Fiscal and Environmental Stress and Local-Level Climate Change Policy Innovation: A Multi-level Event History Modeling Approach

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Broadly speaking, the paper seeks to provide insight into the questions of whether and when municipalities innovate by adopting new (to them) local-level climate change policies. This study implements a multi-level hazards model to explain climate policy innovation through time (2005-2012) by US cities with populations greater than 100,000 located in the eastern region of the United States. The response variable indicates a municipality's signage of the United States Conference of Mayors Climate Protection Agreement. The explanatory variables include: (1) a fiscal stress component (annual municipal unemployment rate, median household income); (2) spatial diffusion component (number of signatory cities within 100 mile radius of each city for each year) (2) environmental stress components (annual hazard index compiled for floods and droughts, population density and coastal location); (3) environmental health (frequency of air quality violations, EPA air quality index); (4) state-level action (state level climate action plan adoption, political party of governor and renewable energy portfolio standard). The variables indicating the structure of local government (mayor vs. city manager), population size, and percent of population with a Bachelor's degree were also included in the models. Using two types of generalized linear models (logit and complementary log-log links), the hazard models were estimated. Across all models, the results indicate that the political party of the mayor, local-level air quality, and the interaction between these two variables, as well as population density, were highly significant in predicting the odds of signing the agreement, given no prior signage. The relationships between coastal location, presence of drought (negative relationship) and floods (positive relationship) with policy adoption were found to be moderately significant in some of the models, although not conclusively so. The models produced little to no evidence that fiscal stress (as measured by unemployment rate) and spatial diffusion of policy innovation is statistically significantly associated with local-level climate change innovation. The fixed- and random-effects multi-level models suggest that state-level adoption of a renewable portfolio standard may be negatively associated with local-level climate change policy innovation, all else constant. These preliminary results suggest that further multi-level, event history analysis of these relationships may be warranted with an expanded dataset across the United States with further refinement of the explanatory and response variables, while using a more robust approach to deal with missing data.

Introduction

This paper, broadly cast, examines the multi-level factors driving municipal climate policy innovation. As of 2012, over one thousand municipalities in the United States have agreed to voluntarily reduce greenhouse gas (GHG) emissions by signing the United States Conference of Mayors Climate Protection Agreement. The number of municipal signatories has increased from 141 in 2005, 600 by 2007 to over 1,000 in 2012, suggesting that over 400 mayors agreed to GHG reductions during the worst national-level economic climate in decades. A number of studies have addressed why local governments agree to take such voluntary innovative action, but to date, these studies have been limited to static analyses by examining whether or not (dichotomous variable) a particular policy was changed or adopted over some time period (Krause, 2011; Sharp et al., 2011; Lubell et al., 2009). A static, cross-sectional modeling approach ignores the time-varying dynamics behind local-level policy innovation and therefore frequently ignores time-varying covariates that may offer increased leverage in predicting policy adoption. In this paper I attempt to expand beyond the question of *whether* a city adopts a new climate change policy, but *when* the city takes this action. Employed in several studies on policy innovation (Berry and Berry, 1990), discrete-time event history modeling (referred to here as hazard modeling) offers a method to incorporate year-to-year changes both in the response variable (likelihood of policy adoption, given that the policy has yet to be adopted) and the explanatory variables. In developing these models, I hope to provide insight into the time-constant and time-varying drivers that might help explain the occurrence of policy innovation.

Building on the multi-level model of Krause, (2011), as well as other studies in local-level policy adoption (Sharp et al., 2011; Lubell et al., 2009; Feiock et al., 2010; Rohan et al., 2008), this paper employs a more dynamic multi-level event history (hazard) model to investigate potential factors influencing municipal climate change policy innovation through time: fiscal stress, environmental stress and state-level climate action. The dataset for this preliminary analysis includes all municipalities with populations greater than 100,000 (as of 2005) located in the eastern region of the United States[1]. As far as I am aware, this paper is the first to implement a multi-level event history (hazard) model to more clearly identify the driving forces behind municipal policy innovation in climate change mitigation.

Local-level Policy Innovation

Policy innovation is defined as the adoption of a new policy by a specific government entity (in this case a municipal government), even though this new policy might have been adopted by other (local, state, etc.) governments (Berry and Berry, 1999; 2007). Policy researchers have attempted to explain and predict policy innovation in the United States both at the state and local levels (Berry and Berry, 1990; Berry and Berry, 1999; Feiock and West, 1993; Glick and Hays, 1991; Krause, 2011; Godwin and Schroedel, 2000; Bery and Berry, 2007; Feiock et al., 2010; Sharp et al., 2011). Several researchers

[1] States include New Hampshire, Massachusetts, Connecticut, Rhode Island, New York, New Jersey, Pennsylvania, Delaware, Maryland, Virginia, North Carolina, South Carolina, Georgia, and Florida.

