release or news article that definitively announced the first hiring of someone in this position. For cities where I could not find an announcement of the creation of the position, I used the date of the first mention of a sustainability officer in the press as the time of the creation of the position[2].

Green Building Policies. To identify green building policy adoptions, I used the U.S. Green Building Council's Public Policy Library. This is an online search engine of Federal, State and Local policies related to green building and LEED. I narrowed their policy library to the "City/Town/Village" government level, and selected policy types of Requirement of Incentives. Green Building Policies vary significantly in their level of commitment, so I opted to only include requirements or incentives, to ensure a certain level of commitment. I excluded the policy types "Encourage," "Program/Initiative," "Enabling/Authorizing Legislation," and "Goal/Target".

The Public Policy Library database included location, year of implementation, the title of the policy and a policy description. Many cities have passed multiple iterations of green building policies. For the purpose of this study, I am only recording a city's first green building policy adoption that is a requirement or incentive. To assess policy diffusion, the first adoption matters much more than subsequent policy alterations.

Within regulatory and incentive policies, there is still notable variation in level of commitment. To address this variation, the policies being used were ranked on a three-point scale based on their conditions. I included a variable titled "Building Score", for which each city with a green building policy took on a value of 1, 2 or 3 based on the specific terms of their policy. The parameters for these scores are as follows:

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[2] Data substitutions of this kind were used for the following cities' Chief Sustainability Officers: Baltimore, Miami, Oakland, Seattle, Berkeley, Sacramento, Orlando, Burlington.

1	Policies that involved incentives only and no requirements
2	Policies that include requirements, but only apply to municipal or public buildings
3	Policies that include requirements that apply to commercial (or non-municipal) buildings

C. Independent variables: Diffusion Mechanisms

Learning. When operationalizing policy diffusion mechanisms, I relied heavily on Shipan and Volden's (2008) empirical strategy. To operationalize learning, they used the proportion of state population that is already subject to the local policy of interest. This effectively measures the proportion of nearby municipalities that have already implemented a policy. Theoretically, learning is more likely to occur when other cities, especially similar cities have already adopted a policy. If a policy has been broadly implemented in similar cities, policymakers have good reason to believe that policy would succeed in their city. To categorize "similar" cities, categories were created for region and size class, since one can assume cities of the same size or close geographic location may reasonably be similar. I created three categories for population size and used the four designated census regions as geographic categories. This was a natural categorization, since these regions are predefined and used by the census bureau. I created two categorical variables "region" and "population category" and coded each region and population category numerically, as shown below.

Population Size Categories

1	<200,000
2	200,000-500,000
3	>500,000

Region Categories

1	Northeast	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, Pennsylvania
2	Midwest	Indiana, Illinois, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
3	South	Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana Oklahoma, Texas
4	West	Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming, Alaska, California, Hawaii, Oregon, Washington

To define size class, I used population counts from the 2010 decennial census because this year is in the middle of the time frame being analyzed in this study (2000-2019). A fixed region and size categorization was then attached to each city in the sample.

To quantify learning, I used the proportion of cities in the same region and the proportion of cities in the same population group that have already adopted the policy. For each year, each population category and region has a corresponding ratio. The ratio is calculated from the equation below, using the year 2000 and Region 1 as an example.

$$Learning\ Proportion_{\ 2000, Region\ 1} = \frac{\#\ cities\ in\ region\ 1\ with\ year\ of\ adoption < 2000}{Total\ \#\ of\ cities\ in\ region\ \#1}$$

This calculation only includes cities in the region that are also included in the sample. The exclusion of cities is a limitation of this study for capturing diffusion. In practice, diffusion processes may involve any the city in a given area, so by excluding some cities our methodology may fall short of capturing the whole diffusion process. The limitations of data, the same reason for the limited sample of this study, is the reason for the exclusion of other cities in the diffusion ratios. Inclusion of every city in the U.S. would require knowledge of the policies of every one of those cities which was not feasible for this research. To capture the diffusion processes more completely, future research should include a wider sample of cities.

Imitation. To test learning, Shipan and Volden (2008) use a "Nearest Bigger City" variable, which indicates whether the closest city with a larger population than the city in question has already adopted the policy. Because of the limited distribution of cities in my sample, the geographic component of Shipan and Volden's measure is not applicable. Though my sample does include cities in all four census regions of the United States, to further divide the sample into population sizes within regions would have resulted in groups with too few cases to calculate meaningful proportions. Rather, to model imitation a "Proportion of Larger Cities" measure is used. This metric is a proportion of cities that have adopted the policy in the population category larger than that which the city is in. This measure should show the diffusion of policies from larger to smaller cities, which is in line with the theory of imitation.

D. Controls

In addition to policy diffusion, cities' policy adoption decisions may be influenced by a variety of other factors. Studies have demonstrated the importance of considering a combination of internal and external factors when studying policy adoptions (Berry & Berry, 1990). When considering both external and internal factors of adoption, researchers have employed a theoretical framework that considers the relative strengths of motivations and obstacles to environmental action (Mohr 1996, Krause, 2011). This conceptual framework creates space to account for a wide variety of factors. Krause considers a variety of potential motivators and resources to enact climate policy including demographics, income, government type and political leanings. She found state level characteristics were insignificant but that local level characteristics such as demographics, city size, educational attainment, city revenue and political leanings are significant determinants of membership in MCPA. The present paper pulls from past studies which have identified factors that have been shown to influence policy adoption in cities.

These factors are included in this analysis as control variables and are described in the following sections.

Climate Risk. To measure a city's predicted climate impacts, I used data from the Urban Adaptation Assessment (UAA) metric . UAA is led by the Notre Dame Global Adaptation Initiative, which measures a city's overall adaptability to climate change. I chose this data source because it encompasses data from over 270 cities in the U.S., which afforded significant choice in selecting cities. The Global Adaptation Initiative also provides detailed descriptions of their methodology and publishes available data on the sub indicators used. This allowed me to tailor their metric to fit the specific needs of this study without having to recalculate it from scratch.