have investigated policy adoption and innovation in the environmental policy realm, particularly in the subfields of sustainability practices (Lubell et al., 2009) and climate change policy (Krause, 2011; Feiock, Francis and Kassekert, 2010; Sharp et al., 2011). In each of these studies, potential factors explaining or predicting policy innovation were examined. The question of why municipalities voluntary adopt climate change policies when they gain no direct climate change benefit due to the global nature of the phenomenon remains a theoretically interesting question (Krause, 2011a; 2011b). When benefits of a policy adoption are dispersed across many actors, Olson's logic of collective action suggests that actors are not likely to individually take on the costs of producing a highly dispersed benefit (Krause, 2011a; 2011b; Olson, 1968). However, a municipality may accrue co-benefits from policy adoption—such as decreased air pollution, being perceived as a policy entrepreneur, or potential cost savings by preparing for future mandatory GHG reduction requirements—potentially motivating municipalities to voluntarily adopt climate change policies. Explanatory factors of the occurrence of climate change policy innovation investigated in past studies range from the health of a city's finances (Krause, 2011a; Sharp et al., 2011), the level of climate vulnerability or stress (Zahran et al., 2008); poor air quality (Krause, 2011a); policy innovation by neighboring municipalities (Krause, 2011a); state-level climate policy action (Krause, 2011a); interest group pressure (Sharp et al., 2011; Zahran et al., 2008); and local-level institutional arrangements (Sharp et al., 2011; Feiock et al., 2010; Krause, 2011a). Again, all of these studies employed a static, cross-sectional analysis, while I attempt a hazard modeling approach to tease out these contributions of these factors in explaining local-level climate change policy adoption. In this study I focus on three groups of potential explanatory variables: fiscal stress, environmental stress and state-level actions.

Fiscal stress

A city's fiscal stress may encourage policy innovation through potential co-benefits of policy adoption (e.g., increased savings due to energy efficiency). Alternatively, with heightened levels of unemployment and dwindling municipal budgets, economic-focused policies may out-compete climate issues on municipal agendas. Krause's (2011) study suggests that a municipality's general revenue is a statistically significant predictor of the likelihood of local-level climate change innovation. Similarly, Lubell et al., (2009) found that local-level per capita tax revenue has a statistically significant effect on the adoption of local-level adoption of sustainability policies in California's Central Valley. Somewhat contradictory to these findings, Sharp et al.'s (2011) model of municipality membership to ICLEI (International Council on Local Environmental Initiatives) , an organization of local-level institutions that provides support to encourage local-level sustainability, suggests that higher levels of fiscal stress is associated with increased likelihood of joining ICLEI's climate change mitigation program. In this program, cities agree to voluntarily make reductions in CO2 emissions in exchange for technical support in doing so. One possible explanation for these findings is that cities under increased fiscal stress seek out participation in climate change programs as a cost-savings measure (Sharp et al., 2009). In addition to a municipality's own fiscal health, adoption of climate-mitigating policies by neighboring cities may affect a city's relative costs and benefits of policy adoption (Krause, 2011), calling for a need to model the spatial diffusion of local-level policies through time when examining the role that fiscal stress plays in policy innovation.

Environmental stress

Environmental stress may work through two avenues in affecting the likelihood of climate change policy innovation. First, the co-benefits of environmental health improvements (e.g., air quality) may motivate local-level climate policy innovation. Secondly, the occurrence of localized natural hazards such as droughts and floods may influence the likelihood of voluntary local-level GHG reductions. While acting alone, a city's reduction in GHG emissions should not affect the probability of climate-driven events. But, that said, such extreme events may increase the local-level salience of climate change as an issue in need of action, potentially strengthening the political feasibility of local-level climate change policy adoption. Sharp et al., (2009) found that 'problem definition', as measured by proxies of level of manufacturing in a city and population density, did not statistically significantly predict climate change policy adoption. Zahran et al., (2008) suggest that casualties from hazards (r=0.134) and amount of coastal area (r=0.115) are positively associated with an MSA's participation in the Cities for Climate Change Protection Campaign (CCP). However, in a more robust OLS regression, Zahran et al. (2008) found that an index of climate risk (precipitation, eco-sensitive area and coastal area) was not significantly associated with CCP participation, while an index of climate stress (based on population density, carbon use, and an automobile transportation measure) was found to be statistically significant. In this paper I include a measure of air quality, a binary variable for coastal cities, dichotomized variables of drought and flood occurrences and population density in an attempt to capture the role of environmental stress in motivating or discouraging local-level climate change policy innovation. Because climate change is often a partisan issue (Dunlap and McCright, 2008; Krause, 2011a), it makes intuitive sense that the effect of environmental stress on policy innovation may be mediated by the political party of the mayor. Further, the structure of the local-level government (mayor-council vs. city manager-council) may also affect the likelihood of policy innovation (Krause, 2011a; Feiock et al., 2010; Sharp et al., 2011) and therefore should be explicitly included in the models.