The Urban Adaptation Assessment metric is composed of "Risk" scores which measure a city's vulnerability to climate change, and "Readiness" scores which measure a city's economic, social and governmental readiness for climate change. Only the risk scores were used in this project since risk represents climate vulnerability. "Readiness" includes components of government actions and would confound my dependent variable of adoption, therefore it was excluded from the analysis.

Risk scores incorporate exposure (number of individuals and critical infrastructure exposed to a climate hazard event), sensitivity (degree to which population of city are affected by climate hazards) and adaptive capacity (city's ability to respond to climate hazards). A lower risk score is better, as it indicates fewer anticipated hazards of climate change. UAA produced risk scores for each of five categories of climate hazards: cold, heat, flood, drought and sea level rise. The indicators that factored into the hazard scores varied depending on the specific hazard, but the overall hazard scores were all on the same scale so they can be averaged together. The risk scores of all five hazards were averaged to produce a city's overall risk score. For each city and each hazard, UAA provides the values of each sub-indicator-- exposure, sensitivity and adaptive capacity. Again, since adaptive capacity incorporated government actions, I recalculated risk scores excluding the adaptive capacity measure.

To recalculate risk scores to only incorporate sensitivity and exposure, I simply averaged the sensitivity and exposure scores for each hazard, and then averaged the resulting scores for all of the hazards together to produce an overall risk score[3].

Ideology and Partisanship. Political factors have also been identified as indicators of climate policy adoption in cities. Political ideology and partisan affiliation are consistent predictors of citizens preferences on environmental issues (Konisky et. al., 2008). Stakeholders with more liberal views are more likely to favor sustainability initiatives (Wang et. al., 2012). Party identification is also a significant motivation for local climate protection initiatives. While partisanship and ideology have historically been independent of one another, in the contemporary context the two are closely related and there is a widening partisan and ideological divide on whether climate change is a big problem (Pew Research Center, 2019). In the U.S., climate protection initiatives, especially those related to Greenhouse Gas emissions reduction, have been characterized by partisanship and are more often favored by Democrats (Krause, 2011). Partisan leaning is shown to be a highly significant predictor of climate engagement, especially for city government climate planning and communitywide climate planning (Krause, 2013). Based on these findings, one may expect that a city with a more liberal leaning population is more likely to adopt climate policies.

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[3] Two data substitutions were made for cities in the sample that were not included in the UAA dataset. Where substitutions were needed, cities that were in a similar geographic location and had a similar population density and landscape were used instead. The risk score of Flagstaff, AZ, was substituted for that of Surprise, AZ, and the risk score of Bloomington, IN was substituted for that of Evansville, IN.

To measure partisan preference across cities, I used the proportion of Democratic votes in presidential elections from 2000-2016. The purpose of this variable is to compare partisan vote shares across cities, and presidential elections ensure uniformity that is impossible to achieve with local election results, as many city governments conduct nonpartisan elections. In local elections, the ideologies of certain Democratic or Republican candidates may vary from place to place. National elections allow for a valid comparison of partisanship in regard to the same candidate in multiple locations.

For this variable, data from the MIT Elections Data and Science Lab was used, specifically from a dataset titled "County Presidential Election Returns 2000-2016." I substituted county level election results for the election results of cities since county-level election returns are more readily available. Although the county level is not a perfect representation of the city, in counties that spread beyond city limits most of the population is typically located within the primary city. I identified the counties that each city was located in and calculated the proportion of votes for the Democratic candidate for president. [4] For the years between presidential election years, the democratic vote percentage from the previous presidential election was used. For example, the percent democratic vote from the 2000 presidential election was used as a control in the years 2000, 2001, 2002 and 2003. In 2004, the variable assumes the percentage of votes from the 2004 election, and so on.

Fiscal Capacity. Many studies have noted that adoption of sustainable policy is more likely in cities with better fiscal capacity (Hawkins et. al., 2016; Homsy & Warner, 2015). Krause (2011) concluded that higher revenue is a significant enabling resource. Sharp and

[4] For cities that are composed of multiple counties, the election results were combined for all counties that make up the city. In Alaska, votes are recorded by districts not counties, so all the districts that make up Anchorage were averaged.

colleagues (2011) used a city's revenue divided by median household income to represent fiscal stress. This study found that higher fiscal capacity, indicating higher revenue, is significantly associated with increased likelihood of membership in the ICLEI climate network. These findings informed my choice of city revenue as a control variable. A city with more financial resources may be more likely to implement a resource intensive policy, but the impact of fiscal resources on policy implementation is not of interest in the present study.

For data on city revenue, the Census Bureau's "Annual Survey of State and Local Government Finances" was used. These datasets provided comprehensive information on local government finances annually. This survey provides a variety of financial indicators, but total revenue was used in this analysis. Local financial data was only available to the year 2017, but my dataset spans up to 2019. To complete the data for revenue up to 2019, the city revenue was interpolated for the years 2018 and 2019 assuming that the values follow a linear pattern.

Population Size. Population size is another form of a "resource" to a city (Krause et. al., 2011; Mohr 1996) that may be correlated with policy adoption. Larger cities may have higher capacity to implement new policies. Krause (2011) found that a city's size was one of the variables with the largest impact on the likelihood of climate commitment. Annual city population size was used as an additional control variable. For annual population estimates for each city in my sample, I used population estimates from the US Census Bureau. These figures were obtained from two separate datasets, one for the years 2000 to 2010[5] and one for 2010 to

[5] U.S. Census Bureau (2012). *Intercensal Estimates of the Resident Population for Incorporated Places and Minor Civil Divisions: April 1, 2000 to July 1, 2010*. Retrieved from https://www.census.gov/data/datasets/time-series/demo/popest/intercensal-2000-2010-cities-and-towns.html.

2018[6]. Linear interpolation was used again to fill in population size data for the final year of the analysis, 2019.

D. Analysis

I chose to use an Event History Analysis (EHA) as my analytical method. Berry and Berry (1990) pioneered the use of this method in policy diffusion research. Event History Analysis, sometimes called survival analysis, is a collection of that seeks to explain the probability of an event occurring. This method is ideal for adoption models that include variables to account for external and internal influences on adoption. EHA has a temporal nature, which makes it useful for analyzing data for which the sequence of events is relevant. This study uses a discrete time model, meaning the period of analysis is divided into distinct units, in this case years (Berry and Berry 1990). Separate analyses were conducted for each of the three climate change mitigation policies in this study, in order to more robustly assess the diffusion of climate change policy.