Multi-level action

Greenhouse gas mitigation efforts at the state level may either encourage or inhibit municipal policy action. State-level policy adoption and political climate may provide the impetus or incentives for cities to innovate (Feiock and West, 1993). Alternatively, mayors may view action at the state level as adequate and therefore be reluctant to take additional measures. In a call for future research, Krause (2011a) recommends the use of an event history multi-level model to study these dynamics. Krause (2011a) did not find state-level characteristics such as the presence of a state climate action plan, a greenhouse gas target, level of manufacturing industry in the state or a measure of 'liberal government ideology' to be statistically significant in explaining local-level signage to the US Conference of Mayors Agreement. However, in studies of state-level effects on local-level policy adoption in other policies arenas, a significant state-level effect has been found, such as in a study of state-level recycling programs and their effect on adoption of local-level recycling programs (Feiock and West, 1993). A multi-level hazard modeling approach may provide insight into the presence or absence of any state-level effect on local climate change policy adoption.

Methods

This longitudinal study implements a multilevel hazards model to explain climate policy innovation through time (2005-2011) by US cities with populations greater than 100,000 located in the eastern portion of the United States. The response variable is the signage of the United States Conference of Mayors Climate Protection Agreement. The time-varying explanatory variables include: (1) a fiscal stress component (annual municipal unemployment rate; median household income); (2) spatial diffusion component (percentage of signatory cities (of all cities >100,000) within 100 mile radius of each city for each year) (2) environmental stress components (flood, drought and population, coastal location and population density); (3) environmental health co-benefits (frequency of air quality violations, EPA air quality index); (4) state-level action (state level climate action plan adoption, presence of a state-level renewable portfolio standard and the political party of the governor) and (5) other demographic variables (government structure of municipality, political party of mayor, level of education of residents). The variables are listed in Table 1. Descriptive statistics of the response variable and covariates are listed in Table 2.

Signatory to the United States Conference of Mayors Climate Change Agreement

The model includes all municipalities with population sizes exceeding 100,000 as of the year 2005 that are located in the eastern portion of the United States[2]. The binary response variable indicates the signage of the US Conference of Mayors Climate Change Agreement that was established in 2005. This agreement signifies a municipality's voluntary goal to reduce greenhouse gas emissions at the level of the Kyoto Protocol agreement (7% reduction of greenhouse gas emissions from the 1990 levels by 2012) (US Conference of Mayors, 2012). A list of municipal signatory municipalities is available on the US Conference of Mayors website, however, the year each municipality signed the agreement was not available from the organization. As a result, internet searches of individual municipal websites were performed to determine the year each municipality signed the agreement. In the sample for this study (68 municipalities total), 13.2 % signed the agreement in 2005, 48.5% by 2006, 64.7% by 2007, and 86.7% by the end of 2011.

One of the weaknesses of this paper is that for some municipalities it was unclear, for example, if they signed in either 2006 or 2007. In these cases, a missing value was assigned to the earlier year and a value of one was assigned the later year. The year with

Table 1. Description of Variables.

Variable	Description and source of data	Time-varying covariate
Response variable		
Signatory to the US Conference of Mayors Climate Change Agreement	US Conference of Mayors, Climate Change Protection Center, individual municipal websites, phone calls.	Yes
Explanatory variables		
Municipal-level		
Population (log)	Logged value of annual population. Source: US Census Bureau.	Yes
Median household income (log)	Logged values of median household income (2006-2010). Source: US Census Bureau	No
Unemployment rate (log)	Seasonally adjusted January unemployment rate for each city for each year 2005-2011. Source: Bureau of Labor Statistics.	Yes
Education (log)	Percentage of individual’s (25+) in a municipality that hold a Bachelor’s degree or higher (2006-2010). Source: US Census Bureau.	No
Political party of mayor	Binary variable (Democrat = 1; Republican or other=0). Source: Municipal websites.	Yes
Form of municipal government	Binary variable (Mayor-Council=1; or other=0) Source: Municipal websites.	
Number of unhealthy air quality days for sensitive populations (log)	Number of days per year that a municipality’s air quality was rated unhealthy for sensitive populations. Source: USEPA Air Quality Index.	Yes
Neighbors	Percentage of municipalities within a 100-mile driving distance that have signed the agreement. Source: Google Maps/US Conference of Mayors.	Yes
Coastal	Binary variable. 1=if a municipality is located within five miles of the Atlantic coast; 0 if not.	No
Drought vulnerability	Binary variable. 1 = if a municipality is located in a region that was rated either extreme drought or severe drought in the Palmer Drought Severity Index in July of each year; 0 if not. Source: National Climatic Data Center, NOAA.	Yes
Flood vulnerability	Binary variable. 1 = if a municipality is located in a region that was rated either extreme drought or severe drought in the Palmer Drought Severity Index in July of each year; 0 if not. Source: National Climatic Data Center, NOAA.	Yes
Population density (log)	Calculated from the land area of each municipality and the annual population.	Yes
State-level		
Political party of governor	Binary variable (Democrat=1; Republican or other = 0). Source: State websites.	Yes
Climate Action Plan	Binary variable (1=climate action plan; 0 = no plan). Source: USEPA.	Yes
Renewable energy portfolio standard	Binary variable (1=renewable energy portfolio standard; 0=no renewable energy portfolio standard)	

Table 2. Descriptive Statistics of Explanatory Variables (Across all years 2005-2007).

Explanatory variables	**Mean**	**Standard Deviation**	**Observations**
Municipal-level			
Population (log)	12.12	0.603	237
Median household income (log)	10.72	0.241	237
Unemployment rate (log)			
Education (% population with Bachelor's) (log)	3.21	0.389	237
Political party of mayor (Democrat=1; Republican or other=0)	0.669	0.472	169
Form of municipal government (1=mayor-council; 0=other)	0.473	0.500	237
Number of unhealthy air quality days for sensitive populations (logged)	2.50	1.02	232
Neighbors (% of municipalities within 100 miles driving distance participating in agreement)	0.483	0.379	237
Coastal (located within 5 miles of coast)	0.409	0.493	237
Drought vulnerability	0.143	0.351	237
Flood vulnerability	0.0886	0.285	237
Population density (logged)	7.95	0.950	237
State-level			
Political party of governor (Democrat=1; Republican or other=0)	0.414	0.493	14 states 237 obs
Climate Action Plan	0.421	0.495	14 states 237 obs
Renewable energy portfolio standard	0.738	0.440	14 states 237 obs

the missing value was excluded from the model estimation because of list-wise deletion for the results shown in Tables 3 and 4. The models were also run on the subset of cities with only complete information for all years (up to the signage) and these are displayed in Appendix I. In future analysis, additional follow-up phone calls will be made to all municipalities to identify the exact date of agreement adoption.

Fiscal Stress and Neighboring Municipality Components

Two measures (both fairly blunt proxy measures) of fiscal stress were included in the models: the seasonally adjusted January unemployment rate for each year for each municipality (US Bureau of Labor Statistics) and the median household income for the time period (averaged over 2006-2010) provided by the US Census Bureau. To capture the level of participation in the climate change agreement of a city's neighbors of similar size, an annual percentage of cities within 100 mile driving radius that were signatories to the agreement was calculated. Google Maps was used to calculate the driving distances between each of the cities. The municipal unemployment rate (logged) and percentage of neighbors that were signatories in any given year were both included in the models as time-varying covariates.

Environmental Stress (Climate and Environmental Health Components)

Three measures of climate vulnerability were included in the model: coastal vulnerability, and drought and flood occurrence. The binary coastal variable captures whether a municipality is located within five miles of the Atlantic coast. The dichotomous drought and flood occurrence variables were derived from the July (of each individual year) Palmer Drought Severity Index produced by the National Climatic Data Center at National Oceanic and Atmospheric Administration (NOAA)[3]. This index rates regions of each of the states on a scale of extreme drought to extreme moisture. If a city was located in a region of extreme or severe drought, the drought vulnerability indicator variable was denoted a one (all others zero), while a municipality located in a very moist or extremely moist region, the value of the dichotomous flood variable was designated a one. All of these measures, except for the coastal variable, are time-varying covariates in the models.

State-Level Component

Three variables were used to capture a potential state level effect on local-level climate change policy innovation. These variables included the annual political party of the governor (1=Democrat, 0=Republican or other); the adoption of a renewable energy portfolio standard (rps) (0/1); and the adoption of a climate action plan (0/1). All three of these measures are time-varying covariates used to explain the conditional probability of signing the agreement, given that the city has not signed the agreement in previous years.

[3] National Oceanic Atmospheric Administration (NOAA) 2012. State of the Climate, National Climate Data Center. http://www.ncdc.noaa.gov/sotc/drought/, Last Accessed October, 2012.

Hazard Modeling/Event History Approach

Based on the suggestion in Krause (2011), I use a hazard modeling (also called survival analysis or event history approach) to provide insight into the relationship between the variables described above and the probability that a municipality will join the US Conference of Mayors climate change agreement. More specifically, discrete-time hazard models the conditional probability of an event occurring, given that it has not occurred previously (Rabe-Hesketh and Skrondral, 2012; Berry and Berry, 1990). This conditional probability is termed the discrete-time hazard rate. Similar to past studies (Krause, 2011), the event to be modeled is the signage of the US Conference of Mayors climate change agreement. This study diverges from previous work by explicitly including the timing of this policy innovation in the model. The dataset was constructed in such a manner that each row of data represents one year for a specific municipality up to and including the year that the city signed the agreement. Data for years after a particular municipality signed the agreement were not included in the dataset. This type of data format is frequently called unit of analysis-time period data (sometimes person-period). Also included in the dataset are municipalities that have yet to sign the agreement (as of 2011)—hazard analysis allows for these right-censored data to be included in the study.