In EHA, the dependent variable of interest captures whether a city adopts a certain policy in a given year. Three separate dependent variables were used for this analysis, each representing the adoptions of one policy. This makes it so there is one observation per city per year per policy. Each of the three dependent variables is constructed so that it is set equal to 0 for each year that a given city does not adopt the policy. In the year that a city adopts the policy, the dependent variable is set to 1 for that policy.

One of the essential components of EHA is the “risk set” which is made up of the “individuals” that are at risk of experiencing the event of interest (Berry and Berry 1990). In this study the

[6] U.S. Census Bureau (2019). *Annual Estimates of the Resident Population for Incorporated Places: April 1, 2010 to July 1, 2018*. Retrieved from https://www.census.gov/data/tables/time-series/demo/popest/2010s-total-cities-and-towns.html#tables..

"individuals" are cities. The analysis only examines initial policy adoptions, so once a city adopts the policy is it removed from the risk set of that policy (Saikawa, 2013). The risk set decreases each year that at least one city adopts the policy.

V. Results

The three policies were analyzed separately using the Cox Proportional Hazards model. The sample is confined to observations between 2000 and 2019 for the 67 cities included in the study. EHA was run separately for each of the three climate mitigation policies. For each analysis, the risk set was the 67 cities included in the study; once a city adopts a climate mitigation strategy, it is no longer at risk of adopting and cities not adopting a climate mitigation strategy prior to the last year in the data set, 2019, are presumed to be at risk of adopting through 2019.

Table 1 shows all the cities included in the analysis, with the population size and years that each city adopted each of the three policies. The smallest city in the sample, Burlington, Vermont, had a population of about 42,000 and the largest, New York City, had a population over 8 million. There are 22 cities in the sample with a population size less than 200,000 (population size category 1), 24 cities with a population size between 200,000 and 500,00 (population size category 2), and 21 cities with a population greater than 500,000 (population size category 3).

Table 1: Sample Cities by Region

Location			Year of Adoption		
City	State	2010 Population	Climate Plan	CSO	Green Building
Northeast					
Boston	MA	617,594	2014	2005	2007
Buffalo	NY	261,310	-	2012	-
Burlington	VT	424,17	2014	2007	2008
Cambridge	MA	105,162	2015	-	2002
Jersey City	NJ	247,597	-	2018	2009
New Haven	CT	129,779	2004	-	2006
New York City	NY	8,175,133	2007	2006	2005
Philadelphia	PA	1,526,006	2009	2008	2007
Pittsburgh	PA	305,704	2017	2008	-
Portland	ME	583,776	-	2001	2012
Syracuse	NY	145,170	-	-	2007
Yonkers	NY	195,976	-	2012	2013
Midwest					
Akron	OH	199,110	-	-	-
Ann Arbor	MI	113,934	2012	2018	2009
Bloomington	IN	80,405	2018	2010	2009
Boise City	IA	205,671	-	-	-
Chicago	IL	2,695,598	2008	2011	2004
Cincinnati	OH	296,943	2008	2010	2006
Cleveland	OH	396,815	2013	2005	2013
Columbia	MO	108,500	-	2010	-
Des Moine	IA	203,433	-	-	-
Detroit	MI	713,777	-	2017	-
Indianapolis	IN	820,445	2019	2008	2010
Kansas City	MO	459,787	2008	2006	2004
Madison	WI	233,209	2019	2018	2008
Minneapolis	MN	382,578	2013	2005	2006
South Bend	IN	101,168	-	2014	-
St. Louis	MO	319,294	2017	2009	2007
South					
Atlanta	GA	420,003	2015	2008	2003
Austin	TX	790,390	2015	2010	2000

Location			Year of Adoption		
City	State	2010 Population	Climate Plan	CSO	Green Building
Baltimore	MD	620,961	2012	2017	2007
Baton Rouge	LA	229,493	-	-	-
Birmingham	AL	212,237	-	-	-
Charleston	SC	120,083	2010	2009	2008
Dallas	TX	1,197,816	-	2009	2003
Durham	NC	228,330	2007	-	2008
Frisco	TX	116,989	-	-	2006
Hollywood	FL	140,768	2017	2015	2009
Houston	TX	2,099,451	2020	2007	2004
Memphis	TN	646,889	-	-	-
Miami	FL	399,457	2008	2016	2009
New Orleans	LA	343,829	2017	2012	-
Orlando	FL	238,300	2013	2017	-
Richmond	VA	103,701	2012	2009	2009
Washington	DC	601,723	2011	2005	2006
West					
Albuquerque	NM	545,852	-	2019	2005
Anchorage	AL	291,826	2019	-	2008
Berkeley	CA	112,580	2009	2005	-
Billings	MT	104,170	-	-	-
Denver	CO	600,158	2007	2012	2013
Eugene	OR	156,185	2010	2007	2006
Flagstaff	AZ	65,870	2018	2007	2008
Fort Collins	CO	143,986	2015	2012	2006
Fremont	CA	214,089	2012	2013	2010
Honolulu	HI	337,256	2019	2017	2006
Los Angeles	CA	3,792,621	2007	2013	2008
Oakland	CA	390,724	2012	2014	2005
Phoenix	AZ	1,445,632	-	2014	2005
Portland	OR	583,776	2015	2001	2001
Richmond	CA	204,214	2012	2009	2007
Sacramento	CA	466,488	2012	2007	2004
Salt Lake City	UT	186,440	2017	2001	2006
San Diego	CA	1,307,402	2015	2015	2003
San Francisco	CA	805,235	2013	1997	2004
San Jose	CA	945,942	2018	2011	2001

Location			Year of Adoption		
City	State	2010 Population	Climate Plan	CSO	Green Building
Seattle	WA	608,660	2013	2000	2006
Tacoma	WA	198,397	2016	2009	-

In the regional groupings, 12 cities are located in the Northeast, 16 cities are the Midwest, 17 cities are the South, and 22 cities are in the West.