This hazard modeling approach permits the inclusion of time-constant and time-varying covariates—one of its greatest strengths (Rabe-Hesketh and Skrondal, 2012). In this particular study, some of the covariates vary through time (air pollution, unemployment, population, political party of the mayor, etc.), while other variables remain constant (coastal location, government structure, median household income). I employ a discrete-time model (as opposed to continuous) in this paper, with the time unit being one year (for each year 2005-2011).

Discrete-time survival analysis can be estimated via generalized linear modeling for dichotomous response (logit link) using maximum likelihood estimation. Dummy variables were used to signify each year (omitting the first year), and therefore requires no specific functional form of the relationship between the discrete-time hazard and the years (Rabe-Hesketh and Skrondal, 2012). However, we do assume the ratio of odds (or the difference of log odds) of signing the agreement, given that they haven't signed previously between municipalities with differing covariates is constant through time (Rabe-Hesketh and Skrondal, 2012: 760).

In addition to the logit-link models described above, I estimated the same models using a generalized linear model with a complementary log-log link using maximum likelihood estimation (Table 5). Using this modeling approach frees us of the proportional odds assumption required in the logit-link models. Building on this hazard modeling approach, I incorporate a multi-level modeling technique (in Models 4 and 5) by incorporating state-level effects (both random intercept and fixed effects). A random-intercept complementary log-log model (generalized linear model with complementary log-log link) was used estimate Models 4 and 5 in Table 4. By using dummy variables for the discrete time intervals, it is not necessary to make assumptions about the shape of the discrete-time hazard function (Rabe-Hesketh and Skrondal, 2012: 778).

Table 3 Modeling Results from the Generalized Linear (Logit-Link) Hazard Models

Variable		Model 1: Demographics	Model 2: Neighbors/Fiscal Stress	Model 3: Environmental Stress
Intercept		Odds Ratios (Robust Standard Errors)		
Dummies for years				
Municipal Variables				
Population (logged)		1.89 (5.45)***	2.06(0.418)***	2.59 (0.768)***
Unemployment (logged)		1.17(1.21)	0.393(0.700)	1.51 (2.39)
Education (logged)		3.61(2.84)	4.45(3.76)*	18.9 (18.33)***
Median Income (logged)		0.299 (0.289)	0.16(0.163)*	0.090 (0.111)*
Political Party of Mayor (1=Dem; 0=Other)		32.6 (35.49)***	36.1(42.5)***	0.0117 (0.015)***
City Government		5.04 (6.11)	5.12(6.40)	52.3 (64.21)***
Interaction: Political Party of Mayor*City Gov.		0.151(0.138)**	0.166(0.165)*	0.0236 (0.0298)***
Neighbors			1.61(3.74)	
Interaction: Neighbors*Unemployment(logged)			2.04(3.22)	
Unhealthy Air Days (Sensitive Populations) (logged)				0.014(0.0107)***
Interaction: Mayor*Unhealthy Air Days (Sensitive)				45.5(31.17)***
Coastal				3.45(2.47)*
Drought Vulnerability				0.327(0.218)*
Flood Vulnerability				3.20(1.94)**
Population Density (logged)				2.53(0.911)***
State-Level Variables				
Fixed Effects				
Political Party of Governor				
Climate Action Program				
Renewable Portfolio Standard				
Constant		0.0356 (0.354)	16.00(179.9)	1.149(14.28)
Log Likelihood		-66.28	-62.7	-49.5
AIC		1.310	1.302	1.188
Efron's Pseudo R2		0.226	0.256	0.412

*p<0.1; **p<0.05; ***p<0.01, robust (clustered) standard errors are in parentheses.

Table 4 Complementary Log-Log Hazard Model Results

Variable	Model 4 Demographics	Model 5 Neighbors/Fiscal Stress	Model 6 Environmental Stress	Model 7 Multilevel Fixed State Effects	Model 8 Multilevel CLL Model Fixed Effects and Random Intercepts
Municipal Variables	Exp(β) Hazard Ratios	Exp(β) Hazard Ratios	Exp(β) Hazard Ratios	Exp(β) Hazard Ratios	Exp(β) Hazard Ratios
Population (logged)	1.62 (0.287)***	1.80 (0.296)***	2.12 (0.459)***	1.88(0.462)**	1.88(0.706)*
Unemployment (logged)	1.19 (0.898)	0.541(0.647)	1.36 (1.36)	0.757(0.818)	0.757(0.822)
Education (logged)	2.41(1.61)	3.10(2.01)*	8.31(5.53)***	9.58(8.60)**	9.59(8.74)**
Median Income (logged)	0.431(0.411)	0.248(0.240)	0.174(0.139)**	0.0714(0.0766)**	0.0714(0.0922)**
Political Party of Mayor (1=Dem; 0=Other)	17.97(17.88)***	19.89(21.46)***	0.0303(0.0280)***	0.0157(0.0149)***	0.0157(0.0317)**
City Government	4.19(4.87)	3.88(4.71)	22.91 (20.00)***	20.79 (22.51)***	20.79 (34.44)*
Interaction: Political Party of Mayor*City Gov.	0.183(0.160)**	0.222(0.218)	0.0548 (0.0535)***	0.0769(0.0867)**	0.0769(0.134)
Neighbors		1.97(4.71)			
Interaction: Neighbors*Unemployment(logged)		1.52(1.60)			
Unhealthy Air Days (Sensitive Populations) (logged)			0.0358 (0.019)***	0.0314(0.0213)***	0.0314(0.0330)***
Interaction: Mayor*Unhealthy Air Days (Sensitive)			19.49(9.80)***	22.96(14.17)***	22.96(23.44)***
Coastal			2.573(1.17)**	4.220(2.23)***	4.220(2.68)**
Drought Vulnerability			0.426(0.205)*	0.497(0.341)***	0.497(0.348)
Flood Vulnerability			2.98(1.40)**	3.30(1.83)**	3.30(2.49)
Population Density (logged)			2.00(0.591)**	2.71(0.626)***	2.71(1.06)**
State-Level Variables					
Fixed Effects					
Political Party of Governor				1.02(0.889)	1.02(0.626)
Climate Action Program				2.15(1.53)	2.15(1.63)
Renewable Energy Portfolio Standard				0.277(0.153)***	0.277(0.213)*
Log Likelihood	-65.63	-62.4	-48.7	-46.67	-46.67
AIC	1.316	1.297	1.175	1.201	
Efron's Pseudo R2	0.224	0.261	0.416	0.438	

1*p<0.1; **p<0.05; ***p<0.01, robust (clustered) standard errors are in parentheses.

Results and Discussion

The results of the eight models are reported in Tables 3 and 4. Table 3 contains the results of the hazard modeling using the generalized linear model (logit link) while Table 4 includes the results from the complementary log-log models, as well as those with the multilevel fixed and random effects. Looking generally across all eight models, the magnitude of the coefficients, as well as their level of statistical significance of the coefficients remains fairly constant. The environmental stress model, as well as the multi-level models, achieved the best fit statistics (minimized the log likelihood, minimized AIC and maximized the pseudo-R2 values). The demographic (control) variables of population size (logged) and political party of the mayor remained consistently statistically significant across all models, while the type of government structure was found to be statistically significant in the environmental stress and multilevel models. These results are consistent with previous findings suggesting that the structure of local institutional arrangements may matter in predicting the propensity towards policy innovation. Further, the findings of the political party of the mayor align well with the significance found of the percentage of Democratic voters of a municipality and its probability of climate change policy innovation, as determined by Krause (2011a). Unlike in the analysis by Krause (2011a), the level of statistical significance of the education coefficient varied across all models.

Fiscal Stress and Participation by Neighbors

In the introduction, I posited that fiscal stress may either encourage climate change policy innovation as a cost-savings measure (increased efficiency) or discourage adoption because of other municipal concerns taking priority. I included two admittedly rough measures of fiscal stress: unemployment rate (time-varying) and median income (time constant) in the models. The unemployment rate (log) remained consistently statistically insignificant across the models, while the median household income (log) was only found to be significant (at alpha = 0.05) in the environmental stress model (Models 3 and 6, Tables 3 and 4). These results do not align with the findings of Krause (2011a) and Sharp et al., (2011: 447). Further, counter to Krause's findings (2011a), I did not find significant evidence that the level of participation by neighboring cities is associated with a municipality's propensity to participate in the agreement (Models 2 and 5 in Tables 3 and 4, respectively). Moreover, the interaction between unemployment rates and level of participation by neighboring cities was also found to be insignificant. These results in total may suggest that either the variables used to capture fiscal stress (unemployment and household median income) may be inadequate in capturing this concept or that the relationship between fiscal stress and climate change policy innovation becomes more tenuous or weakens when using a more time-dynamic modeling approach. In future extensions of this preliminary study, I hope to include a more robust and meaningful time-varying measure of fiscal stress, such as a municipality's per-capita general revenue, as used in the study by Krause (2011).