There is variation in how many of the 3 policies each city has adopted. There are also 7 cities included in the analysis that have not implemented any of the three policies. These cities provide variation in the levels of commitment between the cities. Of the remaining cities in the sample, 39 have adopted all 3 of the policies, 15 have adopted 2 of the 3 policies, and 6 have adopted 1 of the 3 policies of interest.

The adoption patterns of the three policies were analyzed separately, with year of adoption as the dependent variable. Thus, the data set includes a varying number of cities and observations in the risk set for the three climate mitigation strategies analyzed. For example, the dependent variable time series for a city adopting a green building plan in 2002 would have 0s for 2000 and 2001, 1 in 2002, and would be excluded from the risk set for the years 2003 – 2019. For cities that did not adopt a green building plan by 2019, the time series for the dependent variable would have no variation; it would consist of a series of 0s starting in 2000 and ending in 2019.

Table 2: Summary Statistics of all variables

	n	Mean	Std. Dev.	Min	Max
Learning Variables (region)					
Climate Action Plan	1,340	.2103	.2255	0	.7727
CSO	1,340	.3657	.2738	0	.8636
Green Building Plan	1,340	.4725	.3113	0	.8636

	n	Mean	Std. Dev.	Min	Max
Learning Variables (population)					
Climate Action Plan	1,340	.2095	.2240	0	.667
CSO	1,340	.3635	.2740	0	.905
Green Building Plan	1,340	.4692	.3194	0	.905
Imitation Variables					
Climate Action Plan	940	.2270	.2368	0	.667
CSO	940	.3754	.2839	0	.905
Green Building Plan	940	.5134	.3235	0	.905
Control Variables					
Total Risk	1,340	.4202	.1268	.1798	.7150
Total Revenue	1,197	3183263	1.13e07	-380292	1.36e08
Total Revenue (w/ interp)	1,340	3398539	1.26e07	-380292	1.86e08
Population Size	1,273	630400.3	1129283	35734	8475976
Population Size (w/ interp)	1,340	632275.2	1130716	35734	8475976
Percent Democrat	1,340	60.54852	12.95325	25.76829	92.45711

For each policy, four models were tested, two testing the learning variables and two testing the imitation variables. The same four control variables are used across all four models. The models are consistent across the analyses of the three policies (i.e. Model 1 uses the same variables in the Climate Plan, CSO, and Green Buildings analyses), with the policy specific variables applied. The Cox Proportional Hazards model also tests the interactions between the time variables that change over time (Learning variables, imitation variable, revenue, population size and Percent Democrat). The rows labeled "TVC" (time varying covariate) show the changes in the effects of the variable over the study period. Only the sign and level of significance is reported in the following tables for the TVC variables.

Model 1 tests the two indicators of learning as independent variables. Model 1 uses interpolated values for total revenue in the years 2018 and 2019, and interpolated values for population size in the year 2019. For revenue and population size, data was not available for the most recent years in our time period, so linear interpolation was used to fill in data points for those variables in the missing years. This method enabled analysis of the entire time period from 2000 to 2019.

Model 2 measures imitation and includes the proportion of larger cities as the independent variable. Model 2 also uses the interpolated values for revenue and population size in the final years of the analysis. The variable for the proportion of larger cities does not have values for cities in the largest size category, since there are no larger cities to imitate. This characteristic of the variable means that the 21 cities in size category 3 are excluded from any analysis that uses the imitation variable. Because of this, model 2 has fewer observations than model 1.

Model 3, like model 1, measures learning, but it does not use the interpolated values for revenue and population size. I chose to use a model without the interpolated values to ensure that the interpolation wasn't influencing the results. This means that model 3 only includes up to the year 2017, so adoptions that occurred in 2018 and 2019 are excluded from the analysis.

The final model, model 4, measures imitation and excludes interpolated values in revenue and population size, and excludes cities in the population category 3. These two factors mean that this model has the fewest observations.

Climate Action Plans. Table 3 presents these 4 models for climate action plan policy adoptions using the Cox Proportional Hazards test. In Models 1 and 3, Regional learning has a negative and significant relationship to adoption of climate action plans, and that the effect of this variable on adoption increases over time. This finding does not support the learning hypotheses. The hazard ratio for the learning variable indicates that the odds of adoption decrease when a higher proportion of cities in that region have adopted that policy, on average, and controlling for all the other factors in the model. The interaction of learning and time (TVC) also indicates that this effect increases with time. The influence of the regional learning variable increases throughout the period of analysis.

City revenue has a negative relationship to adoption in all 4 models, and this relationship was statistically significant in models 1 and 3. The influence of revenue on the odds of adoption also increases over time. In models 1 and 3, population size has a positive relationship to adoption, and the influence of this variable decreased over the time period.

The analysis of climate action plans is the most impacted by the interpolated values included in Models 1 and 2. Climate action plan analyses are the most affected by the interpolation because the adoptions that occur in 2018 and 2019 are in climate action plans. There were 7 cities that climate action plans in the years 2018 and 2019, which are excluded from the analysis when the interpolated data points are not used.

Chief Sustainability Officers. Table 6 shows the results of Chief Sustainability Officer adoptions. The regional learning variable had a positive relationship to adoption and the population learning variable had a negative relationship to adoption, but neither relationships were statistically significant. The imitation variable had a negative influence on adoption and was statistically significant. In the learning models (1 and 3), population size has a negative relationship to adoption and revenue has a positive relationship to adoption; both were statistically significant in Model 1 . The influence of population size increased during the period of analysis. This means that cities with a larger population size are less likely to adopt a CSO, if all other factors are controlled for, and this effect increased from 2000 to 2019.

Green Building Plans. Table 5 shows the effects of all the variables on the adoptions of green building plans. The regional learning and population learning variables both had a positive relationship to adoption in models 1 and 3, but were not statistically significant. The imitation variable had a negative relationship to adoption, though the hazards ratio was small and the relationship was not statistically significant. In the learning models, revenue had a negative and statistically significant relationship to adoption, and there was a statistically significant increase in this effect over time. Population size had a positive relationship to adoption, though it was not statistically significant, and percent democrat had a negative relationship which was also not statistically significant. The number of observations was lowest for the analyses of green building adoptions as many adoptions occurred at the beginning of the time period.