Environmental Stress

Five variables were used to capture environmental stress experienced by municipalities in my models: air quality (number of days USEPA deemed hazardous for sensitive populations); coastal location; population density and measures of drought and flood occurrence. The model estimates provide moderate-to-strong evidence in support of a statistically significant relationship between level of air quality and likelihood of local-level climate change innovation. Of these five variables, air quality remained highly statistically significant across models, with a negative relationship between the natural logarithm of the number of days polluted and the odds of adopting the climate change policy. The interaction between political party of the mayor and the air quality variable was also highly statistically significant ($p<0.001$). These results potentially indicate that when a Republican (or other non-Democrat) serves as mayor, the odds of signing the agreement decrease with increasing air pollution, holding all else constant. Alternatively, with a Democrat in mayoral office, the odds of signing the agreement increases with an increase in the log of the number of air pollution days, holding all else constant (estimated odds ratio of the interaction is 45.5 (Table 3)). The significance, directionality and relative strength of these relationships remain fairly consistent across the one-level logistic and complementary log-log models, as well as the two-level state fixed- and random-effects models.

The reduction of greenhouse gas emissions through the adoption of a climate change policy, may, as a side benefit, improve local-level air quality (Betsill, 2001; STAPPA/ALQAPCO, 1990). Municipal leadership may connect the two issues of local air quality and climate change (Betsill, 1990). Local-level leadership on climate change may be in part dependent on political ideology, suggesting the effect of air quality on policy innovation may be mediated by the political party of the mayor. Studies assert that beliefs about climate change in the US electorate are diverging by political party (Dunlap and McCright, 2008), and the percentage of Democratic voters in a municipality has been found to be positively lsignificantly statistically related to local-level climate change policy adoption (Krause, 2011a). Stemming from this logic and my modeling results, Democratic mayors may be more willing to link the issue of local air quality to local-level climate change action, as compared to Republican mayors. While my results are preliminary and are based on data from only the eastern states of the United States, I find the significance of these relationships intriguing and worthy of future study.

The environmental health/air quality stress results herein differ from those found by Krause (2011a) in which she did not find a significant relationship between number of unhealthy days and likelihood of signing the US Conference of Mayors agreement. Possible explanation of the difference in findings include: (1) I only examine states in the eastern portion of the United States; (2) I used the number of unhealthy days for sensitive populations as opposed to the general population; and (3) differences in modeling approach between event history modeling versus logistic modeling; and (4) differences of timeframe of the study; (5) differences in explanatory variables used in the models—e.g., Krause (2011a) included a measure of manufacturing production. In future studies, I plan to use a lagged air quality variable to further tease out the relationship and timing between poor air quality and climate change policy adoption, along with a control variable for manufacturing intensity.

An additional measure of environmental stress, the logged value of population density was found to be a statistically significant positive predictor of the occurrence of policy innovation, contrary to the results of Sharp et al., (2011: 447). In my model, as the log of population increases, the probability of policy adoption (given previous non-adoption) increases, holding all else constant. In addition, the models indicate that the coastal variable is positively statistically significantly related to local-level climate change adoption, all else constant. Unlike the significance of the air quality and population density measures, the relationship between the drought and flood indicators and local-level policy adoption remain unsettled in my models. Generally speaking, the flood measure was found to be positively related to policy adoption, while drought was negatively associated, all else constant. However, in the multi-level random and fixed-effects model, both of these variables became insignificant (Model 5, Table 5). These results suggest further study is needed before any solid conclusions can be asserted. A more fine-grained and nuanced measure of flood and drought occurrence may aid to teasing out these relationships, as well as time-lagged measures of drought and flood.

State-Level Fixed and Random Effects

As discussed above, states may motivate or discourage policy innovation at the local level by providing incentives or obstacles to policy adoption (Krauss, 2011a). The influences of state-level effects on the local-level in this study are mixed in these results. The multi-level fixed effects and random- and fixed- effects models suggest that a state's adoption of a renewable energy portfolio standard is negatively associated with a municipality's likelihood of signing the climate agreement, given that they have not previously signed the agreement. If these results were to remain constant with additional, more robust modeling, one might assert that a state's adoption of a renewable energy portfolio standard may act as a disincentive to local-level climate policy adoption, all else constant. A state's adoption of a climate change plan was not found to be statistically significant, similar to the findings of Krause (2011a). Additionally, the political party of a governor was determined to be statistically insignificant across the two multi-level models. The random effects component of Model 8 was not statistically significant, and the fit statistics did not suggest much improvement in model fit as compared to the multi-level fixed effects model.