Figure 1: Number of Cities Adopting Climate Mitigation Strategies, 2000-2019

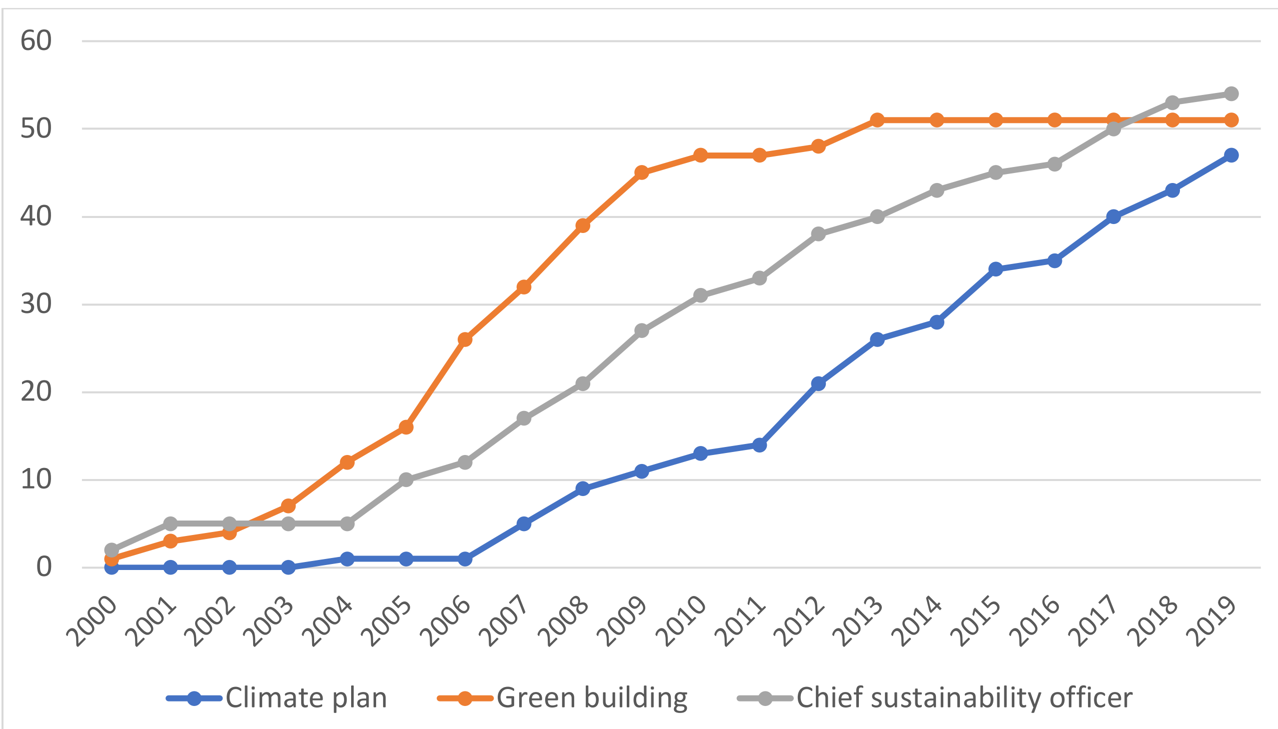

Figure 1 shows the number of policy adoptions by type for each year of the analysis. Green Building Policy adoptions increased most rapidly from 2000 to 2010, and then levelled off in 2013 with no additional adoptions following that. For most of the analysis period, Green

Building Policies are the most common policy to have been adopted until 2017 when Chief Sustainability Officer surpasses it. The number of CSO adoptions increases to 5 and stays steady until it begins to increase in 2005. Climate action plans have the greatest lag, as the number of adoptions doesn't increase above 1 until 2006, at which point the adoptions increase steadily for the rest of the analysis period. Throughout the time period, climate action plans remain the least commonly adopted policy, likely because they are the costliest and require the most commitment.

Figure 2 similarly presents the percentage of cities in each size category that had adopted the policies from 2000 to 2019. Large cities (2010 population above 500,000) have the most policy adoptions overall, followed by medium sized (200,000-500,000) and then small cities (less than 200,000). The trend of green building plan adoptions seems to begin with large cities, followed by medium then small cities, which would be the expected trend if imitation is occurring. In the first half of the analysis, large cities appear to lead in adoptions of climate action plans, though adoptions in mid-sized cities pick up in the final years of the analysis and ultimately surpass the adoptions of large cities. Medium sized cities seem to lag behind both small and large cities in CSO adoptions, but in the last five years of the analysis CSO adoptions seem to level off in small cities while they continue to increase in mid-sized cities.

Figure 2: Percentage of Cities Adopting Climate Mitigation Strategies by Size Class, 2000-2019

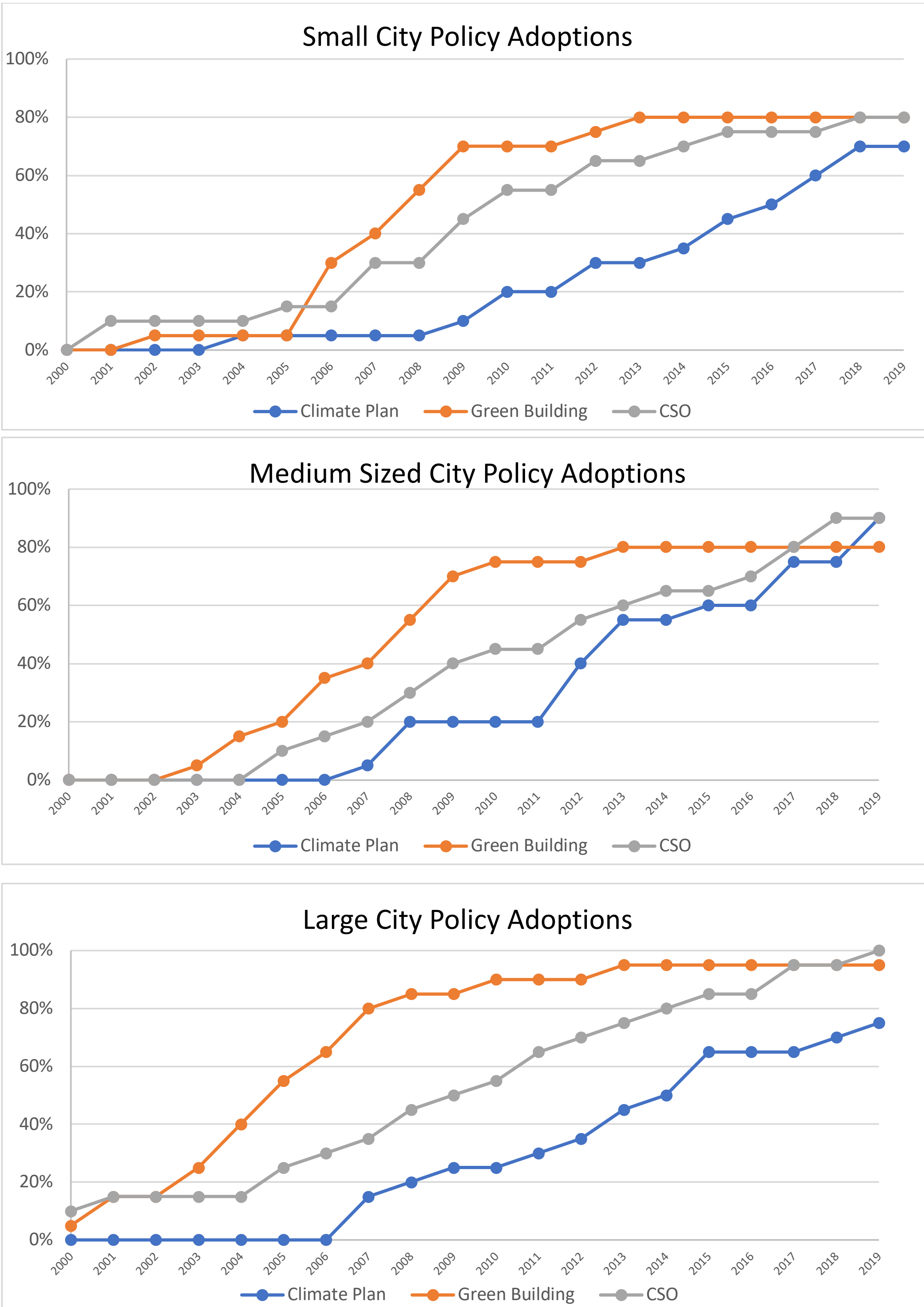

Table 3: Cox Proportional Hazards analyses of Climate Action Plan

	Model 1 Learning[1]	Model 2 Imitation[1]	Model 3 Learning[2]	Model 4 Imitation[2]
Learning				
Region Ratio	- 7.33e-18*** (1.02e-16)		-3.86e-23*** (6.56e-22)	
TVC	+***		+***	
Population Ratio	-.0025 (.034)		-4.58e-7 (6.75e-06)	
TVC	-		-	
Imitation				
Larger Cities ratio		+5.94e10 (9.46e10)		+5.62e13* (9.38e14)
TVC		-		-*
Controls				
Total Risk	-.698 (.034)	-.477 (.945)	+2.765 (6.064)	+2.562 (5.379)
Total Revenue	-.999*** (1.08e-7)	-.999 (2.01e-06)	-.999*** (1.31e-07)	-.999 (2.58e-6)
TVC	+***	+	+***	+
Population Size	+1.002*** (8.13e-7)	-.999 (6.84e-6)	+1.000** (9.22e-07)	-1.000 (7.81e-6)
TVC	-***	+	-*	-
Percent Dem.	-.9914 (.042)	-.976 (.052)	-.981 (.049)	-.954 (.057)
TVC	+*	+	+	+
N	991	709	934	667

Hazard ratios reported with robust standard errors below in parentheses. In rows labeled "TVC" the direction (positive or negative) of the effect of time varying covariates is reported, along with the level of significance.

***p < .01, **p < .05, *p < .1 (one-tailed tests)

[1] With interpolation of missing data
[2] Without interpolation of missing data

Table 4: Cox Proportional Hazards Analyses of CSO Adoption

	Model 1 Learning[1]	Model 2 Imitation[1]	Model 3 Learning[2]	Model 4 Imitation[2]
Learning				
Region Ratio	+4.039 (19.057)		+5.249 (25.904)	
TVC	-		-	
Population Ratio	-.151 (.872)		-.1265 (.786)	
TVC	+		+	
Imitation				
Larger Cities ratio		-7.54e-6* (.000)		-3.38e-6* (.000)
TVC		+		+
Controls				
Total Risk	+1.111 (1.080)	-.445 (.567)	-.981 (.994)	-.441 (.617)
Total Revenue	+1* (2.29e-7)	-1.00 (8.37e-07)	+1.00 (2.30e-7)	-1.00 (9.85e-7)
TVC	-*	+	-	+
Population Size	-.999* (1.98e-6)	1.000 (3.10e-6)	-.999* (1.95e-6)	+1.00 (2.89e-6)
TVC	+**	-	+*	-
Percent Dem.	+1.006 (.026)	-.989 (.035)	+1.013 (.032)	-.994 (.040)
TVC	+	+*	+	+
N	785	579	748	546

Hazard ratios reported with robust standard errors below in parentheses. In rows labeled "TVC" the direction (positive or negative) of the effect of time varying covariates is reported, along with the level of significance.