Conclusions and Future Directions

Over the past few years there has been an increasing number of studies local-level adoption of climate change policies (Krause et al., 2011a; 2011b; Sharp et al., 2011) and sustainability policies (Lubell et al., 2009). Most, if not all, of these studies employ a cross-sectional, static modeling approach (typically OLS, logistic or tobit analysis). Using a multi-level hazard model methodology to explain climate policy innovation through time (2005-2012) by US cities with populations greater than 100,000 located in the eastern region of the United States, I hoped to provide additional insight into the questions of whether and when municipalities choose to enter into the US Conference of Mayors Climate Protection Agreement. Ignoring the obvious and numerous shortcomings of this initial, preliminary multi-level hazard analysis for now, I argue that these models provide preliminary evidence that environmental stress indicators, and in particular air quality measures, may be significantly associated with local-level climate change policy adoption. Further, and perhaps more importantly, it appears that this effect may be mediated by the political party of the sitting mayor when the agreement is signed.

These results align well with the argument that mayors may adopt a climate change policy, in part because of co-benefits received (such as potential air quality improvements). Further, I argue the effect of air quality on policy adoption is mediated by the political party of the sitting mayor. Alternatively, the models provide little to no evidence to suggest that fiscal stress (as measured by unemployment rate), is significantly related to local-level policy adoption. Nor did the models demonstrate that policy adoption by nearby neighbors effects or is associated with policy adoption. The state-level effect of renewable energy portfolio standard adoption had a significant but negative effect on local-level climate change policy innovation. I assert that the modeling approach undertaken in this project may provide insights not possible by more traditional cross-sectional approaches.

While some of these preliminary results may prove interesting, the results are not ready to be sung from atop Mt. Sinai for all to hear. First, the dataset providing the backbone of this analysis is limited to large cities in the eastern portion of the United States. It is my hope to extend this study beyond this region to across all of the US. Second, missing data in several of the variables, including the response variable, may limit the predictive strength of the model, and even worse, may embed some bias into the coefficient estimates. In future analysis, more effort will be extended to minimize the missing data. Additionally, more complex approaches to deal with missing data (such as multiple imputation) will be implemented. Third, and potentially most problematic, the response variable of signage of the US Conference of Mayors Climate Change Agreement may not be a very accurate or indicative measure of actual local-level climate action. It is one thing to sign a voluntary agreement that imposes no penalties for non-compliance, it is quite another for a municipality to adopt on-the-ground greenhouse gas reductions. Future modeling should attempt to incorporate a more nuanced measure of actual climate action (Sharp et al., 2011; Feiock and Francis, 2010).

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APPENDIX I

Table 5 Complementary Log-Log Models on the Reduced Data Set

Variable	Model 1: Demographics	Model 2: Neighbors/Fiscal Stress	Model 3: Environmental Stress	Model 4: Multilevel Fixed State Effects
Municipal Variables	Exp(β) Hazard Ratios	Exp(β) Hazard Ratios	Exp(β) Hazard Ratios	Exp(β) Hazard Ratios
Population (logged)	2.74 (0.877)***	2.86 (0.859)***	3.78 (1.57)***	3.70(6.24)
Unemployment (logged)	2.14 (2.80)	1.86(2.93)	3.91 (6.24)	0.251(1.43)
Education (logged)	7.78(8.07)**	9.85(9.36)**	91.41(155.6)***	1340.8(4490.1)**
Median Income (logged)	0.128(0.148)*	0.0511(0.0635)	0.106(0.148)	0.0001577(0.000766)**
Political Party of Mayor (1=Dem; 0=Other)	9.48e7(1.07e8)***	5.41e7(6.23e7)***	297(1224)	0.0111(0.0760)***
City Government	2.49e7(3.05e7)***	3.88(4.71)	6354170 (1.07e7)***	3.71e8 (3.04e9)***
Interaction: Political Party of Mayor*City Gov.	3.06e-8(4.11e-8)**	6.96e-8(8.51e-8)	0.0548 (0.0535)***	8.72e-8(5.94e-7)**
Neighbors		8.60(34.2)		
Interaction: Neighbors*Unemployment(logged)		0.555(1.42)		
Unhealthy Air Days (Sensitive Populations) (logged)			0.00767 (0.0104)***	0.0000468(0.000095)***
Interaction: Mayor*Unhealthy Air Days (Sensitive)			44.76(42.7)***	3520(6069)***
Coastal			5.44(4.75)*	77.4(109.5)***
Drought Vulnerability			0.188(0.173)*	0.532(0.171)**
Flood Vulnerability			1.29(0.996)	2.24(1.64)
Population Density (logged)			4.677(4.512)	31.8(87.7)
State-Level Variables				
Fixed Effects				
Political Party of Governor				8.63(55.7)
Climate Action Program				39.4 (59.9)**
Renewable Energy Portfolio Standard				0.0155(0.017)***
Log Likelihood	-31.48	-30.5	-20.9	-17.50
AIC	1.151	1.176	1.077	1.066
Efron's Pseudo R2	0.327	0.356	0.538	0.635

*p<0.1; **p<0.05; ***p<0.01, robust (clustered) standard errors are in parentheses.