***p < .01, **p < .05, *p < .125 (one-tailed tests)

[1] With interpolation of missing data
[2] Without interpolation of missing data

Table 5: Cox Proportional Hazards Analyses of Green Building Plan Adoptions

	Model 1 Learning[1]	Model 2 Imitation[1]	Model 3 Learning[2]	Model 4 Imitation[2]
Learning				
Region Ratio	+11.002 (59.984)		+9.868 (53.698)	
TVC	-		-	
Population Ratio	+211.4882 (812.14)		+235.001 (899.148)	
TVC	-		-	
Imitation				
Larger Cities ratio		-.001 (.005)		-.001 (.006)
TVC		+		+
Controls				
Total Risk	+1.010 (.968)	-.274 (.401)	-.996 (.95)	-.274 (.399)
Total Revenue	-1.000* (1.66e-7)	+1.000* (1.82e-06)	-1.00* (1.65e-7)	+1.00* (1.82e-6)
TVC	+*	-	+	-
Population Size	+1.000* (7.71e-7)	+1.000 (3.10e-6)	+1.000* (4.15e-06)	+1.00 (4.15e-6)
TVC	-	+	-	+
Percent Dem.	-.964 (.027)	-.989 (.035)	-.956 (.036)	-.956 (.036)
TVC	+*	+*	+	+*
N	640	504	602	470

Hazard ratios reported with robust standard errors below in parentheses. In rows labeled "TVC" the direction (positive or negative) of the effect of time varying covariates is reported, along with the level of significance.

***p < .01, **p < .05, *p < .125 (one-tailed tests)

[1] With interpolation of missing data
[2] Without interpolation of missing data

VI. Discussion:

Previous scholarship has found environmental policies do diffuse in the American context, but research has not looked specifically at the diffusion of climate mitigation policies in cities. The findings from this analysis suggest that climate mitigation policies in American cities do not follow the conventional patterns of policy diffusion. Our analysis showed that a city's likelihood to adopt a Climate Action Plan significantly decreases for cities in regions where a higher percentage of cities have already adopted such a plan and that this effect strengthens with time. This finding goes against the conventional patterns of the influence of learning on policy adoption, in which policies spread to other cities within the same region. This effect may be explained by cities' desire for recognition as leaders and pioneers on climate change, so if their peers have already implemented a strong policy, they are disincentivized from implementing those same policies. Another possibility is that cities are less likely to adopt strong emissions reduction policies when nearby cities have already done so, because they assume the actions of a nearby city are sufficient to mitigate climate change in that region. This relationship strengthens with time, which could be because as time goes on and an increasing number of cities in the region adopt climate action plans, the remaining cities see the surrounding actions as sufficient, and don't see the purpose in implementing their own climate action plan.

In CSO adoptions, the effects of the learning variables on the odds of adoption were not statistically significant related to the learning variables, but there was a negative and significant relationship between adoption of a CSO and the imitation variable. When controlling for all other variables, the odds of a city adopting a CSO position decreases when a higher proportion of cities in the population size class larger than them have adopted the position already. Figure 2 can help contextualize this finding. Small cities adopted the CSO position earlier than medium-sized cities, which would suggest that small cities are not imitating their mid-sized counterparts in the adoption of this policy. Additionally, the results from the learning models show that as a city's population size increases, their odds of adopting a CSO position decreases, and that this relationship strengthens over time. This also could be because of the relative popularity of CSO policies among small cities. Hiring someone to the position of CSO may be an attractive policy option for small cities because the person in that position can act a point person for a variety of sustainability problems or initiatives. Hiring someone to this position doesn't commit resources to any specific policy but may lead to further sustainability initiatives.

Ordering of the policy adoptions in the three size classes provides important context for our results. Across all size classes, Green Building Plans, which were the lowest commitment policy, were adopted first followed by CSO and then climate action plans, the highest commitment policy that was analyzed. Small cities adopted CSO and Green Building Plans early, and even led mid-sized cities in the number of CSO adoptions for much of the time period, while Climate Action Plan adoptions lagged more in small cities. Green Building Plans and CSOs are relatively lower commitment, so they may be seen as a good starting point for smaller cities with fewer financial resources. CSO adoptions tended to come before climate action plan adoptions and this could be because hiring someone to this role is the first step towards a more robust emissions reduction plan for cities. Further research would be needed to determine the relationship between the hiring of a Chief Sustainability Officer and implementation of substantive mitigative actions like a climate action plan, but it seems like this relationship may exist.

The Cox Proportional Hazard model is designed to remove a city from the analysis after it adopts a policy. This element of the model means that when a large portion of adoptions occur early in the time period, the number of observations in the analysis is smaller, which restricts the potential for statistically significant results. Green building plans were adopted earliest in the time period, and thus the analysis of these policies includes far fewer observations than the analysis of climate action plans, which were generally adopted later in the analysis period. The smaller number of observations in the analysis of green building plans could be the reason for the lack of statistically significant results for this policy. Extending the period of analysis or increasing the sample of cities could help mitigate this problem in future research.

For all three policies, total city revenue had a negative effect on the odds of adoption in the learning models but a positive effect in the imitation models. The switch in direction of influence in the two types of models, and consistency of this pattern across all three policies is noteworthy. The largest sampling difference between the learning and imitation models is the exclusion of the largest size class of cities in the imitation models. This makes up about one third of the sample, so the exclusion of these cities could have a noticeable impact on the results. One should not compare magnitude and significance of variables in two models run on different samples, since one cannot know if the differences are due to inclusion of different predictors or different composition of the sample. This would suggest that the influence of revenue is more negative among large cities, and more positive among small and medium cities. An explanation is that small and medium cities with relatively fewer resources choose to adopt climate policies more based on resource availability, while larger cities with more resources are motivated by other factors.

Our results indicate that the climate risk variable is not a statistically significant predictor of climate policy adoption, which contradicts the Climate Risk Hypothesis. Several factors may account for this. First, this variable was included in the models as a time invariant factor, though it is conceivable that a city's climate risk may change over time. Additionally, the measure of climate risk that was used may be less precise for analyses at the city level than higher levels of geographies such as states, regions, or nations. Research hasn't explicitly addressed the question of whether climate risk determines climate commitment. Emissions reduction measures don't impact the future climate risks experienced in a specific place, but rather contribute to global processes. It's possible that cities understand this, and logically choose not to act based on their own personal climate risk. Our climate risk variable measured the actual risk that a city is expected to experience. It is possible that perception of risk is a more important aspect in policy adoptions. Environmental interest groups are unaccounted for and could play a significant role in policy adoption as well. Public perception of environmental issues has been shown to be important, and environmental activism and lobbying may be a determinant of climate policy adoption.

Prior literature on policy diffusion of climate mitigation policy has almost exclusively observed a city joining a TMN as a commitment to climate mitigation. Very few studies prior studies have looked at adoptions of multiple specific climate mitigation policies, as this paper does. This study only looked at 3 climate mitigation policies, but to draw conclusions about the adoption and diffusion patters of climate policy, it would be useful to examine a broader range of policies that have been adopted by cities. A study that pools the adoptions of many policies would capture a picture of the trends in cities' climate policy adoptions generally. This study also did not account for variation in the level of commitment associated with specific policies that may go by the same general title in different cities. For example, some climate action plans set more ambitious goals than others, so considering the specificities of every policy would provide a more comprehensive view of the true commitment levels of cities. To better capture the processes of diffusion, future studies should account for the differences between specific policies and include a wider sample of cities than was used in this study.

VII. Conclusion

In this thesis, the adoptions of climate action plans, chief sustainability officers, and green building plans were analyzed in 67 American cities to determine the influence of policy diffusion and climate risk on adoption.

This study found that diffusion is not occurring with climate policy in American cities in the same way t have seen with other types of policy. This shouldn't be surprising, as climate policy presents a relatively new challenge with unique features. It appears that a city's own climate risk also does not incite climate policy action. Still, there is more to learn about the ways that cities perceive of their own climate risk, and how that perception influences their actions.

The collective action feature of climate mitigation policy distinguishes it from other categories of policy adoption and presents a new challenge in conceptualizing diffusion of such policies. In tackling such a new and unknown policy problem, intergovernmental cooperation can be hugely beneficial. Arguably, there has never been a policy problem that exists on as large a scale as climate change. This is a global issue and trying to tackle it locally comes with obstacles. In this unique circumstance, collaboration is crucial for local governments to accomplish their goals.

More research is needed to fully understand the motivations behind a city's choice to take mitigative climate action. Despite a lack of incentives to do so, cities around the world are working to enact innovative emissions reduction programs. It is worthwhile for researchers to work to understand the motivations of cities that are taking these actions, to encourage strong climate action among governments. Especially in the American context where federal action is lacking, encouraging the pursuit of climate action at the local levels is of the utmost importance.

Appendix A

An initial analysis was performed using a Rare Event Logistic regression, which is a variation on the traditional logistic analysis for datasets where the occurrence of an event is infrequent. The results from that analysis are displayed here.

Relogit Analyses of Climate Action Plan

	Model 1 Learning[1]	Model 2 Imitation[1]	Model 3 Learning[2]	Model 4 Imitation[2]
Learning				
Region Ratio	5.7401*** (2.128)	-	5.56** (2.232)	
Population Ratio	1.354 (1.965)	-	2.027 (2.114)	
Imitation				
Larger Cities ratio	---	6.414*** (.822)	---	6.500*** (.8192)
Controls				
Total Risk	2.490 (2.593)	1.754 (2.955)	3.037 (2.751)	2.568 (3.009)
Total Revenue	1.69e-8 (3.84e-8)	3.92e-08 (5.06e-7)	1.42e-08 (3.70e-08)	-1.81e-07 (5.98e-07)
Population Size	7.92e-11 (4.25e-7)	-1.97e-07 (2.04e-06)	5.07e-08 (4.04e-07)	1.93e-07 (2.06e-06)
Percent Dem.	.0534 (.0235)**	.0422* (.026)	.0434* (.025)	.0319 (.027)

Coefficients reported with Robust Standard Error below in parentheses.

***p < .01, **p < .05, *p < .100 (one-tailed tests)

[1] With interpolation of missing data
[2] Without interpolation of missing data

Relogit Analyses of CSO adoptions

	Model 1 Learning[1]	Model 2 Imitation[1]	Model 3 Learning[2]	Model 4 Imitation[2]
Learning				
Region Ratio	3.363** (1.697)		3.247* (1.736)	
Population Ratio	1.945 (1.806)		2.049 (1.833)	
Imitation				
Larger Cities Ratio	---	3.543*** (.745)	---	3.491*** (.840)
Controls				
Total Risk	-1.022 (1.836)	-1.136 (1.864)	-1.039 (1.831)	-1.140 (1.854)
Total Revenue	3.34e-8 (3.79e-8)	3.61e-07 (6.12e-07)	4.16e-08 (3.86e-08)	3.67e-07 (5.99e-07)
Population Size	-1.68e-7 (3.55e-7)	-1.27e-06 (2.45e-06)	-2.39e-7 (3.58e-07)	-1.33e-06 (2.48e-06)
Percent Dem.	.0488** (.021)	.031 (.023)	.0436** (.021)	.025 (.023)

Coefficients reported with Robust Standard Error below in parentheses.

***p < .01, **p < .05, *p < .100 (one-tailed tests)

[1] With interpolation of missing data
[2] Without interpolation of missing data

Relogit Analyses of Green Building Policy adoptions

	Model 1 Learning[1]	Model 2 Imitation[1]	Model 3 Learning[2]	Model 4 Imitation[2]
Learning				
Region Ratio	3.215* (1.672)	-	3.102* (1.595)	
Population Ratio	1.769 (1.660)	-	1.904 (1.582)	
Imitation				
Larger Cities ratio	---	3.245*** (.741)	---	3.319*** (.745)

Controls				
Total Risk	-1.026 (1.814)	-1.492 (2.136)	-.936 (1.777)	-1.451 (2.078)
Total Revenue	-3.85e-08* (2.24e-08)	6.12e-07 (7.31e07)	-4.89e-08 (3.11e-08)	5.72e-07 (7.92e-07)
Population Size	6.67e-07* (3.51e-07)	-4.59e-07 (2.12e-06)	7.13e-07* (3.77e-07)	-1.91e-07 (2.19e-06)
Percent Dem.	.025 (.020)	.032 (.025)	.020 (.020)	.028 (.025)

Coefficients reported with Robust Standard Error below in parentheses.

***p < .01, **p < .05, *p < .100 (one-tailed tests)

[1] With interpolation of missing data
[2] Without interpolation of missing dat

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